Dancing in the Dark: Sentiment Shocks and Economic Activity*

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Abstract

The business cycle is driven by expectations—some justified, some not—as documented by a host of studies. What is less clear are the conditions that make the economy susceptible to "sentiment shocks." In this paper, we document that uncertainty, as measured by forecaster disagreement, is essential. At times when disagreement is low, sentiment shocks hardly matter for economic activity but are fully absorbed by prices. If, instead, disagreement is high, they move activity with little impact on prices. We obtain these results based on time-series data and a theoretical account based on a New Keynesian model with dispersed information.

Keywords: belief shocks, noise shocks, animal spirits, business cycles, nowcast errors, disagreement, dispersed beliefs

JEL classification: C32, C34, D84, E21, E23, E32

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1. Introduction

Economic fluctuations are, to no small extent, caused by non-fundamental shocks. These shocks come with various labels, such as noise, animal spirits, or sentiment shocks, yet the underlying notion is similar. It traces back to Pigou (1927) and Keynes (1936) and has been substantiated more recently in quantitative work (for instance, Blanchard, L'Huillier, and Lorenzoni, 2013; Angeletos and La'O, 2013; Lagerborg, Pappa, and Ravn, 2023). Ultimately, such shocks matter because economic actions are based on expectations, which, in turn, are prone to errors or coordination failures and may even become self-fulfilling. In what follows, we refer to this class of shocks as "sentiment shocks". The conditions under which they materialize are likely to affect how they unfold: if there is significant uncertainty—measured by forecaster disagreement—economic activity is potentially more susceptible than when there is little uncertainty about the state of the economy.

In this paper, we thus ask how such disagreement shapes the economic impact of sentiment shocks. Our identification strategy follows Enders, Kleemann, and Müller (2021) and is centered around the nowcast error for output growth. Sentiment shocks induce a negative co-movement between the nowcast error and output: This sets them apart from fundamental shocks and rationalizes the sign restrictions we impose on a VAR model that we estimate on U.S. time-series data. The key contribution of this paper is to allow the effect of sentiment shocks to vary with uncertainty, measured by forecaster disagreement. We find that uncertainty is indeed crucial for how sentiment shocks unfold: in normal times, a sentiment shock has no effect on economic activity and is fully absorbed by rising prices. In contrast, during periods of high uncertainty, economic activity responds strongly while prices remain unchanged.

We rationalize the evidence in a stylized noisy information model à la Lorenzoni (2009). In the model, aggregate technology is not directly observed and forecasts are based on private information and public signals. If aggregate technology becomes more volatile and, hence, uncertain, agents base their expectations more on the signals instead of relying on priors. As a result, the weight on noise in the public signal also increases, resulting in more dispersed expectations—effectively, more "dancing in the dark." In this situation, the model predicts—consistent with the evidence—that economic activity reacts more strongly to random fluctuations in the signal, which operationalizes the notion of a sentiment shock.

More in detail, our empirical analysis is based on a two-step approach. In the first step, we identify sentiment shocks using a bivariate VAR model that incorporates quarterly observations of the nowcast error and output over the 50-year period from 1969 to 2019. The nowcast error is defined as the difference between actual output growth and the median estimate reported in the Survey of Professional Forecasters (SPF) in real time. As a measure of real-time misperceptions, it provides us—ex post—with an informational advantage that is key to identifying sentiment shocks (Blanchard, L'Huillier, and Lorenzoni, 2013).

Importantly, the nowcast errors are only due to sentiment shocks; they may just as well reflect fundamental shocks. Still, we use the nowcast error to identify sentiment shocks, which are distinctive in causing a negative co-movement between output and the nowcast error. For example, an expansionary shock due to an unexpected change in total factor productivity generates a positive nowcast error: output expands and turns out higher than expected, a positive nowcast error obtains.[1] In contrast, a favorable sentiment shock leads perceived growth to overshoot actual growth (resulting in a negative nowcast error) while simultaneously providing a boost to economic activity. Building on this insight, we use sign restrictions to identify sentiment shocks (Enders, Kleemann, and Müller, 2021; Chahrour, Nimark, and Pitschner, 2021).

We move beyond existing work on the effects of sentiment shocks by employing a smooth-transition VAR model, which allows the effects of shocks to vary with the degree of disagreement among forecasters—measured by the cross-sectional interquartile range of individual output growth nowcasts in the SPF. Based on the empirical cumulative density function within our sample, we define two polar regimes of high and low disagreement, allowing for a smooth transition between them. In the second step, we use the sentiment shocks identified in the VAR to estimate their effects using state-dependent local projections. This approach allows us to conveniently expand the set of macroeconomic indicators while consistently accounting for regime dependence.

The central result of our analysis is that the effect of sentiment shocks differs depending on the level of disagreement among forecasters. When disagreement is high, a sentiment shock leads to a significant increase in output that persists for about

[1] This feature is not specific to productivity shocks but is a general property of nonsentiment, or fundamental shocks. Furthermore, the effects are symmetric: A generic contractionary shock induces a decline in output and, at the same time, a negative nowcast error if the shock is not fully observed in real time. The assumption of symmetry extends to sentiment shocks as well.

four to five years. At the same time, we find that sentiment shocks have virtually no effect on prices, provided that disagreement is high. In terms of magnitude, we find a sizable effect: a sentiment shock that implies an overprediction of current output growth by one percentage point increases output by two percent after two years. In contrast, when uncertainty is low, an expansionary sentiment shock has little impact on output. Instead, it is absorbed by rising prices, which increase by approximately 1.5 percent after two to three years before gradually returning to their pre-shock level.

We find that these outcomes are robust to various modifications of the analysis and detect similar patterns across a range of macroeconomic indicators. Consumption and investment increase in response to sentiment shocks when disagreement is high but remain unresponsive or even decline when disagreement is low. We also find that monetary policy reacts to a sentiment shock by raising the federal funds rate in the low-disagreement regime, which helps explain the (mildly) recessionary effect in this case.

The model we put forward to rationalize the evidence is a version of the dispersed information model of Lorenzoni (2009). A key feature of the model is that households and firms do not observe aggregate productivity at the time of decision making. Instead, they rely on expectations, or more specifically, nowcasts, which they form based on a public signal and private information, extracted, in turn, either from their own productivity (firms) or from observed prices (households). We simplify the original model by assuming predetermined (rather than staggered) prices and solve it in closed form: We can show that the response to sentiment shocks varies with the level of disagreement. Intuitively, the optimal weights placed on signals depend on the perceived uncertainty regarding aggregate technology. When the volatility of aggregate productivity is (perceived to be) high, expectations become more responsive to signals and, thus, more sensitive to the noise in the public signal, which corresponds to aggregate sentiment shocks. Specifically, firms overestimate aggregate productivity and, therefore, expect competitors' prices to be lower following an expansionary sentiment shock, leading them to reduce their own prices. Under a mild condition, this boosts output while markups decline. At the same time, households expect better fundamentals and increase consumption accordingly.

The paper is organized as follows. The remainder of the introduction places the paper in the context of the literature, clarifying its contribution. The next section uses a stylized setup to fix ideas and to set the stage for the empirical analysis, for which we develop a framework in Section 3. Section 4 reports the empirical results. Section 5 rationalizes the findings using the dispersed information model. The final section concludes.

Related Literature. Our paper relates to several strands of the literature. First, the existing literature has examined how uncertainty affects the transmission of shocks, with particular emphasis on the effects of fiscal and monetary policy. A robust finding is that policy measures tend to be less effective when uncertainty is high, typically measured using conventional proxies of macroeconomic or financial uncertainty (Aastveit, Natvik, and Sola, 2017; Castelnuovo and Pellegrino, 2018; Hauzenberger, Pfarrhofer, and Stelzer, 2021). Uncertainty, and the state of the economy more broadly, also matter for the transmission of uncertainty and TFP shocks (Lhuissier and Tripier, 2021; Gambetti et al., 2023; Antonova, Matvieiev, and Poilly, 2024). Like us, Ricco, Callegari, and Cimadomo (2016) and Falck, Hoffmann, and Hürtgen (2021) highlight state-dependent effects based on disagreement. However, their focus is on fiscal and monetary policy, and they find that lower degrees of disagreement give rise to stronger effects, possibly due to more effective policy communication. In contrast, we investigate the conditions under which non-fundamental shocks unfold. Our contribution is distinctive in that we provide not only new evidence but also a theoretical account.

More importantly, our focus is distinct as we investigate how disagreement shapes the transmission of sentiment shocks. This is of particular relevance in light of a second strand of the literature that tries to gauge the importance of news and "noise" for business cycle fluctuations, with partly conflicting results (Beaudry and Portier, 2006; Beaudry, Nam, and Wang, 2011; Schmitt-Grohé and Uribe, 2012; Barsky and Sims, 2011; Barsky, Basu, and Lee, 2015; Benhima and Poilly, 2021). Against this background, it is important to condition the effect of sentiment shocks—broadly understood—on the extent of disagreement since it is indicative of the extent of information frictions which, in turn, give rise to sentiment shocks in the first place.

In addition, the concept of news shocks and their link to noise shocks is further clarified by Chahrour and Jurado (2018). We also relate to the paper by Levchenko and Pandalai-Nayar (2020) who identify a "sentiment" shock, which is orthogonal to surprise and news technology shocks. Similarly, we highlight the importance of sentiment shocks in driving the business cycle.

Finally, our work connects to the literature on how public signals shape coordination and welfare. Seminal work by Morris and Shin (2002) and Angeletos and Pavan (2007) show how public information acts as a coordination device in environments with strategic complementarities. Follow-up work in New-Keynesian settings yields mixed welfare implications (Hellwig, 2005; Walsh, 2007; Ehrmann and Fratzscher, 2007; Cornand and Heinemann, 2008), and Angeletos, Iovino, and La'o (2016) stress that the answer depends on the source of aggregate fluctuations. We contribute by providing the first empirical test of when coordination motives actually bite.

2. Fixing ideas

To set the stage for the empirical analysis, we fix ideas and sketch why, in theory, uncertainty matters for how sentiment shocks unfold. Specifically, we zoom in on the signal-extraction problem, which is central to the model in Section 5 below. Firm productivity features both an aggregate and an idiosyncratic component. In real time, firms do not observe aggregate technology, $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, directly. Instead, each firm receives a private signal $a_i = \varepsilon + \eta_i$, which contains idiosyncratic noise $\eta_i \sim \mathcal{N}(0, \sigma_\eta^2)$. By construction, idiosyncratic noise averages out in the aggregate. Firms also observe a public signal, $s = \varepsilon + e$, which is noisy as well, with $e \sim \mathcal{N}(0, \sigma_e^2)$. The disturbance e represents the noise shock, the effects of which we seek to identify below.

In this context, the optimal estimate of aggregate technology is given by

$$\mathbb{E}_i[\varepsilon | s, a_i] = \rho s + \delta a_i = (\rho + \delta)\varepsilon + \rho e + \delta \eta_i,$$

with

$$\rho = \frac{\sigma_\eta^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_e^2 \sigma_\eta^2}{\sigma_\varepsilon^2}} \qquad \delta = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_e^2 \sigma_\eta^2}{\sigma_\varepsilon^2}}.$$

Hence, the impact of both signals on expectations increases in σ_ε^2: if uncertainty is high, firms pay more attention to the signals instead of relying on their prior (which is zero in this case). This has two implications. First, the dispersion of expectations, given by $\delta^2 \sigma_\eta^2$, increases. Second, the impact of the shock on expectations also rises, via a higher ρ.

This matters for economic activity because expectations feed back into the decisions of households and firms. Specifically, as we show formally in Section 5, the increase in uncertainty raises expectation dispersion and amplifies the effect of sentiment shocks on economic activity.[2]

3. Empirical framework

This section presents our empirical framework, explaining how we identify sentiment shocks in a non-linear setting and how we estimate state-dependent local projections. We allow the sentiment shocks to depend on the level of disagreement. For that, we define two polar regimes of disagreement and discuss the regime allocation based on the disagreement series. Before doing that, we introduce the data.

3.1 Data

We use quarterly data for the US, ranging from 1969Q4 to 2019Q4 for a set of macroeconomic quantities: output, nowcast errors of output, the dispersion of nowcast errors, consumer prices, the federal funds rate, the S&P 500 index, and various sub-components of output. We use final-release data from the Bureau of Economic Analysis (BEA) for real gross domestic product to measure output. Nowcast errors of GDP growth are computed as the difference between BEA's actual first-release output growth rate and the equivalent SPF survey nowcast.[3] We measure the dispersion of nowcasts, or disagreement, based on the interquartile range of the participants' forecasts in the SPF for output growth in the current quarter.[4] The remaining variables are relatively standard, and we provide further details in Appendix A.1.

[2] Note that it does not matter whether this is a real or merely perceived change. In a similar vein, Gemmi and Mihet (2023) investigate the impact of uncertainty on household expectations about inflation, distinguishing between uncertainty due to higher volatility of the fundamental or due to higher volatility of the signals (noise).

[3] For the SPF nowcasts of output, we use the series DRGDP2, which we obtain from the Real-time Data Research Center of the Philadelphia Fed. This series corresponds to the median nowcast of the quarterly growth rate of real output, seasonally adjusted at annual rates (real GNP prior to 1992 and real GDP afterwards). Prior to 1981Q3, the SPF asked for nominal GNP only. In this case, the implied nowcast for real GNP is computed based on the nowcast for the price index of GNP. We only investigate the median nowcast, as there is a lack of distinct patterns in response to shocks arising from nowcasts misjudging macroeconomic risk (Boeck and Pfarrhofer, 2025).

[4] As an alternative, we consider the standard deviation across forecasts. We discuss this choice in the robustness section further below.

3.2 Non-linear identification of sentiment shocks

In terms of identification, we build on Enders, Kleemann, and Müller (2021) and the Bayesian variant in Chahrour, Nimark, and Pitschner (2021). However, we move beyond the linear VAR framework to allow for state-dependent effects. Specifically, we estimate a bivariate Bayesian smooth-transition vector autoregressive (STVAR) model, in which we employ the same set of sign restrictions as in Enders, Kleemann, and Müller (2021). The 2×1 vector of endogenous variables $\boldsymbol{y}_t = (ne_t, gdp_t)'$ comprises the nowcast error of output growth and the actual growth rate of GDP. Then we assume the following time series process for $\{\boldsymbol{y}_t\}_{t=1}^{T}$:

$$\begin{aligned}\boldsymbol{y}_t = & (\boldsymbol{c}_{11} + \boldsymbol{A}_{11}\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_{1p}\boldsymbol{y}_{t-p}) \times F(z_{t-1}) \\ & + (\boldsymbol{c}_{21} + \boldsymbol{A}_{21}\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_{2p}\boldsymbol{y}_{t-p}) \times (1 - F(z_{t-1})) \\ & + \boldsymbol{c}_2 t + \boldsymbol{c}_3 t^2 + \boldsymbol{S}_t\boldsymbol{\varepsilon}_t, \qquad\qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, \boldsymbol{I}),\end{aligned} \tag{3.1}$$

where $\boldsymbol{A}_{rj}$ are $n\times n$ coefficient matrices for regime $r \in \{1,2\}$ and lag $j \in \{1,2,\ldots,p\}$, the 2×1 vectors $\boldsymbol{c}_{r1}$, $\boldsymbol{c}_2$, and $\boldsymbol{c}_3$ denote the coefficients corresponding to the intercept, trend, and quadratic trend. The 2×1 vector $\boldsymbol{\varepsilon}_t$ denotes the structural errors, which are normally distributed with zero mean and unit variance.[5] Hence, $\boldsymbol{S}_t$ denotes the structural impact matrix, which is time-varying due to its state-dependence. This implies that the reduced-form errors $\boldsymbol{u}_t = \boldsymbol{S}_t\boldsymbol{\varepsilon}_t$ follow a Gaussian distribution with zero mean and the 2×2 covariance matrix $\boldsymbol{\Sigma}_t = \boldsymbol{S}_t\boldsymbol{S}_t'$. To make the state-dependence explicit, we write

$$\boldsymbol{\Sigma}_t = \boldsymbol{\Sigma}_1 F(z_{t-1}) + \boldsymbol{\Sigma}_2(1 - F(z_{t-1})). \tag{3.2}$$

This leads to $\boldsymbol{\Sigma}_r = \boldsymbol{S}_r\boldsymbol{S}_r'$, where $\boldsymbol{S}_r$ is the regime-specific structural impact matrix. We discuss further details on the Bayesian estimation of the STVAR model in Appendix A.2.

To estimate the state-dependent effects within the STVAR model, we interact the coefficients with the transition function $F(z_{t-1}) \in [0,1]$, which reflects the weight of being in the high-disagreement regime at time $t-1$. This specification reflects the fact that disagreement is not binary; rather, it can vary in intensity over time. In our estimation, we leverage this continuous variation to assess how the effect of sentiment

[5] Without loss of generality, we define the second column of $\boldsymbol{\varepsilon}_t$ to be a sentiment shock, which we use as an exogenous shock in the local projection (3.4) below.

shocks depends on forecaster disagreement. The concept of a regime is used solely to define limiting cases for illustrative purposes.

The specification of the transition function involves two steps: the choice of the indicator and the specification of the mapping of the indicator into weights. First, we identify the regimes with the level of disagreement about GDP growth nowcasts, as captured by the variable z_{t-1}.[6] Second, we specify the transition function on the basis of the empirical cumulative density function (CDF) in our sample, adopting the approach of Born, Müller, and Pfeifer (2020) to our setting.[7] Formally, we have

$$F\left(z_{t-1}\right) = \frac{1}{T}\sum_{j=1}^{T} \mathbb{1}(z_j \leq z_{t-1}),$$

where T is the number of observations in our sample, $\mathbb{1}$ is an indicator function, and j indexes all observations. The function equals one if disagreement is at the maximum value within the sample: a situation in which information is extremely dispersed. Instead, if the function equals zero, disagreement is at its minimum. As disagreement is continuous, the economy is hardly ever in one of these two polar regimes. This is captured in the estimation, as each observation is a weighted average of the dynamics in the two regimes.

Identification is achieved through the same set of sign restrictions in both regimes (Rubio-Ramirez, Waggoner, and Zha, 2010). Specifically, we assume that

$$\begin{bmatrix} u_t^{ne} \\ u_t^{gdp} \end{bmatrix} = \begin{pmatrix} + & + \\ + & - \end{pmatrix} \begin{bmatrix} \varepsilon_t^{ns} \\ \varepsilon_t^{s} \end{bmatrix}, \tag{3.3}$$

where ε_t^{ns} and ε_t^{s} denote the *nonsentiment* and *sentiment* shocks, respectively. For the nonsentiment shock, we restrict the signs such that there is a positive comovement between the nowcast error and GDP growth. For the sentiment shock, we impose a negative comovement. Note that we do this for both regimes, which allows us to back out $\varepsilon_t^s = \boldsymbol{e}_2 \boldsymbol{S}_t^{-1} \boldsymbol{u}_t$, where $\boldsymbol{e}_2$ denotes a unit vector with one in the second row.

[6] We postpone the exact details on the construction and discussion of this indicator to Section 3.4.

[7] In contrast to the literature building on Auerbach and Gorodnichenko (2012), this allows us to avoid imposing a specific parametric transition function. Studies in this tradition (see also, for instance, Auerbach and Gorodnichenko, 2013, Caggiano, Castelnuovo, and Groshenny, 2014, Tenreyro and Thwaites, 2016, or Falck, Hoffmann, and Hürtgen, 2021) use the logistic function as the transition function and calibrate rather than estimate the involved smoothness parameter. We follow their calibration strategy and provide robustness for our baseline results using the logistic function. We report this robustness check in Figure B2 in the appendix.

3.3 State-dependent local projections

In order to study the transmission of sentiment shocks, we resort to local projections. In this way, rather than extending our STVAR model, we can flexibly assess the effects of sentiment shocks on a number of variables of interest. Importantly, to ensure consistency, we combine the local projections approach of Jordà (2005) with a smooth regime-switching mechanism to estimate state-dependent impulse responses that vary with the levels of disagreement between forecasters over time, just as in the STVAR model.

This results in smooth-transition local projections (STLP). Letting y_{t+h} denote the response of a particular variable at time $t+h$ to a sentiment shock ε_t^s at time t, we consider a model that depends on the level of disagreement. It reads:

$$\begin{aligned}\Delta^h y_{t+h} = &\left(\alpha_h^L + \beta_h^L \varepsilon_t^s + \boldsymbol{X}_{t-1}' \boldsymbol{\gamma}_h^L\right) \times \Big(1 - F(z_{t-1})\Big) \\ &+ \left(\alpha_h^H + \beta_h^H \varepsilon_t^s + \boldsymbol{X}_{t-1}' \boldsymbol{\gamma}_h^H\right) \times F(z_{t-1}) \\ &+ \tau_{1h} t + \tau_{2h} t^2 + u_{t+h}^{(h)}, \qquad\qquad u_{t+h}^{(h)} \sim \mathcal{N}(0, \sigma_h^2),\end{aligned} \tag{3.4}$$

where $\Delta^h y_{t+h} = y_{t+h} - y_{t-1}$ denotes cumulative differences and $h = 0, \ldots, H$ the number of periods after the shock hits the economy. The coefficient of interest is β_h^r, which denotes the causal, state-dependent effect at horizon h to a sentiment shock, where $r \in \{L, H\}$ refers to the low (L) and high (H) disagreement regimes, respectively.[8]

The model specification includes a linear-quadratic trend (τ_{1h} and τ_{2h}), state-dependent constants (α_h^r), and state-dependent coefficients ($\boldsymbol{\gamma}_h^r$) for the vector of control variables $\boldsymbol{X}_{t-1}$. The $n_x \times 1$ vector $\boldsymbol{X}_{t-1}$ contains lagged control variables, which include four lags of the shock series and the dependent variable. For the transition function $F(z_{t-1})$, we use the same specification as before. The regression residual is denoted by u_{t+h} and is distributed as Gaussian with zero mean and σ_h^2 variance. To address the issue of autocorrelation in the residuals, we apply the strategy proposed by Lusompa (2023). In all specifications, we use lags of the endogenous variable in the regression as controls, which robustifies inference (Montiel-Olea and Plagborg-

[8] This model nests a linear specification, in which we suppress the state-dependency. The equation then reads as follows: $\Delta^h y_{t+h} = \alpha_h + \beta_h \varepsilon_t^s + \boldsymbol{X}_{t-1}' \gamma_h + \tau_{1h} t + \tau_{2h} t^2 + u_{t+h}^h$ with $u_{t+h}^h \sim \mathcal{N}(0, \sigma_h^2)$. In this case, the sentiment shock ε_t^s is also estimated in a linear VAR setting; for details, we refer to Enders, Kleemann, and Müller (2021).

Møller, 2021). The specification in long differences shows considerable small sample gains when the impulse response of interest is estimated using an externally identified shock (Piger and Stockwell, 2023). We estimate the local projections in a Bayesian framework, which allows us to impose regularization techniques on the vector of coefficients corresponding to the control variables (Carvalho, Polson, and Scott, 2010). We provide further details on the Bayesian estimation of the STLP in Appendix A.3.

For the estimation of impulse responses, the parameter β_h^r ($r \in \{L, H\}$) provides a direct causal estimate of the response of the dependent variable to the sentiment shock ε_t^s. We investigate the two polar cases in which the economy is in a high- or low-disagreement regime today, indexed by z_{t-1}. Formally, we have

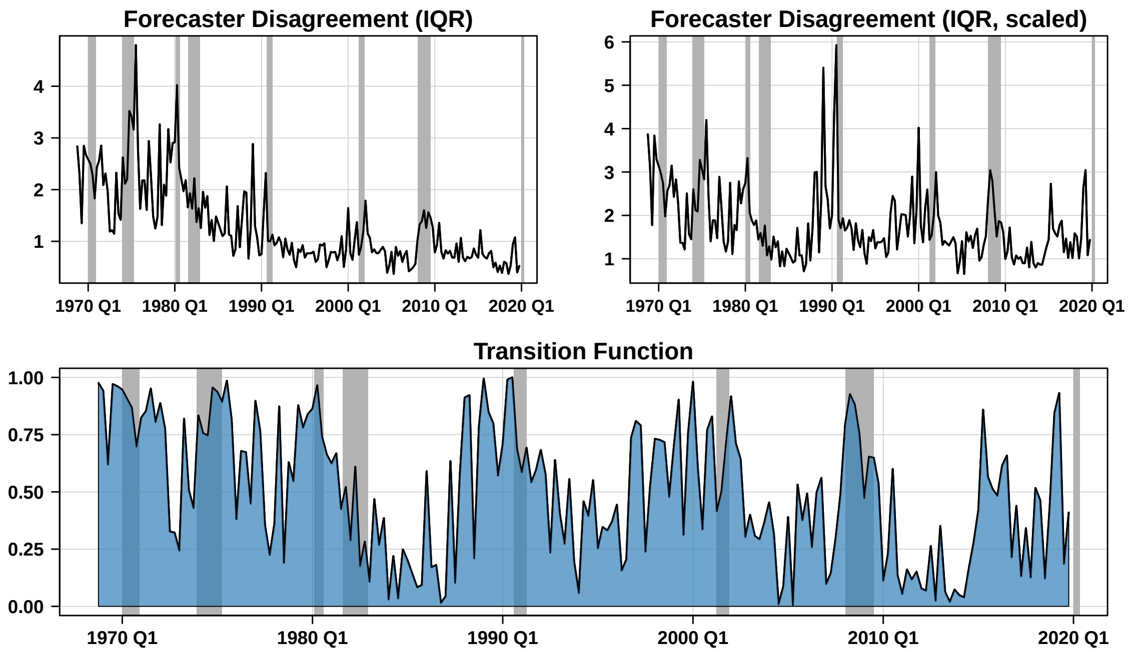
$$\left.\frac{\partial \Delta^h y_{t+h}}{\partial \varepsilon_t^s}\right|_{z_{t-1}} = \beta_h^L \times \Big(1 - F(z_{t-1})\Big) + \beta_h^H \times F(z_{t-1}).$$

Estimation of Equation (3.4) is done for each horizon and variable separately, resulting in a sequence $\{\beta_h^r\}_{h=1}^H$ that reflects the impulse response for y_t within the first H periods. An important advantage of this approach is that it does not rule out potential regime switches after the shock. The state-dependent local projection framework conditions on being in one of the polar cases before the shock hits but does not make any additional assumptions about the economy staying in a particular regime in subsequent periods (see also the discussion in Ramey and Zubairy, 2018). Rather, the local projection at time t directly provides us with a measure of the conditional average response of an economy in state z_{t-1} going forward. Gonçalves et al. (2024) clarify that LPs recover the conditional average response, given that the state is exogenous. In the case of an endogenous state variable, LPs only recover the conditional marginal response function. We show that disagreement does not react systematically in our case, which lends credibility to the state variable being exogenous. Additionally, we fix the ratio $\delta/\sigma_e = 1$, which is the shock magnitude δ divided by the standard deviation of the shock. If exogeneity of the state indicator is a problem, the potential bias increases in this ratio, as pointed out by Gonçalves et al. (2024).

3.4 Regime allocation of low- and high-disagreement about growth

Before we move on to present the results, we discuss how we construct the transition function that provides us with weights for being in a low- or high-disagreement

Figure 1: Transition function based on forecaster disagreement.



Notes: Top left panel: Interquartile range across forecasters in the SPF regarding output growth in the current quarter, raw series. Top right panel: Interquartile range scaled by the moving average of the standard deviation of output growth (moving average over 24 quarters). Bottom panel: Transition function with weights for being in the high disagreement regime based on the scaled interquartile range.

regime. We display our measure of disagreement and the value of the transition function at each point in time in Figure 1. Forecaster disagreement is measured by the interquartile distance of forecasters' forecasts in the SPF regarding output growth in the current quarter. The raw series is reported in the upper left panel and shows substantial variation in the dispersion of growth forecasts over time. It appears cyclical, with increasing disagreement in most, but not all, of the NBER recessions indicated by the gray areas.

The series, however, is non-stationary. It shows a considerable trend or regime shift in both the level and volatility. In particular, the average level and volatility of dispersion are elevated from the beginning of the sample until the mid 1980s. In our sample, the correlation of the standard deviation of GDP growth and the disagreement of professional forecasters is as high as 0.7. Against this background, it seems plausible that a higher variance in GDP growth (and the underlying shocks) may be at least one of the reasons why the dispersion in professional forecasts tends to be higher until the mid 1980s.[9] Therefore, we scale disagreement using the moving standard deviation of output growth. We estimate the moving standard deviation on a moving window of 24 quarters.[10]

We show the adjusted series in the upper right panel of Figure 1. The scaling mutes the large spikes in disagreement in the beginning of the sample but preserves the general pattern of the variable. The highest level of disagreement in the series is now associated with the recessions of the early 1990s and 2000s.

The bottom panel of Figure 1 shows the weight of being in the low- or high-disagreement regime based on the scaled interquartile range. The values of the transition function are derived using Equation (3.2). We observe that we are hardly ever in one of the two polar regimes of disagreement. The figure shows substantial time variation in disagreement, and it is useful to discuss the series and its potential sources in more detail. High disagreement occurs throughout the sample and during most of the NBER recessions, with the exception of the Volcker recession. However, non-recessionary periods are also in the high-disagreement regime.

The literature has pointed towards two main mechanisms why forecasters disagree and form heterogeneous expectations. Either agents disagree due to differences in their information signals or due to differences in their priors or models. Patton and Timmermann (2010) argue that different priors have strong implications for long-run expectations because private information is only of limited value. Conversely, agents' private signals matter more in the short term. When information is more dispersed across agents, they hence form heterogeneous expectations, resulting in higher disagreement. For output growth, forecaster disagreement is largest for short

[9] Similarly, Falck, Hoffmann, and Hürtgen (2021) observe historically high levels of disagreement in inflation expectations. They scale disagreement by the level of expected inflation to control for periods of relatively high inflation rates. This approach works for inflation but not for output growth for two reasons. First, output growth is not positively correlated with disagreement (which is the case for the level of inflation). Second, output growth can become numerically very small and turns negative quite often as well. Scaling disagreement with such a scaling series results in a rather messy series with flipping signs, without disagreement changing, and with huge spikes when the scaling series is close to zero.

[10] The empirical results are robust to using alternative window sizes reflecting typical business cycle frequencies of 5-7 years. Using window sizes of 20 quarters (5 years) and 28 quarters (7 years) does not change the results qualitatively or quantitatively much. As an alternative approach, we regress disagreement on the standard deviation of GDP growth and keep the residuals. We denote this approach as *purification* , and the results are also robust to this choice. We discuss this in the robustness section in more detail.

term survey expectations (see, e.g., Coibion and Gorodnichenko, 2012; Coibion and Gorodnichenko, 2015; Andrade et al., 2016).

Another source of variation affecting the disagreement in output forecasts could also be related to events that affect the productive capacity of the economy, such as the conduct of monetary policy, geopolitical events (e.g., oil shocks in the 1970s, the China-US trade war from the mid-2010s onward), or uncertain growth prospects in the future. If private information matters relatively more than common information, sentiment shocks may exert a stronger impact on the economy.

4. Results

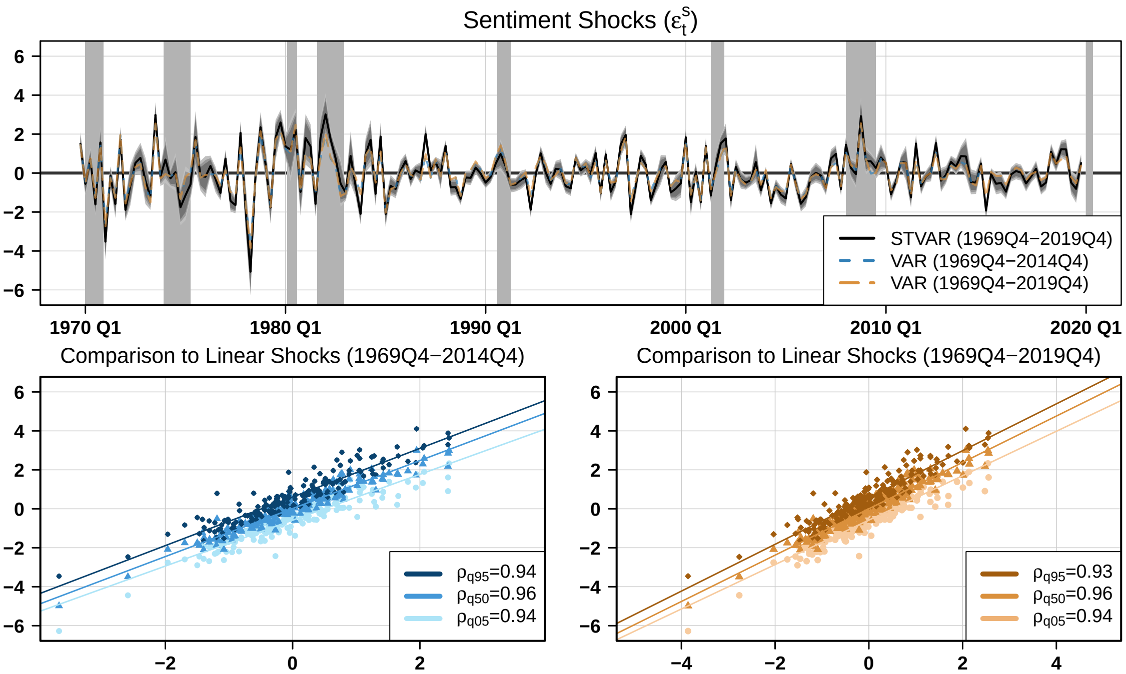
This section presents the empirical results. By focusing on the state-dependence of sentiment shocks, we move beyond the analysis in Enders, Kleemann, and Müller (2021) and Chahrour, Nimark, and Pitschner (2021). To set the stage, we first contrast the identified shocks with those obtained in a linear setting. We conclude the section with an extensive robustness analysis.

4.1 Sentiment shocks

In what follows, we showcase the sentiment shock series, ε_t^s, identified from the STVAR. This series is then used to trace the causal, state-dependent effects of sentiment shocks. Recall that we identify sentiment shocks based on merely imposing a negative co-movement of output and the nowcast error. Nowcast errors provide us with a measure of the mistakes made by market participants in real-time. Including these nowcast errors in the model provides us, therefore, with an informational advantage over market participants. Conventional time series models have difficulties recovering these mistakes (Blanchard, L'Huillier, and Lorenzoni, 2013).

Figure 2 presents the estimated sentiment shocks. There is considerable variation in the whole sample, with larger shocks present at the beginning of the sample and during recessions. We compare the sentiment shock series to the series resulting from a linear framework. The correlations are very high (above 0.9) for both the center and the tails of the distribution. This suggests that the identification also works in a non-linear framework but also indicates that non-linearities seem to play no major role in the identification of the shock itself. After all, the state-dependence we consider does not alter the co-movement of output and the nowcast error. As

Figure 2: Sentiment shocks from the STVAR.



Notes: The upper panel reports the sentiment shocks of the STVAR framework. The black solid line refers to the median estimate while the gray shaded areas refer to the 68%/80%/90% credible sets. The dashed blue and maroon lines refer to sentiment shocks estimated in a VAR framework (1969Q4-2014Q4 refers to the original sample of Enders, Kleemann, and Müller (2021), 1969-2019Q4 extends the sample). They gray shaded rectangles refer to the NBER recession dates. The lower panels report scatter plots to compare different quantiles (q05,q50,q95) to the linear outcomes of sentiment shocks for both samples. We also report correlations between these series. The horizontal and vertical axis denotes the shock: linear (x-axis) or non-linear (y-axis).

sentiment shocks are surrounded by uncertainty, they constitute a generated regressor in the local projection framework. Inference is still asymptotically valid under the null hypothesis that the coefficients are zero (Pagan, 1984).[11] In an additional exercise, we use our Bayesian framework to integrate out the uncertainty surrounding the generated regressor when estimating the STLPs.

In the appendix, we report the impulse response functions of the nowcast error and output to the sentiment shock from the STVAR framework (see Figure B1). In general, they are similar to the linear impulse responses reported by Enders, Kleemann, and Müller (2021). However, differences arise across the regimes. In the

[11]This argument is put forward in the context of state-dependent local projections by Born, Müller, and Pfeifer (2020) and also discussed in Coibion and Gorodnichenko (2015), footnote 18.

low disagreement regime, the effects on output are smaller and are estimated with higher precision. These effects are not strongly statistically different across regimes. Responses of the nowcast errors do not differ markedly across regimes.

4.2 The effects of sentiment shocks

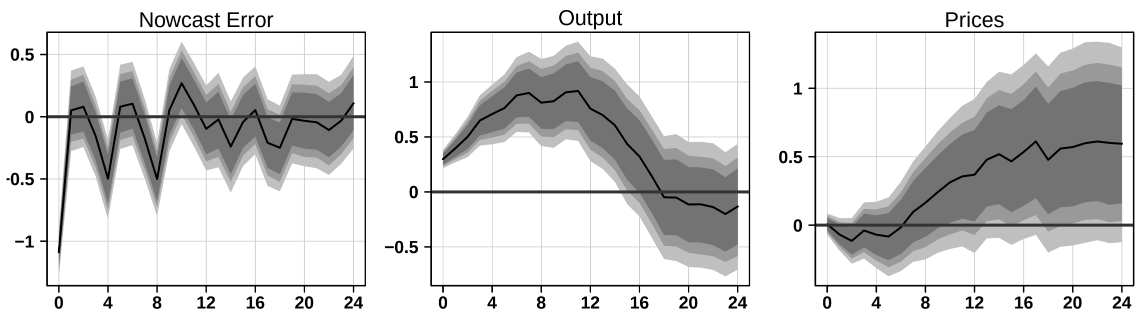
Before we present the outcomes of the state-dependent model, we show the results of a linear specification. We reduce Eq. (3.4) to a linear specification by suppressing the dependency on the level of disagreement. We display the sequence of $\{\beta_h\}_{h=1}^{H}$, which represents the dynamic causal effects of a sentiment shock.[12] The black solid lines show the median estimates, while the shaded areas indicate the 68%, 80%, and 90% credible sets. The horizontal axis measures the impulse response horizon in quarters. The vertical axis measures deviations from the trend in percent. In the baseline specification, we include four lags of the dependent variable and the shock series. The results are based on treating the sentiment shock series, ε_t^s, as observed. In the appendix, we report the outcomes once we take the estimation uncertainty of the first stage into account (see Figure B3).

Figure 3 shows the responses of the nowcast error, output, and prices to a sentiment shock normalized to unity. This translates into a negative nowcast error of one percentage point; that is, the consensus forecaster is mistakenly excessively *optimistic*. The reaction of output is positive—as imposed via the sign restrictions to identify a sentiment shock. It is an expansionary sentiment shock, where optimism about current output growth causes actual output to increase. Expectations exceed output, such that the response of the nowcast is negative. Prices, however, do react only after some time. Prices increase by a maximum of 0.5 percent compared to the pre-shock level, but this effect is not statistically significant.

We move on to the presentation of the state-dependent effects of sentiment shocks in Figure 4. We now split the dynamic causal effects of a sentiment shock into two sequences, $\{\beta_h^r\}_{h=1}^{H}$ for each regime $r \in \{L, H\}$. The black solid lines (gray shaded areas) show the median (quantile) estimates for the high disagreement case, and the blue dashed line (blue shaded areas) shows the results for the low disagreement case. In the appendix, we report the outcomes once we take the estimation uncertainty of the first stage into account (see Figure B4).

[12]Note that in the linear specification, the construction of the shock series, ε_t^s, is also done in a linear VAR setting.

Figure 3: The linear effects of a sentiment shock.

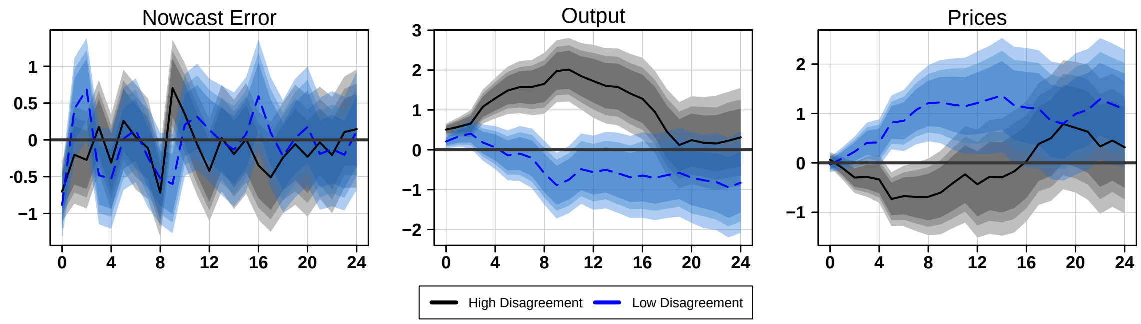


Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid lines refer to the median estimate; the gray areas refer to the 68%/80%/90% credible sets. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

Figure 4 shows the responses of the nowcast error, output, and prices to a sentiment shock normalized to unity. This translates into a nowcast error of one percentage point; that is, the consensus forecaster mistakenly overpredicts output by one percentage point in real time. This means the consensus forecaster is excessively *optimistic*. The shock transmits differently across regimes. The reaction of the nowcast errors in both regimes is negative on impact, while the reaction of output is positive—the defining feature of a sentiment shock. It is an expansionary sentiment shock, where optimism about current output growth causes actual output to increase. Expectations exceed output, such that the response of the nowcast is negative.

However, the transmission differs fundamentally depending on the initial level of disagreement. In the case of high disagreement, output increases strongly and persistently. We find a two percent increase in output after two years. The response of prices, in contrast, is basically flat. There is even a mild and short-lived decline 4-6 quarters after the shock takes place, but estimated with little statistical precision. We observe the opposite pattern in cases where initial disagreement is low. In this case, prices increase by a full 1.5 percent after two to three years, while output is fairly unresponsive: After the initial increase, it quickly reverts back to its initial level. It even undershoots the pre-shock level; however, this effect is not significant. The differences across regimes are statistically significant for output and prices after

Figure 4: The state-dependent effects of a sentiment shock.



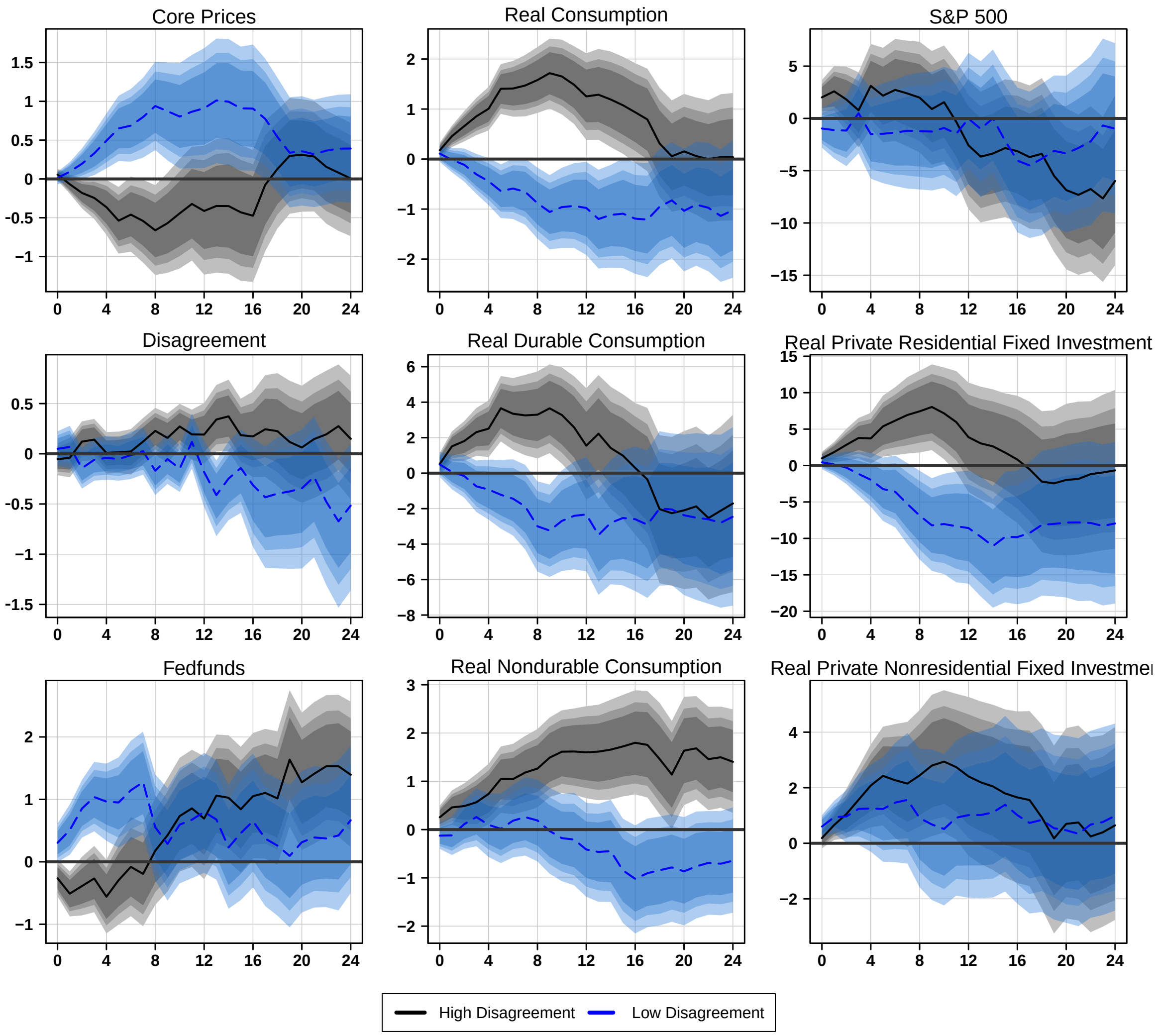
Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

four quarters. Only after three (prices) and four (output) years following the shock do the credible sets start to overlap again.

We offer a structural account of these patterns in Section 5. In a nutshell, if there is high volatility in and hence uncertainty about aggregate technology, agents rely less on their priors. They are, instead, more attentive to the signals they receive, which also makes them more susceptible to the noise contained therein. As this noise is responsible for sentiment shocks, their (positive) effect on demand and, subsequently, output increases. The muted reaction of inflation results from firms' pricing decisions. A stronger effect of sentiment shocks implies that they (incorrectly) expect other firms to have much lower prices due to better technology, which, together with strategic complementarity, explains the muted price reaction.

In Figure 5, we report several additional state-dependent effects of a sentiment shock. We report the outcomes of core prices, dispersion, various subcomponents of GDP (consumption and investment), and financial variables (stock market and the federal funds rate). It is reassuring that dispersion, the threshold variable, is not reacting to the shock. The estimates are around zero on average, with uncertainty bands ranging from -0.2 to 0.2. Note that this variable is standardized, implying a standard deviation of one. The effects are thus far from sizable.

Figure 5: Additional state-dependent effects of a sentiment shock.



Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the core prices (log), real consumption (log), stock market index measured through the S&P 500 (log), disagreement, real durable consumption (log), real private residential fixed investment (log), federal funds rate, real nondurable consumption (log), and real private nonresidential fixed investment (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. and The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (dispersion, federal funds rate) or percent (core prices, real consumption, S&P 500, real durable consumption, real private residential fixed investment, real nondurable consumption, real private nonresidential fixed investment).

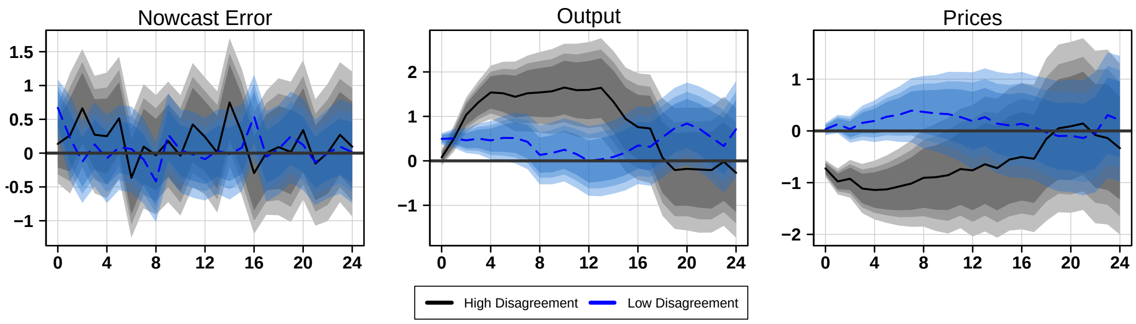
The shock transmits through both consumption and investment. Looking closer at durable and nondurable consumption, we observe that the reaction of real durable consumption is more front-loaded, while the reaction of real nondurable consumption is more persistent in the high disagreement regime. Similarly, the reaction of real private investment builds up in the beginning before starting to flatten out. In the low disagreement regime, on the other hand, consumption responds negatively but with high statistical uncertainty. Although real private residential investment responds negatively, nonresidential investment increases before turning zero and becomes insignificant, with no strong differences across regimes. In summary, in the high disagreement regime, we observe significant positive responses for consumption and investment, while reactions are more muted in the low disagreement regimes (except for residential investment).

Lastly, we turn to the financial variables. We do not observe strong differences for the S&P 500 stock market index, setting the financial economy aside as a possible explanation for these differences. For the federal funds rate, we observe different reactions across the regimes. In the low disagreement regime, the central bank reacts relatively quickly to the rise in prices. In the high disagreement regime, the central bank has an accommodative stance, although not strongly statistically significant, before turning restrictive after two to three years to prevent the economy from overheating.

4.3 Relation to (technology) news shocks

There is a tight connection between noise shocks—or "sentiment shocks"—and news shocks. In fact, Chahrour and Jurado (2018) show the observational equivalence between these information structures. To investigate this link more closely, we also examine the state-dependent effects of news shocks. Specifically, we examine a news shock to technology that maximizes the forecast error variance of total factor productivity (TFP) at a long but finite horizon (Francis et al., 2014). To isolate the shock, we estimate a non-linear vector autoregression and use the modified max share approach by Kurmann and Sims (2021) to identify the technology news shock. Then, we use the framework of state-dependent local projections to examine the responses to our core set of variables. The approach is thus equivalent to the one we use for sentiment shocks.

Figure 6: The state-dependent effects of a news shock.



Notes: Estimates based on STLP with identified technology news shock (Kurmann and Sims, 2021). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

Similar to the specification of Barsky and Sims (2011), the VAR features TFP, consumption, output, and hours worked.[13] All variables are in real per-capita terms (except for hours worked, which are not deflated) and enter the VAR in (log)-levels. We use three lags with a Minnesota prior. The identification of a technology news shock rests on the assumption that a distinguishing feature of a technology shock is its ability to have long-run implications for the macroeconomy. The technology news shock maximizes the forecast error variance share of TFP at a horizon of 10 years.[14]

We present the results in Figure 6. We show the responses of the nowcast error, output, and prices to a technology news shock normalized to unity. The state-dependent response of output to a news shock is similar to that of a sentiment shock: In the high-disagreement regime, we find stronger output effects than in the low disagreement regime. In terms of the nowcast error and prices, the outcomes differ from those of sentiment shocks. We find no strong effect on the nowcast error. For prices, we find a negative effect in the high disagreement regime, while in the low disagreement regime, the outcomes are not statistically significant. The negative effect on

[13]We use the TFP measure provided by Fernald (2014), which is based on the growth accounting methodology in Basu, Fernald, and Kimball (2006) and corrects for unobserved capacity utilization.

[14]Additionally, we do not impose zero-impact restrictions to separate anticipated from surprise shocks to technology (Kurmann and Sims, 2021). This helps to avoid measurement issues that may arise with a variable like TFP in the short-run. Our approach is robust to imposing the zero restriction.

prices is consistent with the findings in Barsky and Sims (2011) and Kurmann and Sims (2021).

To summarize, we highlight the similar state-dependent response of output to a news shock compared to that of a sentiment shock. This underscores the tight connection between noise and news shocks. We stress that both shocks are identified using completely different setups, work through other transmission mechanisms, but show similar real effects on the macroeconomy. Hence, uncertainty, as measured by forecaster disagreement, is essential in the transmission of a shock to expectations.

4.4 Subsample stability and robustness

We conduct several exercises to inspect the robustness of our main results. As a first check, we re-do the analysis on certain subsamples to assess the stability of the estimates. The second check consists of several robustness checks in the state-dependent local projections framework. We present the results in Figure 7 and Figure 8.

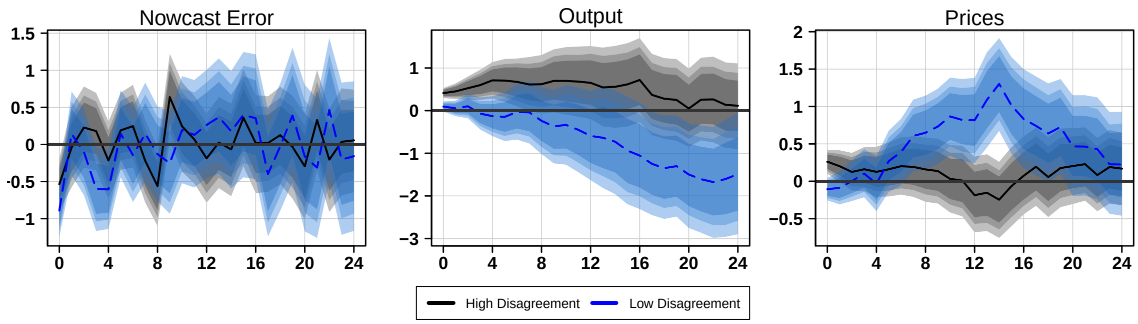
For the subsample stability analysis, we re-estimate both the STVAR and the STLP on shortened subsamples. We investigate two subsamples: a "Post Volcker sample" starting in 1983Q1 and a "Pre financial crisis sample" ending in 2007Q4. For the former subsample, we show the results in panel (a) of Figure 7. Macroeconomic volatility was substantially heightened in the 1970s and early 1980s due to the large oil price shocks and the Volcker shock. Hence, our results may be sensitive to this particular episode. However, our results are robust: In the high-disagreement regime, output reacts stronger while prices react rather muted. On the contrary, in the low-disagreement regime, output reacts muted and prices increase. In the latter regime, output may even decrease in the long run. Furthermore, magnitudes seem to be subdued in comparison to the baseline results. Now, we turn to the second subsample reported in panel (b) of Figure 7, in which we exclude all observations starting from the financial crisis. In this case, the impulse responses are similar in shape and magnitude to the baseline results. Again, we observe a decrease in output in the low-disagreement regime.

We also provide robustness to specification choices in the STLP in Figure 8.[15] In our baseline results, we scale disagreement using the moving-average standard deviation of output growth over the last 24 quarters. The window of 6 years (=24

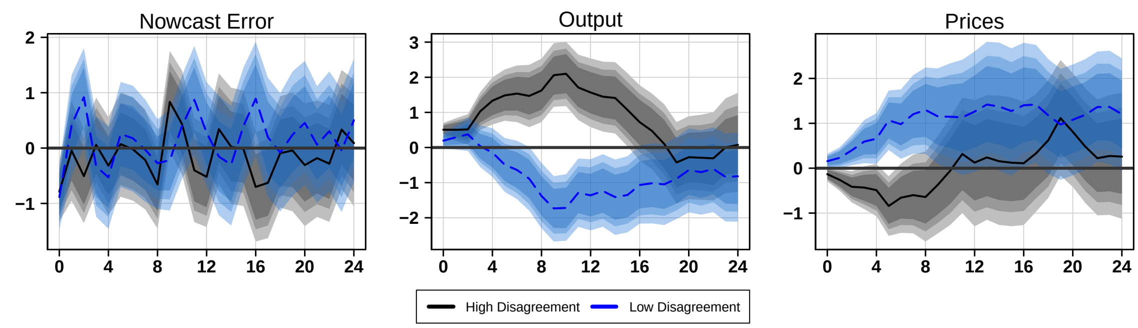
[15] We report robustness checks for the impulse response functions of the remaining variables in the appendix; see Figure B7 and Figure B8.

Figure 7: Subsample stability to the state-dependent effects of a sentiment shock.

(a) Post Volcker sample: 1983Q1 - 2019Q4



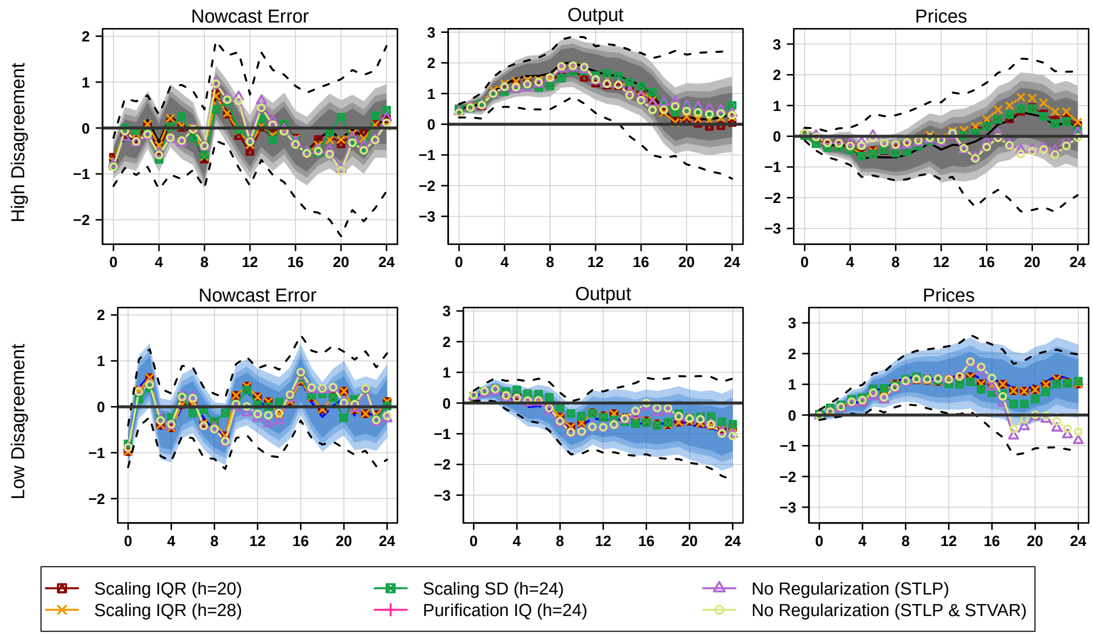
(b) Pre financial crisis sample: 1968Q4 - 2007Q4



Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), prices measured by consumer prices (log). The estimation covers either the period 1983Q1-2019Q4 (upper panel) or 1968Q4-2007Q4 (lower panel). The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

quarters) reflects a typical business cycle frequency of 5 to 7 years. Hence, changing the window to 5 years (=20 quarters) or 7 years (=28 quarters) does not change the results much. We argue that measuring disagreement through the interquartile range is a more robust measure than using the standard deviation. However, using the standard deviation as a measure of disagreement does not change the results either. Lastly, we also use an alternative approach to transform the disagreement series. Instead of scaling, we regress disagreement on the standard deviation of output growth and keep the residuals. We denote this approach as *purification* , and the results are again robust to this choice. As we utilize Bayesian shrinkage priors for regularization

Figure 8: Robustness to the state-dependent effects of a sentiment shock.



Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. Colored lines with circles refer to robustness specifications: Scaling using a different moving average process (20 or 28 quarters), scaling using the standard deviation as dispersion measure, using purification instead of scaling, and prior sensitivity analysis (no regularization in the second or both estimation steps). The black dashed lines refer to the maximum/minimum 90% credible interval across all robustness specifications. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

in the empirical framework, we also perform prior sensitivity checks. Results do not change qualitatively or quantitatively when imposing no regularization on the STLP or on both the STLP and the STVAR. In these cases, no regularization means using a totally uninformative prior that resembles ordinary least squares.

We also report the maximum and minimum of the 90% credible interval bounds (period-by-period) across all robustness specifications in the figure. This allows us to examine robustness regarding the second moment. Generally, credible intervals tend to widen when we consider a larger set of specifications. While the main results concerning the nowcast error and output do not change, we observe that the response of prices in the high disagreement regime turns statistically insignificant. This aligns well with most median responses, also moving more towards the null line. This underscores that we tend to interpret the outcome of prices in the high disagreement regime as a null effect.

5. Theory

We now put forward a model that allows us to formally define sentiment shocks, discuss their impact on economic activity, and the role of expectation dispersion. The model captures, in a stylized way, the informational friction that gives rise to nowcast errors.

Lorenzoni (2009) and Coibion and Gorodnichenko (2012) find that models of information rigidities, in general, and of noisy information, in particular, are successful in predicting the empirical regularities of survey data on expectations. Our model thus builds on the noisy and dispersed information model of Lorenzoni (2009). As our goal is to derive robust qualitative predictions, we simplify the original model, notably by assuming predetermined rather than staggered prices. As a result, it is possible to solve an approximate model in closed form.

5.1 Setup and timing

There is a continuum of islands (or locations), indexed by $l \in [0, 1]$, each populated by a representative household and a unit mass of producers, indexed by $j \in [0, 1]$. Each household buys from a subset of all islands, chosen randomly in each period. Specifically, it buys from all producers on n islands included in the set $\mathcal{B}_{l,t}$, with $1 < n < \infty$.[16] Households have an infinite planning horizon. Producers produce differentiated goods on the basis of island-specific productivity, which is determined by a permanent, economy-wide component and a temporary, idiosyncratic component.[17] Both components are stochastic. Financial markets are complete such that, assuming identical initial positions, wealth levels of households are equalized at the beginning of each period.

[16] This setup ensures that households cannot exactly infer aggregate productivity from observed prices. At the same time, individual producers have no impact on the price of households' consumption baskets.

[17] As argued by Lorenzoni (2009), this setup can account for the empirical observations that the firm-level volatility of productivity is large relative to aggregate volatility and that individual expectations are dispersed.

The timing of events is as follows: each period consists of three stages. During stage one of period t, information about all variables of period $t-1$ is released. Subsequently, nominal wages are determined, and the central bank sets the interest rate based on expected inflation. Shocks emerge during the second stage. We distinguish between shocks that are directly observable and shocks that are not. Sentiment and technology shocks are not directly observable in the following sense: information about idiosyncratic productivity is private to each producer, but, in addition, all agents observe a signal about average productivity. While the signal is unbiased, it contains an i.i.d. zero-mean component: the sentiment shock. We allow for one generic shock that is observable. To simplify the discussion, we refer to this shock as a "monetary policy shock" with the understanding that other observable shocks would play a comparable role in terms of identification. Given these information sets, producers set prices.

During the third and final stage, households split up. Workers work for all firms on their island, while consumers allocate their expenditures across differentiated goods based on public information, including the signal, and information contained in the prices of the goods in their consumption bundle. Because the common productivity component is permanent and households' wealth and information are equalized in the next period, agents expect the economy to settle on a new steady state from period $t+1$ onwards.

5.2 Households

A representative household on island l ("household l", for short) maximizes lifetime utility, given by

$$U_{l,t} = \mathbb{E}_{l,t} \sum_{k=t}^{\infty} \beta^{k-t} \ln C_{l,k} - \frac{L_{l,k}^{1+\varphi}}{1+\varphi} \qquad \varphi \geq 0, \quad 0 < \beta < 1,$$

where $\mathbb{E}_{l,t}$ is the expectation operator based on household l's information set at the time of its consumption decision in stage three of period t (see below). $C_{l,t}$ denotes the consumption basket of household l, while $L_{l,t}$ is its labor supply. The flow budget constraint is given by

$$\mathbb{E}_t \varrho_{l,t,t+1} \Theta_{l,t} + B_{l,t} + \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 P_{j,m,l,t} C_{j,m,l,t} dj \leq$$
$$\int_0^1 \Pi_{j,l,t} dj + W_{l,t} L_{l,t} + \Theta_{l,t-1} + (1 + r_{t-1}) B_{l,t-1},$$

where $C_{j,m,l,t}$ denotes the amount bought by household l from producer j on island m and $P_{j,m,l,t}$ is the price for one unit of $C_{j,m,l,t}$. At the beginning of the period, the household receives the payoff $\Theta_{l,t-1}$, given a portfolio of state-contingent securities purchased in the previous period. $\Pi_{j,l,t}$ are the profits of firm j on island l and $\varrho_{l,t,t+1}$ is household l's stochastic discount factor between t and $t+1$. The period-t portfolio is priced conditional on the (common) information set of stage one, hence we apply the expectation operator $\mathbb{E}_t$. $B_{l,t}$ are state non-contingent bonds paying an interest rate of r_t. The complete set of state-contingent securities is traded in the first stage of the period, while state-non-contingent bonds can be traded via the central bank throughout the entire period. The interest rate of the non-contingent bond is set by the central bank. All financial assets are in zero net supply. The bundle $C_{l,t}$ of goods purchased by household l consists of goods sold in a subset of all islands in the economy

$$C_{l,t} = \left(\frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 C_{j,m,l,t}^{\frac{\gamma-1}{\gamma}} dj \right)^{\frac{\gamma}{\gamma-1}} \qquad \gamma > 1.$$

While each household purchases a different random set of goods, we assume that the number n of islands visited is the same for all households. The price index of household l is therefore

$$P_{l,t} = \left(\frac{1}{n} \sum_{m \in \mathcal{B}_{l,t}} \int_0^1 P_{j,m,l,t}^{1-\gamma} dj \right)^{\frac{1}{1-\gamma}}.$$

5.3 Producers and monetary policy

The central bank follows an interest-rate feedback rule but sets r_t before observing prices, that is during stage one of period t:

$$r_t = \psi \mathbb{E}_{cb,t} \pi_t + \nu_t \qquad \psi > 1,$$

where π_t is economy-wide net inflation, calculated on the basis of all goods sold in the economy. The expectation operator $\mathbb{E}_{cb,t}$ is conditional on the information set of the central bank. This set consists of information from period $t-1$ only, that is, the central bank enjoys no informational advantage over the private sector.[18] ν_t is a monetary policy shock that is observable by producers and households alike.

Producer j on island l produces according to the following production function

$$Y_{j,l,t} = A_{j,l,t} L_{j,l,t}^{\alpha} \qquad 0 < \alpha < 1,$$

featuring labor supplied by the local household as the sole input. $A_{j,l,t} = A_{l,t}$ denotes the productivity level of producer j, which is the same for all producers on island l. During stage two, the producer sets her optimal price for the current period. Given prices, the level of production is determined by demand during stage three.

5.4 Productivity and signal

Log-productivity on each island is the sum of an aggregate and an island-specific idiosyncratic component

$$a_{l,t} = x_t + \eta_{l,t},$$

where $\eta_{l,t}$ is an i.i.d. shock with variance σ_η^2 and mean zero. This variance will be responsible for the dispersion of expectations. A higher value of σ_η^2 also worsens the signal-to-noise ratio of the signals received by private agents, which creates a positive link between dispersion and uncertainty. The idiosyncratic shock aggregates to zero across all islands. That is, even if private sentiment shocks were included here, they would cancel in the aggregate. The aggregate component x_t follows a random walk

$$\Delta x_t = \varepsilon_t.$$

The i.i.d. productivity shock ε_t has variance σ_ε^2 and mean zero. During stage two of each period, agents observe a public signal about x_t. This signal takes the form

$$s_t = \varepsilon_t + e_t,$$

[18] Pre-set prices and interest rates allow us to discard the noisy signals about quantities and inflation observed by producers and the central bank in Lorenzoni (2009), simplifying the signal-extraction problem without changing the qualitative predictions of the model. Pre-set wages, on the other hand, guarantee determinacy of the price level. They do not affect output dynamics after sentiment and technology shocks, because goods prices may still adjust in the second stage of the period.

where e_t is an i.i.d. sentiment shock with variance σ_e^2 and mean zero. Producers also observe their own productivity. Hence, their expectations of Δx_t are

$$\mathbb{E}_{j,l,t}\Delta x_t = \rho_x^p s_t + \delta_x^p(a_{j,l,t} - x_{t-1}),$$

with $\mathbb{E}_{j,l,t}$ being the expectation of producer j on island l when setting prices (in stage two). The coefficients ρ_x^p and δ_x^p are the same for all producers, where these and the following ρ and δ-coefficients are functions of the structural parameters that capture the informational friction. They are non-negative and smaller than unity; see Appendix C. Finally, while shopping during stage three, consumers observe a set of prices. Given that they have also observed the signal, they can infer the productivity level of each producer in their sample. Consumers' expectations are thus given by

$$\mathbb{E}_{l,t}\Delta x_t = \rho_x^h s_t + \delta_x^h \tilde{a}_{l,t},$$

where $\tilde{a}_{l,t}$ is the average over the realizations of $a_{m,t} - x_{t-1}$ for each island m in household l's sample. ρ_x^h and δ_x^h are equal across households. The model nests the case of complete information about all relevant variables for households and producers if $\sigma_e^2 = 0$. If $\sigma_e^2 > 0$, producers will set prices based on potentially overly optimistic or pessimistic expectations of productivity. Consumers also have complete information if $n \to \infty$.

5.5 Market clearing

Goods and labor markets clear in each period:

$$\int_0^1 C_{j,m,l,t}dl = Y_{j,m,t} \;\; \forall j, m \qquad L_{l,t} = \int_0^1 L_{j,l,t}dj \;\; \forall l,$$

where $C_{j,m,l,t} = 0$ if household l does not visit island m. The asset market clears in accordance with Walras' law.

5.6 Results

We derive a solution of the model based on a linear approximation to the equilibrium conditions around the symmetric steady state; see Appendix C for details. Lower-case letters denote percentage deviations from the steady state. In line with our empirical identification strategy, we obtain the following propositions for which we provide proofs in Appendix D.

Proposition 1 *A sentiment shock, e_t, induces a negative correlation between the reactions of output and the nowcast error, while a technology shock, ε_t, induces a positive correlation. A monetary policy shock, ν_t, does not cause a nowcast error. Formally, we have*

$$y_t = x_{t-1} + \underbrace{\rho_x^h(1-\Omega)}_{>0} e_t + \underbrace{\left[(\delta_x^h + \rho_x^h)(1-\Omega) + \Omega\right]}_{>0} \varepsilon_t \underbrace{-\frac{\alpha}{\alpha + \psi(1-\alpha)}}_{<0} \nu_t, \qquad (5.5)$$

with $0 < \Omega = \frac{n - \delta_x^h(1-\alpha)[(n-1)\delta_x^p + 1]}{n\alpha + (1-\alpha)\left\{(1-\delta_x^h)[1+\delta_x^p(n-1)] + (n-1)\gamma(1-\delta_x^p)\right\}} < 1$, *and*

$$y_t - \mathbb{E}_{k,t} y_t = \underbrace{-\rho_x^k \left[\delta_x^h(1-\Omega) + \Omega\right]}_{<0} e_t + \underbrace{\left[\delta_x^h(1-\Omega) + \Omega\right](1 - \delta_x^k - \rho_x^k)}_{>0} \varepsilon_t,$$

with $\mathbb{E}_{k,t}$ standing for either expectations of producers, $\mathbb{E}_{j,l,t}$, or households, $\mathbb{E}_{l,t}$, and ρ^k, δ^k correspondingly for ρ^p, δ^p or ρ^h, δ^h.

Hence, positive productivity and sentiment shocks raise actual output but also lead to output misperceptions. Consider first the sentiment shock. Producers expect aggregate productivity to be high—resulting in higher demand—but also observe that their own productivity is unchanged, which they attribute to a negative realization of the idiosyncratic productivity component. Consequently, they raise prices above what they expect the average price level to be. Consumers, in turn, observe higher prices besides the public signal. They, too, attribute this increase to adverse temporary productivity shocks suffered by those particular firms from which they buy. This allows households to entertain the notion of higher aggregate productivity and future income. They thus raise expenditures despite the observed price increase and, hence, economic activity expands.[19] Yet, as each producer and each household considers itself unlucky relative to its peers, current output is actually lower than expected: a negative nowcast error obtains.

After a positive productivity shock, producers also do not fully trust the signal about the aggregate component and attribute some of the increased productivity to an idiosyncratic advantage. They therefore reduce prices below what they expect the average price level to be. Consumers, in turn, observe lower prices and expect higher income. They consequently raise consumption. However, both producers and their

[19]As pointed out by Lorenzoni (2009), the sentiment shock provides a possible microfoundation for the traditional concept of a demand shock: agents are too optimistic about economic fundamentals, resulting in unusually high demand.

customers expect other producers to set higher prices and consequently underestimate actual output. A positive nowcast error obtains, inducing an opposite correlation between output and the nowcast error for sentiment and productivity shocks.

Finally, we stress that monetary policy shocks have no impact on nowcast errors. More generally, any other shock that enters the information set of households and producers will not generate nowcast errors, as both are aware of the economic environment and, hence, the effect of shocks. Misperceptions about economic activity thus arise only after imperfectly observed shocks, such as innovations in productivity or sentiment shocks.

Building on the above, the next proposition establishes that the model can also rationalize our empirical findings regarding the role of uncertainty (which we measure by forecaster disagreement).

Proposition 2 *A higher volatility σ_ε^2 of aggregate technology leads to a higher dispersion of now- and forecasts of output by firms and households and a lower impact of positive sentiment shocks on prices. It also leads to a higher impact of positive sentiment shocks on output if*

$$Q\left(\frac{\sigma_\eta^2/n}{\sigma_\varepsilon^2}+\frac{\sigma_\eta^2/n}{\sigma_e^2}\right)^2>1,$$

where

$$Q=\{1+(n-1)[\gamma(1-\alpha)+\alpha]\}/\alpha>1.$$

If the variance of, and hence uncertainty about, aggregate technology increases, agents put more weight on the signals they receive. On the one hand, a higher weight on private signals raises the dispersion of now- and forecasts, as these signals contain an idiosyncratic component. On the other hand, a higher weight on the public signal changes the impact of noise on consumption and price-setting decisions. Specifically, due to consumers' higher attention to the signal, the effect of noise on demand and thus output increases. The impact of noise on producers' expectations also rises, letting them (incorrectly) expect even lower prices from competitors due to better aggregate technology, which induces them to set lower prices themselves. Thus, higher volatility of aggregate technology lowers prices in reaction to noise shocks, which amplifies the increase in demand.[20]

[20]A simple extension in which agents obtain another public signal with a fixed signal-to-noise ratio in stage one of the period can also generate the sign flip of the price response between the high-

This can also be seen in the equations governing the reaction of output and prices to noise. Turning to output first, we have, according to Equation (5.5)

$$\frac{\partial y_t}{\partial e_t} = \rho_x^h(1-\Omega).$$

The parameter ρ_x^h is households' optimal weight on the public signal when forming expectations about the economic fundamentals (productivity) and, hence, future income, where higher expected income increases current demand. The parameter $-\Omega$ reflects the impact of a technology shock on current prices. After a noise shock, households expect future prices to be lower than their current price sample, which reduces the positive impact of the noise shock on current demand. Whenever the variance of aggregate productivity increases, uncertainty increases and households pay closer attention to the signal. Thus, ρ_x^h and the expectations of permanent income are higher after a noise shock. At the same time, firms also put a higher weight on the public signal when setting prices, which raises Ω, the impact of an (perceived) increase in overall technology on prices. In principle, this would exert positive pressure on output. However, the demand channel dominates unless the informational content of the private signal observed by the households is very large ($\sigma_\eta^2/n << \sigma_\varepsilon^2$) and contains much less noise than the public signal ($\sigma_\eta^2/n << \sigma_e^2$). In this case, $\sigma_\eta/(n\sigma_\varepsilon^2)+\sigma_\eta/(n\sigma_e^2)$ can be smaller than α/Q (where $Q > 1$ and $\alpha < 1$), which would violate the condition given in the proposition. However, as the volatility of idiosyncratic technology shocks σ_η^2 is much larger than the aggregate one (see, e.g., Lorenzoni, 2009) and households are unlikely to have a very large informational advantage over firms (such that n is not too large), this is a very mild condition, likely to be always fulfilled. Assuming, say, that a person/agency/media outlet which produces the public signal collects at least as much information as an average household would automatically satisfy the condition (as $\sigma_e^2 < \sigma_\eta^2/n$ in this case).

Turning to prices, Equation (C.14) in the appendix gives the impact of noise on prices:

$$\frac{\partial p_t}{\partial e_t} = \frac{1-\alpha}{\alpha}\left[(1-\Omega)\left(\rho_x^h + \delta_x^h\frac{n-1}{n}\rho_x^p\right) - \Omega(\gamma-1)\frac{n-1}{n}\rho_x^p\right], \tag{5.6}$$

and low disagreement regimes documented in Figure 4. A positive signal in stage 0 would raise wage demands. The described dynamics in stage 2 would then overturn this upward pressure on prices only in the case of high values of σ_ε^2.

which represents the impact of noise on demand and hence expected marginal costs. It is zero in the case of constant returns to scale ($\alpha = 1$), as demand is then irrelevant for price setting. The first term in the bracket reflects the (positive) impact of changes in overall household demand following a noise shock. This is governed by households' reaction to the public signal ρ_x^h, influencing estimates about long-run income, and households' reaction δ_x^h to observed prices, determining intertemporal substitution. Specifically, the term $\rho_x^p(n-1)/n$ represents an individual firm's assessment of the price signals received by its customers. This assessment increases in the number n of observed prices by households, and the reaction ρ_x^p of producers to the signal. Since a higher variance of aggregate technology leads households and firms to pay more attention to the signals, this whole term is increasing in σ_ε^2.

The second term of Equation (5.6) reflects the (negative) impact of strategic complementarity, i.e., intratemporal substitution: after a positive noise shock, firms set lower prices as they expect competitors to have lower prices. This effect is stronger for higher effective degrees of substitutability $\gamma(n-1)/n$. Producers pay more attention to the public signal (ρ_x^p rises) for a higher volatility of aggregate technology and hence reduce prices further after noise shocks. Since changes in competitors' prices have an over-proportional impact on own demand (as $\gamma > 1$), compared to the overall increase in demand, this strategic-complementarity effect dominates the demand effect of the first term. Thus, $\partial p_t / \partial e_t$ falls in σ_ε^2.

6. Conclusion

This paper examines the conditions that make the economy susceptible to non-fundamental shocks. Specifically, we look into business cycle shocks that are driven by expectations—we label those "sentiment shocks." We document that forecaster disagreement is essential for the transmission of sentiment shocks. If there is significant disagreement, economic activity is affected more, while we do not observe an effect on prices. If, instead, disagreement is low, the effect is absorbed by prices and has only a little impact on output.

We show these outcomes in a state-dependent local projections framework. Before that, we identify sentiment shocks using a bivariate smooth-transition VAR model, in which we apply the same sign restrictions as in Enders, Kleemann, and Müller (2021). In both frameworks, we define two polar regimes of high and low disagreement. Each observation is assumed to be a weighted average between these polar cases allowing for a continuous switching between the polar cases. We use the empirical cumulative density function within our sample to assess the relative degree of disagreement.

In the last part of the paper, we put forward a New Keynesian model with dispersed information to rationalize our findings. The key assumption in the model is that households and firms do not observe aggregate productivity at the time of decision making. Instead, they rely on expectations, which they form based on a public signal and private information. If aggregate technology is more volatile, agents turn more to the available signals, which makes them increase demand and lower prices after noise shocks in anticipation of a currently higher technology level.

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Online Appendix: Dancing in the Dark: Sentiment Shocks and Economic Activity

A. Further details on data and econometric methodology

A.1 Data sources

All series were gathered from the sources listed below, including the Bureau of Economic Analysis (BEA), the Federal Reserve Economic Data (FRED) database, the Real-Time Data Set for Macroeconomists and the Survey of Professional Forecasters (SPF) provided by the Federal Reserve Bank of Philadelphia.

In Table A1, we provide an overview of the data, their transformations, and sources.

Table A1: Data definitions, transformations, and sources.

Variable (y_{it})	Transformation	Mnemonic	Source
Output	$100 \log x_t$	`GDPC1`	FRED
Output (first-release)	x_t	`routput`	BEA
Output Nowcast	y_t	`RGDP`	SPF
Output Disagreement	$D(x_t)$	`RGDP`	SPF
Consumer prices	$100 \log x_t$	`CPIAUCSL`	FRED
Core prices	$100 \log x_t$	`CPILFESL`	FRED
Federal funds rate	x_t	`FEDFUNDS`	FRED
Real consumption	$100 \log x_t$	`PCE`	FRED
Real durable consumption	$100 \log x_t$	`PCEDG`	FRED
Real nondurable consumption	$100 \log x_t$	`PCEND`	FRED
S&P 500	$100 \log x_t$	`P`	Robert Shiller's website
Real private residential fixed investment	$100 \log x_t$	`PRFI`	FRED
Real private nonresidential fixed investment	$100 \log x_t$	`PNFI`	FRED
Financial uncertainty ($h = 1$)	x_t	`finunc`	Sydney Ludvigson's website
Macro uncertainty ($h = 1$)	x_t	`macrounc`	Sydney Ludvigson's website

Notes: The dispersion function $D(y_{it})$ refers to either the standard deviation or the interquartile range.

A.2 Smooth-transition vector autoregression

As detailed in Section 3, we use a bivariate smooth-transition vector autoregression (STVAR) to identify sentiment shocks non-linearly. In this appendix, we provide additional information on the model and its estimation. The time series process $\{\boldsymbol{y}_t\}_{t=1}^{T}$ (2×1) follows

$$\begin{aligned} \boldsymbol{y}_t = {} & (\boldsymbol{A}_{11}\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_{1p}\boldsymbol{y}_{t-p}) \times F(z_{t-1}) \\ & + (\boldsymbol{A}_{21}\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_{2p}\boldsymbol{y}_{t-p}) \times (1 - F(z_{t-1})) \\ & + \boldsymbol{c}_1 + \boldsymbol{c}_2 t + \boldsymbol{c}_3 t^2 + \boldsymbol{u}_t, \qquad\qquad \boldsymbol{u}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma_t}), \end{aligned} \tag{A.1}$$

where $\boldsymbol{A}_{rj}$ are 2×2 coefficient matrices for regime $r \in \{1, 2\}$ and lag $j \in \{1, 2, \ldots, p\}$, the 2×1 vectors $\boldsymbol{c}_1$, $\boldsymbol{c}_2$, and $\boldsymbol{c}_3$ denote the coefficients corresponding to the intercept, trend, and quadratic trend. The 2×1 vector $\boldsymbol{u}_t$ denotes the reduced-form innovations, which are normally distributed with zero mean and time-varying variance, $\boldsymbol{\Sigma}_t$. The time-variation results from the state-dependency as follows

$$\boldsymbol{\Sigma}_t = \boldsymbol{\Sigma}_1 F(z_{t-1}) + \boldsymbol{\Sigma}_2(1 - F(z_{t-1})), \tag{A.2}$$

where $F(z_{t-1})$ denotes the transition function. It reads as follows

$$F\left(z_{t-1}\right) = \frac{1}{T}\sum_{j=1}^{T} \mathbb{1}(z_j \leq z_{t-1}), \tag{A.3}$$

where T is the number of observations in our sample, $\mathbb{1}$ is an indicator function, and j indexes all observations. The function equals one if disagreement is at the maximum of the sample: a situation in which information is extremely dispersed. On the contrary, if the function equals zero, the disagreement is at its minimum.

As an alternative, we also use the logistic function as a transition, as is often done in the literature (Auerbach and Gorodnichenko, 2012; Caggiano, Castelnuovo, and Groshenny, 2014; Tenreyro and Thwaites, 2016; Falck, Hoffmann, and Hürtgen, 2021). Therefore, we specify the transition function based on the logistic function, following Granger and Teräsvirta (1993). We assume that the alternative $\tilde{F}(z_{t-1})$ follows

$$\tilde{F}\left(z_{t-1}\right) = \frac{\exp\left(\theta \frac{z_{t-1}-c}{\sigma_z}\right)}{1 + \exp\left(\theta \frac{z_{t-1}-c}{\sigma_z}\right)}, \tag{A.4}$$

where c corresponds to the mean and σ_z to the standard deviation of z_{t-1}. The smoothness parameter θ determines the curvature of $\tilde{F}(z_{t-1})$ and how strongly the economy switches from the low- to the high-disagreement regime when z_t changes. Several previous studies have calibrated rather than estimated the smoothness parameter θ. We follow their suggestion and use a value of $\theta = 5$.

The model estimation is done in a Bayesian fashion and thus we discuss our prior choices. Conditional on the state indicator function $F(z_{t-1})$, the model is linear. Hence, we collect VAR parameters of regime r in the $K \times 1$ vector $\boldsymbol{a}_r = \text{vec}(\boldsymbol{A}_{r1}, \ldots, \boldsymbol{A}_{rp})$ with $K = n^2 p$. The prior variances are collected in $\underline{\boldsymbol{V}_r} = \text{diag}(\underline{v_{r1}}, \ldots, \underline{v_{rK}})$, with $\underline{v_k} = \lambda_r^2 \psi_{rk}^2$ for $k = 1, \ldots, K$ and $r \in \{1, 2\}$. We propose a hierarchical global-local shrinkage prior setup based on the horseshoe (HS) prior following Carvalho, Polson, and Scott (2010), which reads as follows

$$\boldsymbol{a}_r \sim \mathcal{N}_k\left(\underline{\boldsymbol{a}_r}, \underline{\boldsymbol{V}_r}\right), \quad \lambda_r \sim C^+(0, 1), \quad \psi_{rk} \sim C^+(0, 1), \tag{A.5}$$

where C^+ denotes the half-Cauchy distribution. The parameter λ_r denotes the global shrinkage parameter of regime r, which exerts shrinkage on all coefficients. The parameter ψ_{rk} allows for individual, coefficient-specific shrinkage. Both parameters are estimated, and we do not have to specify any hyperparameters. We use the procedure outlined in Makalic and Schmidt (2015) to sample from the corresponding conditional posterior densities. We center the prior distribution of $\boldsymbol{a}_r$ on $\underline{\boldsymbol{a}_r}$, which is either unity for series in log-levels (mimicking the Minnesota-type prior in Doan, R Litterman, and Sims, 1984 and R B Litterman, 1986) or zero in all other cases. For the deterministic terms, we assume a non-informative Gaussian prior $\boldsymbol{c}_l \sim \mathcal{N}(0, 10^5)$ where $l = \{0, 1, 2\}$. The prior distribution of the covariance matrix is

$$\Sigma_r \sim iW(\underline{\nu}, \underline{\boldsymbol{S}}), \tag{A.6}$$

where $iW(\nu, \boldsymbol{S})$ denotes the inverse Wishart distribution with prior degrees of freedom ν and prior scaling matrix $\boldsymbol{S}$. Following the recommendation in Kadiyala and Karlsson (1997), we specify $\underline{\nu} = n + 2$ and $\underline{\boldsymbol{S}} = \text{diag}(s_1,^2, \ldots, s_n^2)$. Here, the diagonal elements of the scaling matrix s_j^2 $(j = 1, \ldots, n)$ denote the sample variance of the residuals of an AR(4) process for each individual series. If we also estimate the parameter of the transition function, we must specify a prior density. For the speed of adjustment parameter θ, we then specify a Gamma distribution such that

$$\theta \sim \mathcal{G}(\underline{a}, \underline{b}), \tag{A.7}$$

where $\underline{a} = 20$ and $\underline{b} = 4$. This translates into a prior mean of 5 and a prior variance of 1.25. In case we do not estimate this parameter, we fix it to 5.

As a last step, we briefly discuss the posterior simulation within an MCMC algorithm. Conditional on the regime indicator function $F(z_{t-1})$, the model is fully linear, and all conditional posterior distributions are available in closed form, rendering a Gibbs sampler convenient. Although the conditional posterior distribution of the VAR coefficients and the covariance matrix are standard, we use the auxiliary sampler of Makalic and Schmidt (2015) to sample from the conditional posterior densities for the HS prior. Lastly, if necessary, the parameter related to the transition function, θ, must be sampled with the help of a Metropolis-Hastings within-Gibbs step since the posterior distribution is not available in closed form.

A.3 State-dependent Bayesian local projections

We summarize the state-dependent local projections (LP) specified in Equation (3.4) in the following formulation

$$\Delta^h y_{t+h} = \boldsymbol{\varepsilon}_t' \boldsymbol{\beta}_h + \boldsymbol{Z}_{t-1}\boldsymbol{\gamma}_h + u_{t+h}^{(h)}, \qquad u_{t+h}^{(h)} \sim \mathcal{N}(0, \sigma_h^2), \tag{A.8}$$

where $\Delta^h = y_{t+h} - y_{t-1}$ denotes cumulative differences, $\boldsymbol{\varepsilon}_t = \left[\varepsilon_t^b \times (1 - F(z_{t-1}))\,,\right.$ $\left.\varepsilon_t^b \times F(z_{t-1})\right]'$ and $\boldsymbol{\beta}_h = \left[\beta_h^L, \beta_h^H\right]'$ are 2×1 vectors. Similarly, we gather all (lagged) control variables in $\boldsymbol{Z}_{t-1} = [(1, \boldsymbol{X}_{t-1}) \times (1 - F(z_{t-1}))\,, (1, \boldsymbol{X}_{t-1}) \times F(z_{t-1}), t, t^2]'$ and define the corresponding coefficient vector $\boldsymbol{\gamma} = \left[\alpha_h^L, \boldsymbol{\gamma}_h^L, \alpha_h^H, \boldsymbol{\gamma}_h^H, \tau_{1h}, \tau_{2h}\right]'$, both as $k \times 1$ vectors where $k = 2(n_x + 1) + 2$.

Lusompa (2023) noted that the error term u_{t+h} follows an autocorrelation process, which is known. Given that the data $\{y_t\}$ are stationary and purely non-deterministic, such that there exists a Wold representation $y_t = \eta_t + \sum_{j=1}^{\infty} \Theta_j \eta_{t-j}$, Lusompa (2023) shows that the autocorrelation process in the error terms is known as

$$u_{t+h}^{(h)} = \Theta_h \eta_t + \ldots + \Theta_1 \eta_{t+h-1} + \eta_{t+h}, \tag{A.9}$$

which implies there exists a linear and time-invariant vector moving average representation (VMA) of the uncorrelated one-step ahead forecast errors $\{\eta_t\}$. In population, the error process is a VMA(h) even if the true model is not a (V)AR. Furthermore, it holds that

$$\phi_{1h} = \Theta_h \quad \Longrightarrow \quad u_{t+h}^{(h)} = \phi_{1h}\eta_t + \ldots + \phi_{11}\eta_{t+h-1} + \eta_{t+h}, \tag{A.10}$$

where $\phi_{1h} \in \boldsymbol{\gamma}_h$ corresponds to the coefficient of the first lag of the endogenous variable, Δy_{t-1}. Lusompa (2023) proposes to use the following transformation

$$\Delta^h \tilde{y}_{t+h} = \Delta^h y_{t+h} - \phi_{1h}\hat{\eta}_t - \ldots - \phi_{11}\hat{\eta}_{t+h-1}, \tag{A.11}$$

which eliminates the autocorrelation in the residuals. For an estimate of the residuals, $\hat{\eta}_t$, we note that for the horizon 0 LP, $\eta_t = u_{t+h}^{(h)}$ holds.

This transformation can also be used in conjunction with Bayesian estimation. In the Bayesian treatment, one needs to set up the likelihood and elicit prior densities. Due to LP being standard linear regressions, we elicit well-known independent priors for linear regressions. On both coefficient vectors, $\boldsymbol{\beta}_h$ and $\boldsymbol{\gamma}_h$, we impose independent Gaussian priors. Note that we are interested in treatment effect estimation of $\boldsymbol{\beta}$ where the number of control variables is potentially large relative to the number of observations. Hence, we use a regularization prior for $\boldsymbol{\gamma}$. On each element of $\boldsymbol{\beta}$ we do not want to impose any form of regularization and impose an uninformative Gaussian prior given by

$$\beta_h^x \sim \mathcal{N}\left(\underline{\mu}_{h,\beta}^x, \underline{V}_{h,\beta}^x\right), \quad \forall x \in \{L, H\}, \tag{A.12}$$

where $\underline{\mu}_{h,\beta}^x = 0$ and $\underline{V}_{h,\beta}^x = 100$. Following the results in Hahn et al. (2018), the presence of a regularization prior can still introduce a bias to the treatment effects. This bias arises due to confounding and depends on the predictability of $\boldsymbol{Z}_{t-1}$ by $\boldsymbol{e}_t$. Given the exogeneity of the sentiment shock and the predeterminedness of $\boldsymbol{Z}_{t-1}$, we argue that this is not a major issue.

For $\boldsymbol{\gamma}$, we define the prior variances as $\underline{\boldsymbol{V}}_{h,\gamma} = \text{diag}(\underline{v_1}, \ldots, \underline{v_k})$ with $\underline{v_i} = \lambda^2\psi_i^2$ for $i = 1, \ldots, k$. We propose a hierarchical global-local shrinkage prior setup based on the horseshoe (HS) prior following Carvalho, Polson, and Scott (2010), which reads as follows

$$\boldsymbol{\gamma}_h \sim \mathcal{N}\left(\underline{\boldsymbol{\mu}_{h,\gamma}}, \underline{\boldsymbol{V}_{h,\gamma}}\right), \quad \lambda \sim C^+(0,1), \quad \psi_i \sim C^+(0,1) \tag{A.13}$$

where C^+ denotes the half-Cauchy distribution. The parameter λ_r denotes the global shrinkage parameter of regime r, which exerts shrinkage on all coefficients. The parameter ψ_{rk} allows for individual, coefficient-specific, shrinkage. Both parameters are estimated and we do not have to specify any hyperparameters. We use the procedure outlined in Makalic and Schmidt (2015) to sample from the according conditional posterior densities. We center the prior distribution of $\boldsymbol{\gamma}$ on zero although other options are feasible as well (e.g., unity on the coefficient corresponding to the first own lag to resemble the Minnesota prior in Bayesian LPs; see also Ferreira, Miranda-Agrippino, and Ricco, 2023). For the deterministic terms, we do not impose any shrinkage and assume zero mean and a large variance, e.g., 10^5. The prior distribution of the variance term, σ_h^2, we impose a conjugate inverse-Gamma prior distribution,

$$\sigma_h^2 \sim iG(\underline{c}, \underline{d}), \tag{A.14}$$

where we set $\underline{c} = 3$ and $\underline{d} = 1$ to be uninformative.

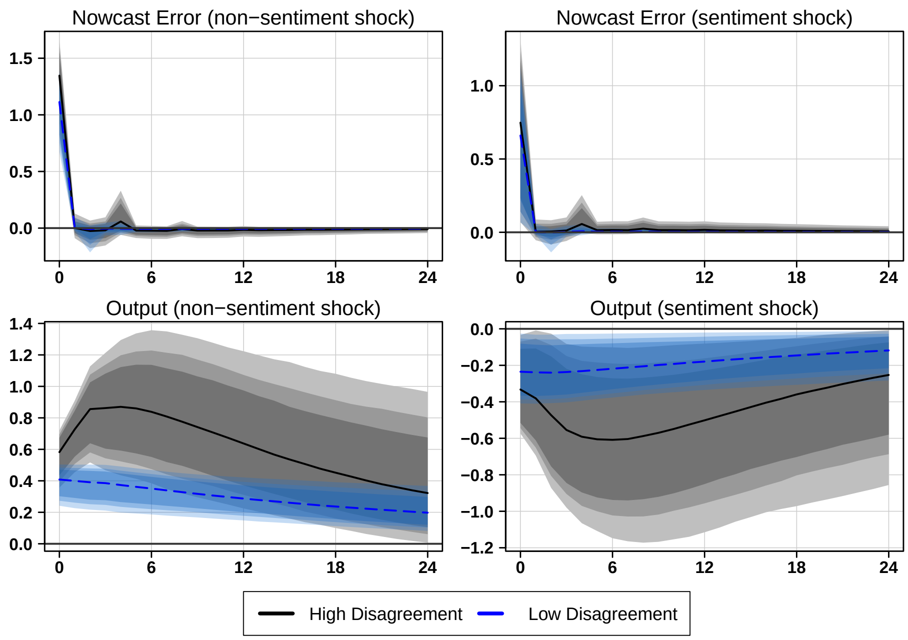
Similarly to the sampler of the STVAR, we briefly discuss the posterior simulation within an MCMC algorithm. Conditional on the regime indicator function $F(z_{t-1})$ the model is fully linear and all conditional posterior distributions are available in closed-form, rendering a Gibbs sampler convenient. Although the conditional posterior distribution of the VAR coefficients and the covariance matrix are standard, we use the auxiliary sampler of Makalic and Schmidt (2015) to sample from the conditional posterior densities for the HS prior. Lastly, and if necessary, the parameter related to the transition function, θ, has to be sampled with the help of a Metropolis-Hastings-within-Gibbs step since the posterior distribution are not available in closed-form.

B. Additional empirical results

This section reports additional empirical results not reported in the main text. We split this section into two parts. First, we report any additional results regarding the outcomes of the smooth-transition vector autoregression. In the second part, we report additional results of the state-dependent local projections.

B.1 Additional results of the smooth-transition vector autoregression

Figure B1: Impulse responses by regime.



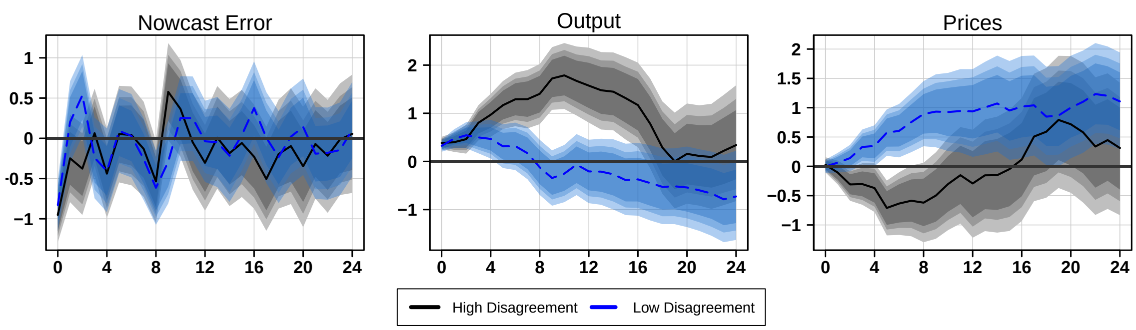
Notes: Estimates based on STVAR model. Identification based on sign-restrictions. The estimation covers the period 1969Q4-2019Q4. Black solid (blue dashed) line refers to the median response, while gray (blue) shaded areas indicates the 68%/80%/90% credible sets. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast errors) and percent (output).

Figure B1 reports the state-dependent impulse response functions of the STVAR model. We use the bivariate STVAR model to distinguish between sentiment and nonsentiment shocks. As is clearly visible in the figure, the nonsentiment shock shows a positive comovement between the nowcast error and output as imposed on impact through the sign restrictions. Similarly, we impose on impact a negative comovement between the nowcast error and output to identify a sentiment shock.

In terms of differences across regimes, we find as well stronger effects on output in the high disagreement regime. However, the impulse response function is much more hump-shaped, obscuring the effects we find in the local projections framework. This is due to the relatively small amount of lags in the STVAR model, which may introduce a bias in the impulse responses beyond the horizon of the number of lags introduced to the STVAR.

B.2 Additional results of the state-dependent local projections

Figure B2: Using the logistic function as transition function.

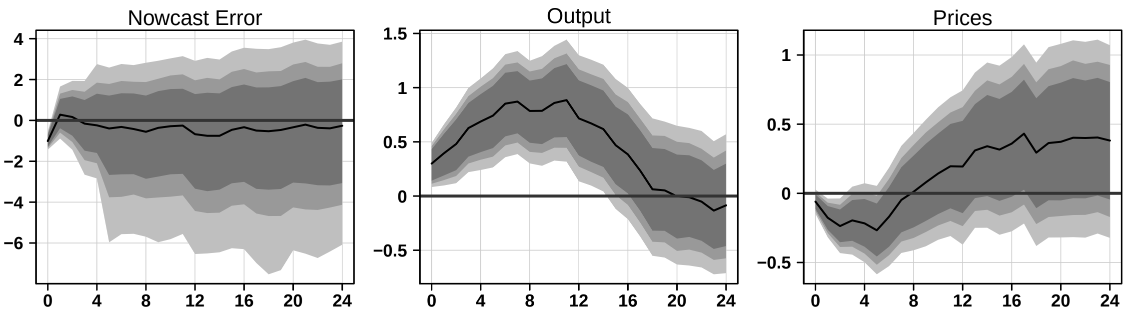


Notes: Estimates based on STLP with identified sentiment shock (ε_t^b) using a logistic transition function. Dependent variables are the nowcast error, output (log), prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. and The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

In this section, we report a couple of additional results of the state-dependent local projections. First, we provide robustness to the type of transition function. While we use the empirical cumulative distribution function for our main results, we provide robustness to using the logistic function as the transition function. Therefore, we specify the transition function on the basis of the logistic function, as discussed in Equation (A.4). We follow several previous studies, which have calibrated rather than estimated the smoothness parameter θ. We follow their suggestion and use a value of $\theta = 5$. Figure B2 reports the results, which show only negligible differences to the main outcomes in Figure 4.

In a next step, we account for the uncertainty of the generated regressor. As we pursue a Bayesian approach to estimation, we retrieve a full posterior distribution of

Figure B3: Accounting for the uncertainty of the generated regressor (LP).

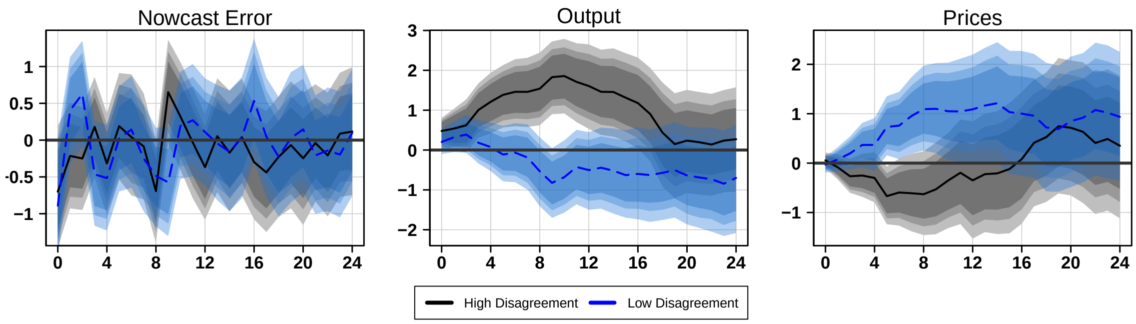


Notes: Estimates based on LP with identified sentiment shock (ε_t^b) accounting also for the uncertainty around the sentiment shock. Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid lines refer to the median estimate; the gray areas refer to the 68%/80%/90% credible sets. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

the sentiment shock, which we denote as $p(\varepsilon_t^b)$. Note that this constitutes a posterior distribution, but we do not indicate that we condition on the data. In a next step, we adapt the algorithm for the Bayesian (ST)LP slightly. In each iteration of the Gibbs sampler, we draw from the distribution of the sentiment shocks: $(\varepsilon_t^b)^{(s)} \sim p(\varepsilon_t^b)$, where (s) denotes the s-th iteration of the Gibbs sampler. This fully accounts for the uncertainty of the sentiment shock as a generated regressor when estimating the (ST)LP. We report the outcomes of this adjusted procedure in Figure B3 and Figure B4. While the posterior median is the same, credible sets have increased as we account for the additional uncertainty transmitted through the estimation of the sentiment shock itself. However, credible sets are still indicating significant results similar to the baseline results. Hence, our results are robust when accounting for this uncertainty explicitly. This comes as no surprise since already Wooldridge (2002, p. 117) notes that generated instruments do not suffer from the inference problem associated with generated regressors highlighted by Pagan (1984). We note that our sentiment shock series is not an instrument but an exogenous shock, but the conditions imposed are similar.

We perform some additional robustness checks regarding the threshold variable. In the baseline, we use the interquartile range of the forecasters' forecasts in the SPF regarding output growth as a measure of disagreement. Additionally, we scale the

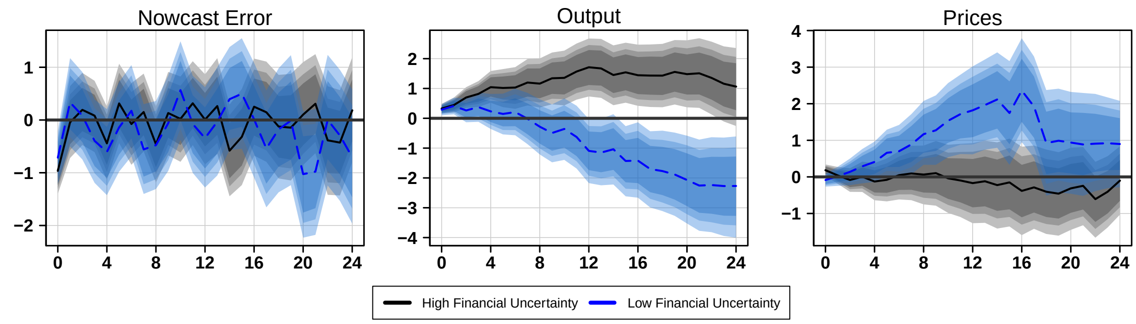
Figure B4: Accounting for the uncertainty of the generated regressor (STLP).



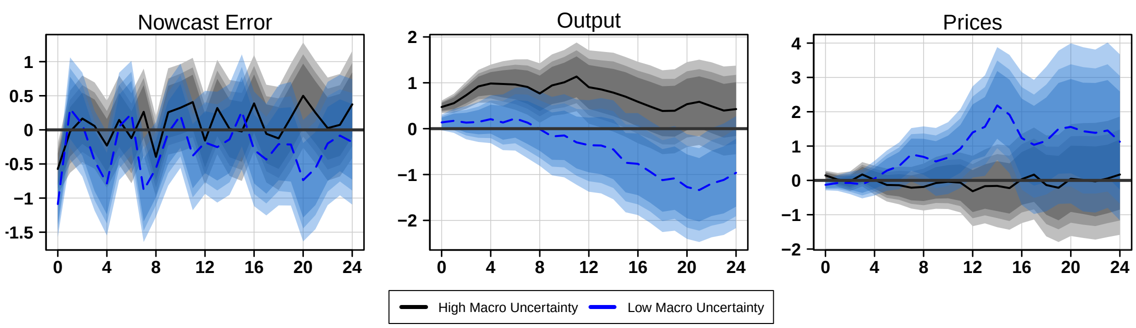
Notes: Estimates based on STLP with identified sentiment shock (ε_t^b) accounting also for the uncertainty around the sentiment shock. Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

series using the moving standard deviation of output growth using a window of 24 quarters. However, we could have chosen other threshold variables as well. Here, uncertainty measures come to our mind as effects may differ for disagreement and uncertainty measures (Born, Dovern, and Enders, 2023; Gambetti et al., 2023). We thus provide a robustness check, in which we use the financial and macro uncertainty measures provided by Jurado, Ludvigson, and Ng (2015). These measures are statistically significantly correlated to our baseline measure. The correlation coefficients are 0.35 ($p < 0.01$) and 0.22 ($p < 0.01$) for financial and macro uncertainty, respectively. As a last check, we scale our baseline disagreement series by the real-time moving standard deviation of output growth.

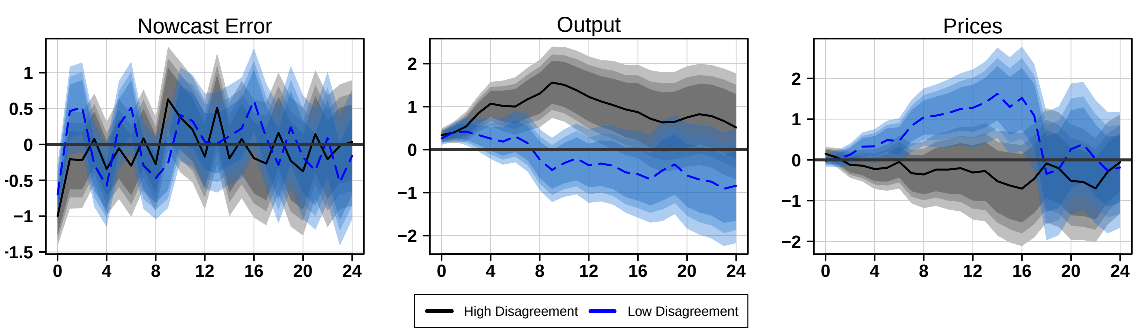
Figure B5: Additional robustness checks: uncertainty and real-time threshold variable.



(a) Threshold variable: Financial uncertainty.



(b) Threshold variable: Macro uncertainty.



(c) Threshold variable: Real-time disagreement.

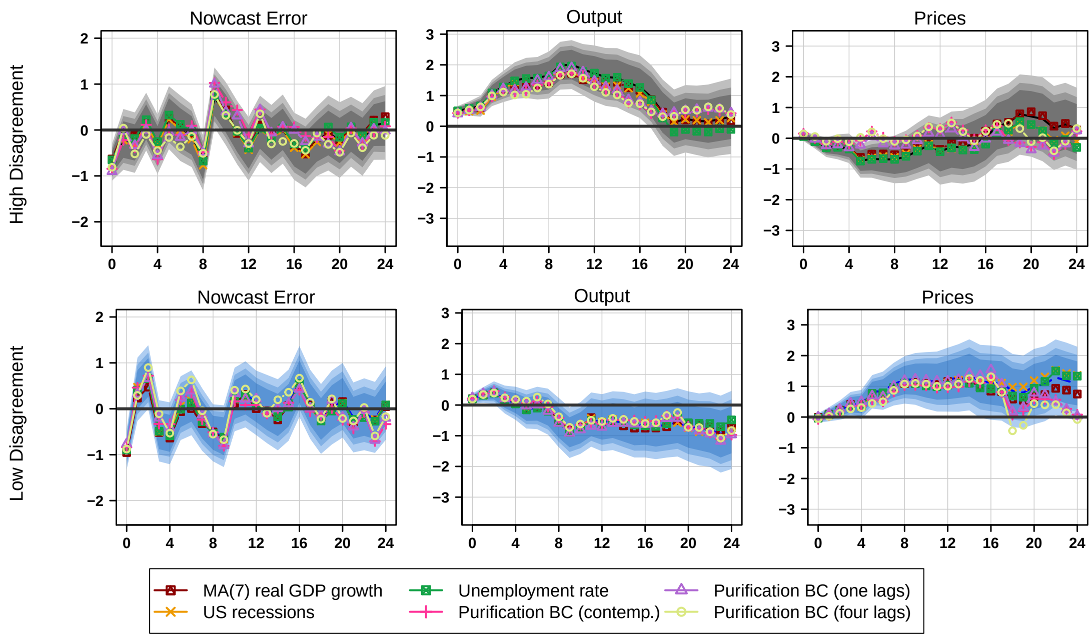
Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

We report the results of these checks in Figure B5. Our main findings are robust to these alternative indicators for uncertainty/disagreement. We find a stronger output reaction in the high disagreement/uncertainty regime, while we find a stronger price reaction in the low disagreement/uncertainty regime. In the high disagreement/uncertainty regime, prices are not statistically different from zero. For output in the low disagreement regime, the outcomes are more mixed. When using disagreement, we find, similar to our main results, only a short-lived positive reaction before it quickly turns insignificant and fluctuates around zero. For the uncertainty measures, we even find a reversal of the initial positive reaction after three years. Although we think the comparison to uncertainty measures is important, we opt for disagreement in our baseline. The reason is mainly consistency: Similar to our construction of the nowcast error, we use consistently the same survey, which asks the same respondents. This allows us to investigate the effect of sentiment shock conditional on the level of disagreement these forecasters operate. In contrast, the uncertainty measures are constructed outside of the SPF and thus may not ideally mimic the informational environment of these forecasters.

We conduct further robustness checks with the state of the business cycle. As disagreement is correlated with the business cycle Dovern, Fritsche, and Slacalek (2012), an alternative interpretation is that our results are not due to information frictions but that capacity utilization differs over the business cycle. During recessions, a demand impulse boosts output, while during booms, the economy is near full capacity and a demand impulse is absorbed by prices. First, we report low correlations to the state of the business cycle ($\rho = -0.06$ of the baseline disagreement measure with a seven-period moving average process of quarterly growth rates; $\rho = -0.14$ for year-on-year growth rates). This is in contrast to Dovern, Fritsche, and Slacalek (2012) who focus not on nowcasts for the disagreement but on one-year ahead expectations for constructing disagreement.

Then, we conduct two exercises. In the first, we re-estimate the baseline version of the model but control additionally for the level of the business cycle. We use three different measures: MA(7) of real GDP growth, a dummy for recessions, and the unemployment rate. This eliminates any potential level effect of the business cycle. In the second exercise, we off-project the information contained in the business cycle information from the disagreement series before constructing the state indicator (*purification)*. This orthogonalizes the disagreement series to the business cycle.

Figure B6: Controlling for the state of the business cycle.

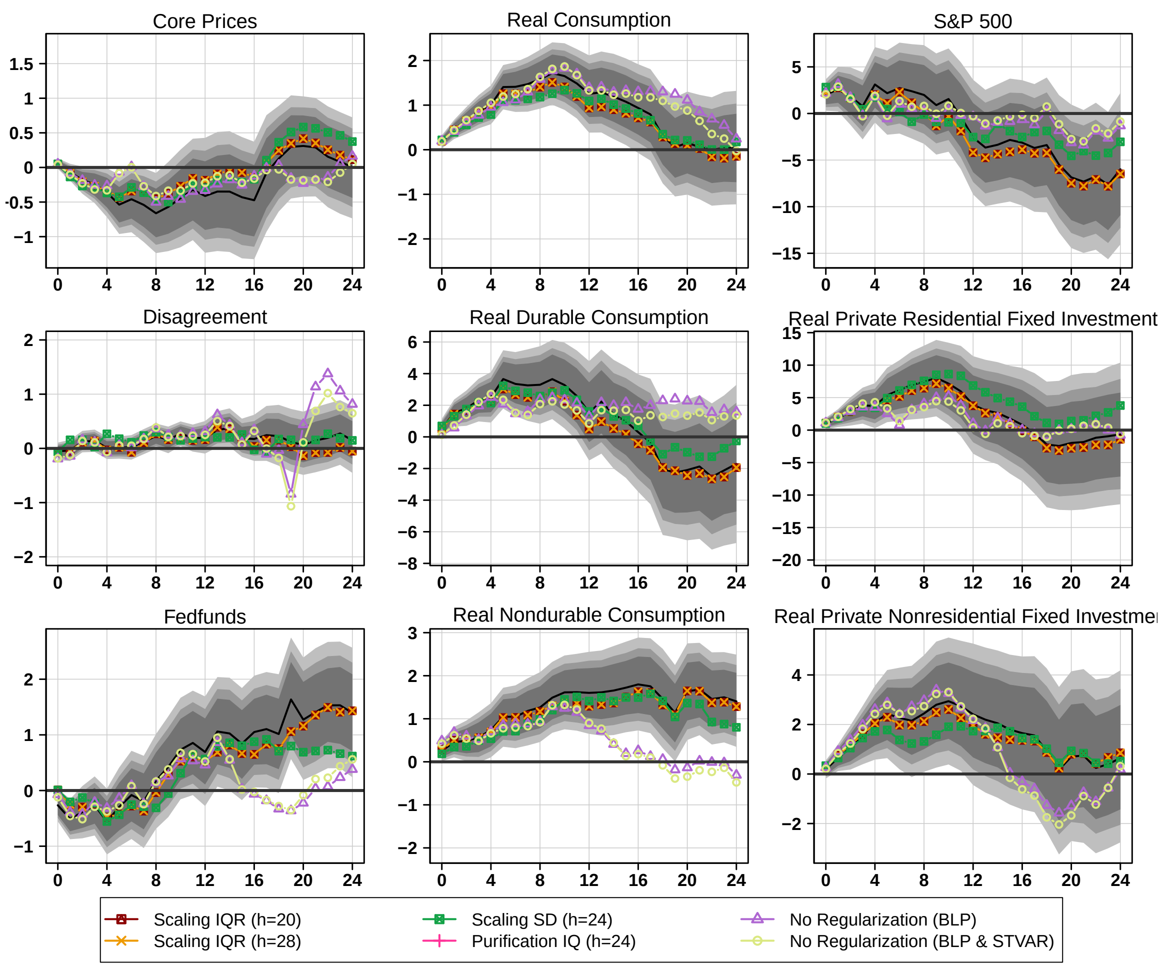


Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. Colored lines with symbols refer to robustness specifications: adding business cycle controls (MA(7) of real GDP growth, dummy for recessions, and the unemployment rate) and purification of the disagreement series by the state of the business cycle (only contemporaneous correlation or adding one or four lags). The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error) or percent (output, prices).

Figure B6 reports the results showing the median estimate and credible sets of the baseline model and the median estimates of the alternative specifications. The baseline model is both robust to the level of the state of the business cycle and off-projecting (*purifying*) the information of the business cycle from the disagreement state indicator series. None of the alternative models diverge strongly from the baseline model.

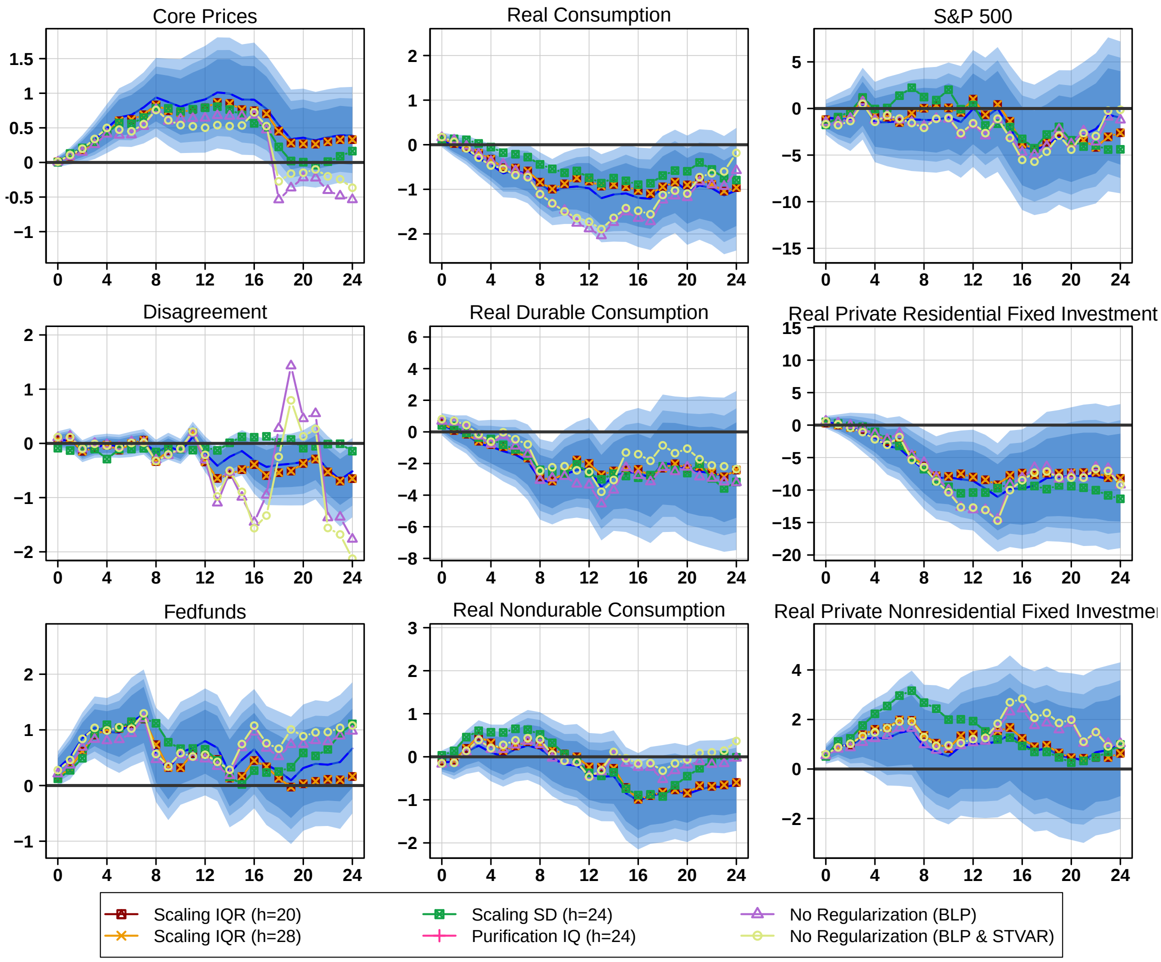
In Figure 8, we report robustness regarding the window size, using the standard deviation instead of the interquartile range, or doing purification. We refer to purification as off-projecting the information contained in the moving standard deviation via a linear regression. Additionally, we also report robustness checks for using different prior distributions imposing no regularization. We only report those robustness checks for our main variables of interest (nowcast error, output, and prices) but not for our extended set of variables. Here, we report those additional variables in Figure B7 and Figure B8.

Figure B7: Robustness to the state-dependent effects of a sentiment shock (high disagreement).



Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. Colored lines with symbols refer to robustness specifications: Scaling using a different moving average process (20 or 28 quarters), scaling using the standard deviation as dispersion measure, using purification instead of scaling, and prior sensitivity analysis (no regularization in the second or both estimation steps). The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error, dispersion, federal funds rate) or percent (output, prices, core prices, real consumption, S&P 500, real durable consumption, real private residential fixed investment, real nondurable consumption, real private nonresidential fixed investment).

Figure B8: Robustness to the state-dependent effects of a sentiment shock (low disagreement).



Notes: Estimates based on STLP with identified sentiment shock (ε_t^b). Dependent variables are the nowcast error, output measured by real GDP (log), prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (β_h^L) in the high (low) disagreement regime. The gray (blue) areas refer to the 68%/80%/90% credible sets of the respective regime. Colored lines with symbols refer to robustness specifications: Scaling using a different moving average process (20 or 28 quarters), scaling using the standard deviation as dispersion measure, using purification instead of scaling, and prior sensitivity analysis (no regularization in the second or both estimation steps). The horizontal axis measures the impulse response horizon in quarters. The vertical axis denotes deviations from trend in percentage points (nowcast error, dispersion, federal funds rate) or percent (output, prices, core prices, real consumption, S&P 500, real durable consumption, real private residential fixed investment, real nondurable consumption, real private nonresidential fixed investment).

C. Model solution

In Appendix D, we provide the proofs for Propositions 1-2 in Section 5. In a preliminary step, we outline the model solution and key equilibrium relationships in Appendix C. Throughout, we consider a linear approximation to the equilibrium conditions of the model. Lower-case letters indicate percentage deviations from steady state.

We solve the model by backward induction. That is, we start by deriving inflation expectations regarding period $t+1$. Using the result in the Euler equation of the third stage of period t allows us to determine price-setting decisions during stage two. Eventually, we obtain the short-run responses of aggregate variables to unexpected changes in productivity or sentiment shocks.

Expectations regarding period t+1. Below, $\mathbb{E}_{k,t}$ stands for either $\mathbb{E}_{j,l,t}$, referring to the information set of producer j on island l at the time of her pricing decision, or for $\mathbb{E}_{l,t}$, referring to the information set of the household on island l at the time of its consumption decision. Variables with only time subscripts refer to economy-wide values. The wage in period $t+1$ is set according to the expected aggregate labor supply

$$\mathbb{E}_{k,t}\varphi l_{t+1} = \mathbb{E}_{k,t}(w_{t+1} - p_{t+1} - c_{t+1}).$$

This equation is combined with the aggregated production function

$$\mathbb{E}_{k,t}y_{t+1} = \mathbb{E}_{k,t}(x_{t+1} + \alpha l_{t+1}),$$

the expected aggregate labor demand

$$\mathbb{E}_{k,t}(w_{t+1} - p_{t+1}) = \mathbb{E}_{k,t}[x_{t+1} + (1-\alpha)l_{t+1}],$$

and market clearing $y_{t+1} = c_{t+1}$ to obtain $\mathbb{E}_{k,t}x_{t+1} = \mathbb{E}_{k,t}y_{t+1} = \mathbb{E}_{k,t}c_{t+1}$. Furthermore, the expected Euler equation, together with the Taylor rule, is

$$\mathbb{E}_{k,t}c_{t+1} = \mathbb{E}_{k,t}(c_{t+2} + \pi_{t+2} - \psi\pi_{t+1}).$$

Agents expect the economy to be in a new steady state tomorrow ($\mathbb{E}_{k,t}c_{t+1} = \mathbb{E}_{k,t}c_{t+2}$), given the absence of state variables other than technology, which follows a unit root process. Ruling out explosive paths yields

$$\mathbb{E}_{k,t}\pi_{t+2} = \mathbb{E}_{k,t}\pi_{t+1} = 0.$$

Stage three of period *t*. After prices are set, each household observes n prices in the economy. Since the productivity signal is public, the productivity level $a_{j,l,t} = a_{l,t}$—which is the same for all producers $j \in [0,1]$ on island l—can be inferred from each price $p_{j,l,t}$ of the good from producer j on island l. Hence, household l forms its expectations about the change in aggregate productivity according to

$$\mathbb{E}_{l,t}\Delta x_t = \rho_x^h s_t + \delta_x^h \hat{a}_{l,t},$$

where $\hat{a}_{l,t}$ is the average over the realizations of $a_{m,t} - x_{t-1}$ for each location m in household l's sample. The coefficients ρ_x^h and δ_x^h are equal across households and depend on $n, \sigma_e^2, \sigma_\varepsilon^2$, and σ_η^2 in the following way:

$$\rho_x^h = \frac{\sigma_\eta^2/n}{\underbrace{\sigma_e^2 + \sigma_\eta^2/n + \frac{\sigma_e^2\sigma_\eta^2/n}{\sigma_\varepsilon^2}}_{\to 0 \text{ if } n\to\infty}}, \qquad \delta_x^h = \frac{\sigma_e^2}{\underbrace{\sigma_e^2 + \sigma_\eta^2/n + \frac{\sigma_e^2\sigma_\eta^2/n}{\sigma_\varepsilon^2}}_{\to 1 \text{ if } n\to\infty}}. \tag{C.1}$$

Producers, on the other hand, only observe the signal and their own productivity. They thus form expectations according to

$$\mathbb{E}_{j,l,t}\Delta x_t = \rho_x^p s_t + \delta_x^p (a_{l,t} - x_{t-1}), \tag{C.2}$$

with

$$\rho_x^p = \frac{\sigma_\eta^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_\eta^2\sigma_e^2}{\sigma_\varepsilon^2}} \qquad \delta_x^p = \frac{\sigma_e^2}{\sigma_e^2 + \sigma_\eta^2 + \frac{\sigma_\eta^2\sigma_e^2}{\sigma_\varepsilon^2}},$$

such that $\delta_x^h > \delta_x^p$ because of the higher information content of households' observations. Consumption follows an Euler equation with household-specific inflation, as only a subset of goods is bought. Agents expect no differences between households for $t+1$, such that expected aggregate productivity and the overall price level impact today's individual consumption. Also using $\mathbb{E}_{l,t}p_{t+1} = \mathbb{E}_{l,t}p_t$ and $\mathbb{E}_{l,t}x_{t+1} = \mathbb{E}_{l,t}x_t$ gives

$$c_{l,t} = \mathbb{E}_{l,t}x_t + \mathbb{E}_{l,t}p_t - p_{l,t} - r_t. \tag{C.3}$$

Similar to the updating formula for technology estimates, households use their available information to form an estimate about the aggregate price level p_t according to

$$\mathbb{E}_{l,t}p_t = \rho_p^h s_t + \delta_p^h \hat{a}_{l,t} + \kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t. \tag{C.4}$$

Combining the above gives

$$c_{l,t} = (1+\tau_p^h)x_{t-1} + \rho_{xp}^h s_t + \delta_{xp}^h \hat{a}_{l,t} + \kappa_p^h w_t - (1+\eta_p^h) r_t - p_{l,t}, \tag{C.5}$$

where $\rho_{xp}^h = \rho_x^h + \rho_p^h$ and $\delta_{xp}^h = \delta_x^h + \delta_p^h$. We will solve for the undetermined coefficients below.

Stage two of period t. During the second stage, firms obtain idiosyncratic signals about their productivity. In the following, the index $\tilde{p}_{l,t}$ is the average price index of customers visiting island l. If customers bought on all (that is, infinitely many) islands in the economy, $\tilde{p}_{l,t}$ would correspond to the overall price level. Since consumers only buy on a subset of islands, the price of their own island has a non-zero weight in their price index, which is taken into account further below. Firms set prices according to

$$\begin{aligned} p_{j,l,t} &= w_t + \frac{1-\alpha}{\alpha}\mathbb{E}_{j,l,t} y_{j,l,t} - \frac{1}{\alpha} a_{l,t} \\ &\equiv k' + k_1' \mathbb{E}_{j,l,t}\tilde{p}_{l,t} + k_2' \mathbb{E}_{j,l,t} y_t - k_3' a_{l,t}, \end{aligned}$$

with

$$k' = \frac{\alpha}{\alpha+\gamma(1-\alpha)} w_t \quad k_1' = \frac{\gamma(1-\alpha)}{\alpha+\gamma(1-\alpha)} \quad k_2' = \frac{1-\alpha}{\alpha+\gamma(1-\alpha)} \quad k_3' = \frac{1}{\alpha+\gamma(1-\alpha)}. \tag{C.6}$$

From here onwards, expressions that are based on common knowledge only (such as k') are treated like parameters in notation terms, i.e. they lack a time index. This facilitates the important distinction between expressions that are common information and those that are not. Evaluating the expectation of firm j about aggregate output in period t, given equation (C.5), results in

$$\mathbb{E}_{j,l,t} y_t = \kappa^h + \rho_{xp}^h s_t + \delta_{xp}^h \mathbb{E}_{j,l,t}\left(\frac{1}{n} a_{l,t} + \frac{n-1}{n}\mathbb{E}_{j,l,t} x_t - x_{t-1}\right) - \left(\frac{1}{n} p_{j,l,t} + \frac{n-1}{n}\mathbb{E}_{j,l,t} p_t\right),$$

where $\kappa^h = (1+\tau_p^h)x_{t-1} - (1+\eta_p^h) r_t + \kappa_p^h w_t$ contains only publicly available information. Furthermore, it is taken into account that the productivity of island l has a non-zero weight in the sample of productivity levels observed by consumers visiting island l. Note that producers still take the price index of the consumers as given, since they buy infinitely many goods on the same island. Inserting the above into the pricing equation (C.6) yield (here, p_t is the average of the prices charged by producers of all other islands, which is the overall price index as there are infinitely many locations)

$$p_{j,l,t} \equiv k + k_1 \mathbb{E}_{j,l,t} p_t + \tilde{k} s_t - k_3 a_{l,t},$$

with

$$\Xi = 1 - \frac{1}{n}(k_1' - k_2') \qquad k = \frac{1}{\Xi}\left\{k' + k_2'\kappa^h + \frac{k_2'\delta_{xp}^h}{n}\left[(n-1)(1-\delta_x^p) - 1\right]x_{t-1}\right\} \quad \text{(C.7)}$$

$$k_1 = \frac{n-1}{n\Xi}\left(k_1' - k_2'\right) \qquad \tilde{k} = \frac{k_2'}{\Xi}\left(\rho_{xp}^h + \delta_{xp}^h\rho_x^p\frac{n-1}{n}\right) \qquad k_3 = \frac{1}{\Xi}\left\{k_3' - \frac{k_2'\delta_{xp}^h}{n}\left[(n-1)\delta_x^p + 1\right]\right\}.$$

Note that, according to (C.6), $0 < k_1' - k_2' < 1$ because $0 < \alpha < 1$ and $\gamma > 1$. Using the definition of k_1 in (C.7), this implies (observe that $n > 1$)

$$0 < k_1 < 1.$$

Aggregating over all producers gives the aggregate price index

$$p_t = k + k_1\overline{E}_t p_t + \tilde{k}s_t - k_3 x_t,$$

where $\int a_{l,t}dl = x_t$, and $\overline{E}_t p_t = \iint \mathbb{E}_{j,l,t}p_t \; djdl$ is the average expectation of the price level.

The expectation of firm j of this aggregate is therefore

$$\begin{aligned}\mathbb{E}_{j,l,t}p_t &= k + \tilde{k}s_t - k_3\mathbb{E}_{j,l,t}x_t + k_1\mathbb{E}_{j,l,t}\overline{E}_t p_t \\ &= k + \left(\tilde{k} - k_3\rho_x^p\right)s_t - k_3\delta_x^p a_{l,t} - k_3(1-\delta_x^p)x_{t-1} + k_1\mathbb{E}_{j,l,t}\overline{E}_t p_t. \qquad \text{(C.8)}\end{aligned}$$

Inserting the last equation into (C.7) gives

$$p_{j,l,t} = k + k_1 k - k_1 k_3(1-\delta_x^p)x_{t-1} + \left[\tilde{k} + k_1\left(\tilde{k} - k_3\delta_x^p\right)\right]s_t - \left(k_3 + k_1k_3\delta_x^p\right)a_t^j + k_1^2\mathbb{E}_{j,l,t}\overline{E}_t p_t.$$

To find $\mathbb{E}_{j,l,t}\overline{E}_t p_t$, note that firm j's expectations of the average of (C.8) are

$$\mathbb{E}_{j,l,t}\overline{E}_t p_t = k - k_3(1-\delta_x^p)(1+\delta_x^p)x_{t-1} + \left(\tilde{k} - k_3\rho_x^p - k_3\delta_x^p\rho_x^p\right)s_t - k_3\delta_x^{p2}a_{l,t} + k_1\mathbb{E}_{j,l,t}\overline{E}_t^{(2)}p_t,$$

where $\overline{E}^{(2)}$ is the average expectation of the average expectation. The price of firm j is found by plugging the last equation into the second-to-last:

$$\begin{aligned}p_{j,l,t} = &\left(k + k_1 k + k_1^2 k\right) - \left[k_1k_3(1-\delta_x^p) + k_1^2k_3(1-\delta_x^p)(1+\delta_x^p)\right]x_{t-1} \\ &+ \left[\tilde{k} + k_1\left(\tilde{k} - k_3\rho_x^p\right) + k_1^2\left(\tilde{k} - k_3\rho_x^p - k_3\delta_x^p\rho_x^p\right)\right]s_t \\ &- \left(k_3 + k_1k_3\delta_x^p + k_1^2k_3\delta_x^{p2}\right)a_{l,t} + k_1^3\mathbb{E}_{j,l,t}\overline{E}^{(2)}p_t.\end{aligned}$$

Continuing like this results in some infinite sums

$$\begin{aligned}
p_{j,l,t} =& k\left(1+k_1+k_1^2+k_1^3\dots\right) \\
&- k_1k_3(1-\delta_x^p)\Big[1+k_1(1+\delta_x^p)+k_1^2(1+\delta_x^p+\delta_x^{p2})+k_1^3(1+\delta_x^p+\delta_x^{p2}+\delta_x^{p3}\dots)\Big]x_{t-1} \\
&+\Big[\tilde{k}+k_1\left(\tilde{k}-k_3\rho_x^p\right)+k_1^2\left(\tilde{k}-k_3\rho_x^p-k_3\delta_x^p\rho_x^p\right)+k_1^3\left(\tilde{k}-k_3\rho_x^p-k_3\rho_x^p\delta_x^p-k_3\rho_x^p\delta_x^{p2}\right)+\dots\Big]s_t \\
&- k_3\left(1+k_1\delta_x^p+k_1^2\delta_x^{p2}+k_1^3\delta_x^{p3}\dots\right)a_{l,t}+k_1^\infty\mathbb{E}_{j,l,t}\overline{E}^{(\infty)}p_t.
\end{aligned}$$

For the terms in the third line, we have

$$\begin{aligned}
&\tilde{k}+k_1\left(\tilde{k}-k_3\rho_x^p\right)+k_1^2\left(\tilde{k}-k_3\rho_x^p-k_3\delta_x^p\rho_x^p\right)+k_1^3\left(\tilde{k}-k_3\rho_x^p-k_3\rho_x^p\delta_x^p-k_3\rho_x^p\delta_x^{p2}\right) \\
&+k_1^4\left(\tilde{k}-k_3\rho_x^p-k_3\rho_x^p\delta_x^p-k_3\rho_x^p\delta_x^{p2}-k_3\rho_x^p\delta_x^{p3}\right)\dots \\
=&\tilde{k}(1+k_1+k_1^2+k_1^3\dots)-\left(k_1k_3\rho_x^p+k_1^2k_3\rho_x^p+k_1^3k_3\rho_x^p\dots\right) \\
&-\left(\delta_x^pk_1^2k_3\rho_x^p+\delta_x^pk_1^3k_3\rho_x^p+\delta_x^pk_1^4k_3\rho_x^p\dots\right)-\left(\delta_x^{p2}k_1^3k_3\rho_x^p+\delta_x^{p2}k_1^4k_3\rho_x^p+\delta_x^{p3}k_1^5k_3\rho_x^p\dots\right)\dots \\
=&\tilde{k}(1+k_1+k_1^2+k_1^3\dots)-k_1k_3\left(\frac{\rho_x^p}{1-k_1}+\frac{\rho_x^p\delta_x^pk_1}{1-k_1}+\frac{\rho_x^p\delta_x^{p2}k_1^2}{1-k_1}\dots\right) \\
=&\frac{\tilde{k}}{1-k_1}-\frac{k_1k_3\rho_x^p}{1-k_1}\left(1+\delta_x^pk_1+\delta_x^{p2}k_1^2\dots\right) \\
=&\frac{\tilde{k}}{1-k_1}-\frac{k_1k_3\rho_x^p}{(1-k_1)(1-\delta_x^pk_1)}.
\end{aligned}$$

Proceeding similarly with the terms in the other lines results in

$$p_{j,l,t}=\frac{k}{1-k_1}-\frac{k_1(1-\delta_x^p)}{1-k_1}\frac{k_3}{1-k_1\delta_x^p}x_{t-1}+\frac{1}{1-k_1}\left(\tilde{k}-\rho_x^p\frac{k_1k_3}{1-k_1\delta_x^p}\right)s_t-\frac{k_3}{1-k_1\delta_x^p}a_{l,t}+\underbrace{k_1^\infty\overline{E}_t^{(\infty)}}_{\to 0}p_t.$$

Setting idiosyncratic technology shocks equal to zero in order to track the effects of aggregate shocks and observing that all firms then set the same price gives

$$p_t\equiv\bar{k}_1+\bar{k}_2s_t+\bar{k}_3x_t,$$

with

$$\bar{k}_1=\frac{1}{1-k_1}\left[k-(1-\delta_x^p)\frac{k_1k_3}{1-k_1\delta_x^p}x_{t-1}\right]\quad\bar{k}_2=\frac{1}{1-k_1}\left(\tilde{k}-\rho_x^p\frac{k_1k_3}{1-k_1\delta_x^p}\right)\quad\bar{k}_3=-\frac{k_3}{1-k_1\delta_x^p}. \tag{C.9}$$

To arrive at qualitative predictions for the impact of the structural shocks ε_t and e_t on output growth and the nowcast error, we need to determine the sign and the size of $\bar{k}_3$. Note that, according to (C.7),

$$-k_3=\delta_{xp}^h\frac{k_2'-nk_3'/\delta_{xp}^h+k_2'(n-1)\delta_x^p}{n-(k_1'-k_2')},$$

where the first part of the numerator can be rewritten, by observing (C.6), as

$$k_2' - nk_3'/\delta_{xp}^h = \frac{1 - n/\delta_{xp}^h - \alpha}{\alpha + \gamma(1-\alpha)}.$$

Using (C.6) and (C.7) thus yields

$$-k_3 = \delta_{xp}^h \frac{(1-\alpha)[(n-1)\delta_x^p + 1] - n/\delta_{xp}^h}{(n-1)[\alpha + \gamma(1-\alpha)] + 1}.$$

Plugging this into the definition of $\overline{k}_3$ in (C.9) gives

$$\overline{k}_3 = \delta_{xp}^h \frac{\frac{(1-\alpha)[(n-1)\delta_x^p+1] - n/\delta_{xp}^h}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}{1 - \delta_x^p \frac{(n-1)(\gamma-1)(1-\alpha)}{(n-1)[\alpha+\gamma(1-\alpha)]+1}}.$$

To obtain $\delta_{xp}^h = \delta_x^h + \delta_p^h$, we need to find the undetermined coefficients of equation (C.4). Start by comparing this equation with household l's expectation of equation (C.9):

$$\mathbb{E}_{l,t} p_t = \underbrace{\overline{k}_1 + \overline{k}_3 x_{t-1}}_{\kappa_p^h w_t + \tau_p^h x_{t-1} - \eta_p^h r_t} + \underbrace{\left(\overline{k}_2 + \overline{k}_3 \rho_x^h\right)}_{\rho_p^h} s_t + \underbrace{\overline{k}_3 \delta_x^h}_{\delta_p^h} \hat{a}_{l,t}. \tag{C.10}$$

Hence, $\delta_{xp}^h = \delta_x^h(1 + \overline{k}_3)$. Inserting this into the above expression for $\overline{k}_3$ yields

$$\overline{k}_3 \equiv -\frac{n/\Upsilon - \delta_x^h \Psi}{\Phi - \delta_x^h \Psi}, \tag{C.11}$$

with

$$\Upsilon = (n-1)[\alpha + \gamma(1-\alpha)] + 1 > 0 \qquad \Psi = (1-\alpha)[(n-1)\delta_x^p + 1]/\Upsilon > 0$$
$$\Phi = 1 - \delta_x^p (n-1)(\gamma-1)(1-\alpha)/\Upsilon.$$

The signs obtain because $n > 1, 0 < \alpha < 1, \delta_x^p > 0$, and $\gamma > 1$. Observe that $\Psi\Upsilon < n$ because $\delta_x^p \leq 1$. Hence, $n/\Upsilon - \delta_x^h \Psi > 0$ because

$$n - \underbrace{\delta_x^h}_{>0,<1} \underbrace{\Psi\Upsilon}_{<n} > 0,$$

implying that the numerator of (C.11) is positive. Turning to the denominator $\Phi - \delta_x^h \Psi$, observe that $\Phi - \Psi > 0$. The denominator of (C.11) is therefore positive as well, and we have $\overline{k}_3 < 0$. Next, consider that $n/\Upsilon < \Phi$ and we obtain

$$-1 < \overline{k}_3 < 0.$$

This is a key result for the derivation of Propositions 1 and 2; see Appendix D. Multiplying the numerator and the denominator of the fraction in equation (C.11) by Υ and rewriting gives the expression used in Proposition 1.

Prices We now investigate the effect of a noise shock on prices, that is, we set the other shocks to zero. Using equation (C.9), we get

$$p_t = \bar{k}_1 + \bar{k}_2 e_t,$$

where $\bar{k}_1$ includes the wage. Furthermore,

$$\bar{k}_1 = \frac{k}{1-k_1} \qquad \bar{k}_2 = \frac{1}{1-k_1}\left[\tilde{k} + \underbrace{k_1\bar{k}_3\rho_x^p}_{>-1,<0}\right],$$

where we have used equation (C.9). According to (C.7),

$$k = \frac{1}{\Xi}\left[k' + k_2'\kappa_p^h w_t\right].$$

Remember that,

$$k' = \frac{\alpha}{\alpha+\gamma(1-\alpha)}w_t \qquad k_2' = \frac{1-\alpha}{\alpha+\gamma(1-\alpha)} \qquad \Xi = 1 - \frac{1}{n}(k_1' - k_2'),$$

see (C.6) and (C.7). As a result,

$$\Xi = \frac{n\alpha + (1-\alpha)[(n-1)\gamma+1]}{n\alpha + n\gamma(1-\alpha)}.$$

Note that $1-k_1$ can be written as

$$1 - k_1 = \frac{n}{(n-1)[\alpha+\gamma(1-\alpha)]+1}.$$

Taken together, this gives

$$k = \frac{1}{\Xi}\frac{1}{\alpha+\gamma(1-\alpha)}\left[\alpha + (1-\alpha)\kappa_p^h\right]w_t \tag{C.12}$$

$$\rightarrow \bar{k}_1 = \frac{k}{1-k_1} = \left[\alpha + (1-\alpha)\kappa_p^h\right]w_t. \tag{C.13}$$

According to (C.10)

$$\bar{k}_1 = \kappa_p^h w_t.$$

Combining the last two equations yields

$$\bar{k}_1 = w_t \quad \rightarrow \quad \kappa_p^h = 1.$$

Turning to $\bar{k}_2$, observe that according to (C.7)

$$\tilde{k} = \frac{1}{\Xi}\frac{1-\alpha}{\alpha+\gamma(1-\alpha)}\left[\rho_{xp}^h + \delta_{xp}^h\frac{n-1}{n}\rho_x^p\right].$$

Hence, keeping in mind the derivation of (C.13),

$$\bar{k}_2 = \frac{1}{1-k_1}\left[\tilde{k} + k_1 \bar{k}_3 \rho_x^p\right]$$
$$= (1-\alpha)\left[\rho_{xp}^h + \delta_{xp}^h \frac{n-1}{n}\rho_x^p\right] + \frac{k_1}{1-k_1}\bar{k}_3 \rho_x^p.$$

Inserting the insights from (C.10) yields

$$\bar{k}_2 = (1-\alpha)\left[\rho_x^h + \rho_p^h + (\delta_x^h + \delta_p^h)\frac{n-1}{n}\rho_x^p\right] + \frac{k_1}{1-k_1}\bar{k}_3 \rho_x^p$$
$$= \frac{1-\alpha}{\alpha}\left[\rho_x^h(1+\bar{k}_3) + \delta_x^h(1+\bar{k}_3)\frac{n-1}{n}\rho_x^p\right] + \frac{k_1}{\alpha(1-k_1)}\bar{k}_3 \rho_x^p.$$

Then observe that, see (C.12),

$$\frac{1}{\alpha}\frac{k_1}{1-k_1} = \frac{n-1}{n}(\gamma-1)\frac{1-\alpha}{\alpha}.$$

The total effect of noise on inflation, according to

$$p_t = w_t + \bar{k}_2 e_t$$

is then

$$\frac{\partial p_t}{\partial e_t} = (1+\bar{k}_3)\frac{1-\alpha}{\alpha}\left[\rho_x^h + \delta_x^h \frac{n-1}{n}\rho_x^p\right] + (\gamma-1)\frac{n-1}{n}\frac{1-\alpha}{\alpha}\bar{k}_3 \rho_x^p, \tag{C.14}$$

where $\Omega \equiv -\bar{k}_3$ is used in the main text.

Stage one of period *t* As information sets of agents are perfectly aligned during stage one, we use the expectation operator $\mathbb{E}_t$ to denote (common) stage-one expectations in what follows. Combining the results regarding expectations about inflation in period $t+1$ with the Euler equation, the Taylor rule, and the random-walk assumption for x_t gives

$$\mathbb{E}_t y_t = \mathbb{E}_t x_t - \psi \mathbb{E}_t \pi_t.$$

Remember that the monetary policy shock emerges after wages are set. Its expected value before wage-setting is zero. Combining labor supply and demand with the production function then yields $\mathbb{E}_t \pi_t = 0$, such that $\mathbb{E}_t y_t = \mathbb{E}_t x_t = x_{t-1}$. Nominal wages are set in line with these expectations. We thus have determinacy of the price level. The central bank also expects zero inflation in the absence of monetary policy shocks.

D. Proofs

Proof of Proposition 1 Aggregating individual Euler equations (C.3) over all individuals, using (C.9) and (C.10),

$$\begin{aligned} y_t =& \mathbb{E}_{l,t} x_t + \mathbb{E}_{l,t} p_t - p_t - r_t \\ =& x_{t-1} + \rho_x^h (1+\overline{k}_3) s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h - 1)\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t \\ =& x_{t-1} + \underbrace{\rho_x^h(1+\overline{k}_3)}_{>0} e_t + \underbrace{\left[\delta_x^h + \rho_x^h - \overline{k}_3(1-\delta_x^h-\rho_x^h)\right]}_{>0}\varepsilon_t - \underbrace{\frac{\alpha}{\alpha+\psi(1-\alpha)}}_{<0}\nu_t, \end{aligned} \tag{D.1}$$

where $1-\delta_x^h-\rho_x^h > 0$ because of (C.1). Note that, if households have full information $(n \to \infty)$, we get $\rho_x^h \to 0$ and $\delta_x^h \to 1$. Defining $\Omega \equiv -\overline{k}_3$, we can write

$$y_t = x_{t-1} + \rho_x^h(1-\Omega)e_t + \left[(\delta_x^h + \rho_x^h)(1-\Omega) + \Omega\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t.$$

The signs indicated above result from $0 < \Omega = -\overline{k}_3 < 1$ (derived in Appendix C).

Now consider the nowcast error, where expectations are either those of households or producers, that is, $\mathbb{E}_{k,t}$ substitutes for either $\mathbb{E}_{j,l,t}$ or $\mathbb{E}_{l,t}$, and ρ^k, δ^k correspondingly for ρ^p, δ^p or ρ^h, δ^h. Taking expectations of equation (D.1) gives

$$\begin{aligned} \mathbb{E}_{k,t} y_t =& x_{t-1} + \rho_x^h\left(1+\overline{k}_3\right)s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h-1)\right]\mathbb{E}_{k,t}\varepsilon_t - r_t \\ =& x_{t-1} + \left\{\rho_x^h(1+\overline{k}_3) + [\delta_x^h + \overline{k}_3(\delta_x^h-1)]\rho_x^k\right\}s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h-1)\right]\delta_x^k\varepsilon_t - r_t. \end{aligned}$$

$$\begin{aligned} y_t - \mathbb{E}_{k,t} y_t =& -\rho_x^k\left[\delta_x^h + \overline{k}_3(\delta_x^h-1)\right]s_t + \left[\delta_x^h + \overline{k}_3(\delta_x^h-1)\right](1-\delta_x^k)\varepsilon_t \\ =& \underbrace{-\rho_x^k\left[\delta_x^h + \overline{k}_3(\delta_x^h-1)\right]}_{<0} e_t + \underbrace{\left[\delta_x^h + \overline{k}_3(\delta_x^h-1)\right]}_{>0}\underbrace{(1-\delta_x^k-\rho_x^k)}_{>0}\varepsilon_t, \end{aligned}$$

or

$$y_t - \mathbb{E}_{k,t} y_t = -\rho_x^k\left[\delta_x^h(1-\Omega)+\Omega\right]e_t + \left[\delta_x^h(1-\Omega)+\Omega\right](1-\delta_x^k-\rho_x^k)\varepsilon_t.$$

The fact that $0 < \Omega < 1$ allows us to determine the signs of the effects of the shocks on the nowcast error. ■

Proof of Proposition 2 *A higher volatility σ_ε^2 of aggregate technology leads to...*

...a higher dispersion of now- and forecasts of output by firms
As stated by equation (C.2), firms form their expectations according to

$$\mathbb{E}_{j,l,t}\Delta x_t = \rho_x^p s_t + \delta_x^p(a_{l,t} - x_{t-1}),$$

such that the dispersion of expectations is given by $(\delta_x^p)^2\sigma_\eta^2$. Remember that the public signal s_t and the common productivity shock ε_t are the same for all firms. The effect of σ_ε^2 on expectation dispersion is then

$$\frac{\partial(\delta_x^p)^2\sigma_\eta^2}{\partial\sigma_\varepsilon^2} = 2(\delta_x^p)^2\rho_x^p\frac{\sigma_\eta^2\sigma_e^2}{\sigma_\varepsilon^4},$$

which is positive, such that the impact of σ_ε^2 on the dispersion of nowcasts of x_t is also positive. It follows that also now- and forecasts of inflation and output are more dispersed for a higher σ_ε^2.

...a higher dispersion of now- and forecasts of output by households
The derivation for households is equivalent to that of firms, with the only difference that δ_x^h is used instead of δ_x^p.

...a higher impact of positive optimism shocks on output
Equation (D.1) states

$$y_t = x_{t-1} + \rho_x^h(1+\overline{k}_3)e_t + \left[\delta_x^h + \rho_x^h - \overline{k}_3(1-\delta_x^h-\rho_x^h)\right]\varepsilon_t - \frac{\alpha}{\alpha+\psi(1-\alpha)}\nu_t.$$

Taking the derivative w.r.t. e_t gives

$$\frac{\partial y_t}{\partial e_t} = \rho_x^h(1+\overline{k}_3). \tag{D.2}$$

We are then interested in whether the effect of dispersion, governed by σ_ε^2, on the above derivative is positive, that is whether

$$\frac{\partial\partial y_t/\partial e_t}{\partial\sigma_\varepsilon^2} > 0.$$

We proceed in two steps. First, we define, as in the main text, $\Omega = -\bar{k}_3$ for better readability and derive its derivative with respect to σ_ε^2. Writing $\Omega = N/D$ with

$$N = n - \delta_x^h(1-\alpha)\left[(n-1)\delta_x^p + 1\right] \quad D = n\alpha + (1-\alpha)\left\{(1-\delta_x^h)[1+\delta_x^p(n-1)] + (n-1)\gamma(1-\delta_x^p)\right\},$$

we have

$$\frac{\partial \Omega}{\partial \sigma_\varepsilon^2} = \frac{D\,\frac{\partial N}{\partial \sigma_\varepsilon^2} - N\,\frac{\partial D}{\partial \sigma_\varepsilon^2}}{D^2}.$$

Turning to the derivatives of the ρ and δ coefficients, we define

$$\frac{\partial \delta_x^p}{\partial \sigma_\varepsilon^2} = \sigma_e^2/V^2 \qquad \frac{\partial \rho_x^p}{\partial \sigma_\varepsilon^2} = \sigma_\eta^2/V^2 \qquad \frac{\partial \delta_x^h}{\partial \sigma_\varepsilon^2} = n\sigma_e^2/W^2 \qquad \frac{\partial \rho_x^h}{\partial \sigma_\varepsilon^2} = \sigma_\eta^2/W^2,$$

with $V \equiv \sigma_\varepsilon^2\left[\sigma_e^2 + \sigma_\eta^2 + \sigma_\eta^2\sigma_e^2/\sigma_\varepsilon^2\right]/\sigma_e\sigma_\eta$ and $W \equiv \sigma_\varepsilon^2\left[\sigma_e^2 + \sigma_\eta^2/n + \sigma_\eta^2\sigma_e^2/(n\sigma_\varepsilon^2)\right]n/\sigma_e\sigma_\eta$.
Using the definition $X \equiv [1 + (n-1)\delta_x^p] = W/V$ gives

$$\frac{\partial \Omega}{\partial \sigma_\varepsilon^2} = \frac{1-\alpha}{D^2}\sigma_e^2\left\{(N-D)nX/W^2 - (n-1)\left[D\delta_x^h + N[(1-\delta_x^h) - \gamma]\right]/V^2\right\}.$$

Second, to derive the sign of

$$\frac{\partial \partial y_t/\partial e_t}{\partial \sigma_\varepsilon^2} = \frac{\partial \rho_x^h}{\partial \sigma_\varepsilon^2}(1-\Omega) - \rho_x^h\frac{\partial \Omega}{\partial \sigma_\varepsilon^2} = \sigma_\eta^2\frac{D-N}{DW^2} - \rho_x^h\frac{\partial \Omega}{\partial \sigma_\varepsilon^2},$$

we define $\bar{\Pi} := (\partial Y/\partial \sigma_\varepsilon^2)V^2W^2D^2/\sigma_\eta^2$, such that

$$\bar{\Pi} = (D-N)\,V^2D - (1-\alpha)\,\rho_x^h\,\frac{V^2W^2\sigma_e^2}{\sigma_\eta^2}\left[(N-D)Xn/W^2 + (n-1)\left[N(\gamma - (1-\delta_x^h)) - D\delta_x^h\right]/V^2\right].$$

Now use the identities $\rho_x^h = \sigma_\eta\,\sigma_\varepsilon^2/(\sigma_e\,W)$ and

$$N[\gamma - (1-\delta_x^h)] - D\delta_x^h = (\gamma-1)n\left[1 - (1-\alpha)\delta_x^h\right].$$

Substituting these and simplifying the common factors yields

$$\bar{\Pi} = (D-N)V^2D - (1-\alpha)\,\frac{\sigma_e}{\sigma_\eta}\,\sigma_\varepsilon^2\left[n(N-D)\,V + n(n-1)(\gamma-1)W\big(1 - (1-\alpha)\delta_x^h\big)\right].$$

Note that

$$1 - \delta_x^p = \frac{\sigma_\eta(\sigma_e^2 + \sigma_\varepsilon^2)}{\sigma_e\,V} \qquad 1 - \delta_x^h = \frac{\sigma_\eta(\sigma_e^2 + \sigma_\varepsilon^2)}{\sigma_e\,W}$$

and, hence,

$$D = n\alpha + (1-\alpha)\,\frac{\sigma_\eta(\sigma_e^2 + \sigma_\varepsilon^2)}{\sigma_e\,V}\,[1 + (n-1)\gamma].$$

Therefore

$$\begin{aligned}\frac{\sigma_\eta(\sigma_e^2 + \sigma_\varepsilon^2)}{\sigma_e}VD &= \frac{\sigma_\eta(\sigma_e^2 + \sigma_\varepsilon^2)}{\sigma_e}V\left[n\alpha + (1-\alpha)\,\frac{\sigma_\eta(\sigma_e^2 + \sigma_\varepsilon^2)}{\sigma_e\,V}\,[1 + (n-1)\gamma]\right] \\ &= \frac{\sigma_e^2 + \sigma_\varepsilon^2}{\sigma_e^2}\Big\{[\sigma_\varepsilon^2\sigma_e^2 + \sigma_\varepsilon^2\sigma_\eta^2 + \sigma_\eta^2\sigma_e^2]n\alpha + \sigma_\eta^2(1-\alpha)(\sigma_e^2 + \sigma_\varepsilon^2)\,[1 + (n-1)\gamma]\Big\}.\end{aligned}$$

This can be used, together with $N-D=-(1-\alpha)(n-1)(1-\delta_x^p)(\gamma-1)$, in the following derivations:

$$\bar{\Pi}/[(n-1)(\gamma-1)(1-\alpha)] = (1-\delta_x^p)V^2D - \frac{\sigma_e}{\sigma_\eta}\sigma_\varepsilon^2\Big\{n[-(1-\alpha)(1-\delta_x^p)]V + nW\big(1-\delta_x^h+\alpha\delta_x^h\big)\Big\}$$
$$= \sigma_\eta^2\frac{(\sigma_e^2+\sigma_\varepsilon^2)^2}{\sigma_e^2}\left\{n\alpha+(1-\alpha)\left[1+(n-1)\gamma\right]\right\} - \alpha n^2\frac{\sigma_e^2\sigma_\varepsilon^4}{\sigma_\eta^2}.$$

With this, one obtains, after collection of terms, a single scalar factor deciding the sign:

$$\bar{\Pi} = \frac{(1-\alpha)(n-1)(\gamma-1)}{\sigma_e^2\sigma_\eta^2}\left[Q\sigma_\eta^4(\sigma_e^2+\sigma_\varepsilon^2)^2 - \alpha n^2\sigma_e^4\sigma_\varepsilon^4\right],$$

where

$$Q = \gamma(n-1)(1-\alpha)+\alpha(n-1)+1>0.$$

Because the prefactor $[(1-\alpha)(n-1)(\gamma-1)]/(\sigma_e^2\sigma_\eta^2)$ is positive, we have

$$\operatorname{sign}\Big(\frac{\partial\partial y_t/\partial e_t}{\partial\sigma_\varepsilon^2}\Big) = \operatorname{sign}(\bar{\Pi}) = \operatorname{sign}\Big(Q\sigma_\eta^4\,(\sigma_e^2+\sigma_\varepsilon^2)^2 - \alpha\, n^2\,\sigma_e^4\,\sigma_\varepsilon^4\Big).$$

That is, the effect of σ_ε^2 on the impact of noise shocks on GDP is positive if

$$Q\left(\frac{\sigma_\eta^2/n}{\sigma_\varepsilon^2}+\frac{\sigma_\eta^2/n}{\sigma_e^2}\right)^2 > \alpha.$$

Given that $Q>1$ and $\alpha<1$, this inequality holds in realistic cases, in particular if

1. The volatility of the idiosyncratic technology shock is large, $\sigma_\eta^2\to\infty$.

2. Households have a minimal informational advantage over firms, n close to unity, and the volatility of the idiosyncratic technology shock is larger than the aggregate and/or noise volatility ($\sigma_\eta^2>\sigma_\varepsilon^2$ or $\sigma_\eta^2>\sigma_e^2$).

Alternatively, one can express this condition in terms of the informational content of the signals. The condition does *not* hold if σ_ε^2 and σ_e^2 are both very large relative to σ_η^2. That is, the condition holds, except if the private signal of the households, composed of price observations, is very precise (σ_η^2/n much smaller than σ_ε^2) and simultaneously contains much more information than the public signal (σ_η^2/n much smaller than σ_e^2).

...a lower impact of positive optimism shocks on prices

Equation (C.14) gives the impact of noise on prices. Its derivative w.r.t. σ_ε^2 equals the effect of dispersion on the impact of noise on prices.

The derivative of p_t with respect to σ_ε^2 is

$$\frac{\partial p_t}{\partial e_t} = (1-\Omega)\frac{1-\alpha}{\alpha}\left[\rho_x^h + \delta_x^h \frac{n-1}{n}\rho_x^p\right] - \Omega(\gamma-1)\frac{n-1}{n}\frac{1-\alpha}{\alpha}\rho_x^p.$$

If we define $K = \sigma_e^2 + \sigma_\eta^2/n + \sigma_\eta^2\sigma_e^2/(n\sigma_\varepsilon^2)$ and $L = \sigma_e^2 + \sigma_\eta^2 + \sigma_\eta^2\sigma_e^2/(\sigma_\varepsilon^2)$, we can write

$$\frac{\partial p_t}{\partial e_t} = \frac{1-\alpha}{\alpha}\frac{\sigma_\eta^2}{nD}\left\{\frac{D-N}{K}\left[L+(n-1)\sigma_e^2\right] - \frac{N}{L}(\gamma-1)(n-1)\right\}.$$

Since $L+(n-1)\sigma_e^2 = nK$ and $D-N$ are given above, we have

$$\frac{\partial p_t}{\partial e_t} = \frac{1-\alpha}{\alpha}\frac{\sigma_\eta^2}{nDL}(\gamma-1)(n-1)\left\{n(1-\alpha)(1-\delta_x^p) - N\right\}.$$

Observing that $n-(n-1)\delta_x^h = L/K$, we can also write

$$\frac{\partial p_t}{\partial e_t} = -(\gamma-1)(n-1)(1-\alpha)\frac{\sigma_\eta^2}{DL} = -(\gamma-1)(n-1)(1-\alpha)\frac{\rho_x^p}{D}.$$

We know that ρ_x^p increases in σ_ε^2, such that we only need the sign of the derivative of D. Note that

$$\begin{aligned} D &= n\alpha + (1-\alpha)\left\{\frac{K-\sigma_e^2}{K}\frac{nK}{L} + (n-1)\gamma\frac{L-\sigma_e^2}{L}\right\} \\ &= n\alpha + (1-\alpha)\frac{\sigma_\eta^2\left(1+\sigma_e^2/\sigma_\varepsilon^2\right)}{L}[1+(n-1)\gamma] \\ &= n\alpha + (1-\alpha)\left[1+\frac{\sigma_e^2}{\sigma_\eta^2}\frac{1}{1+\sigma_e^2/\sigma_\varepsilon^2}\right]^{-1}[1+(n-1)\gamma], \end{aligned}$$

where we used $1+\delta_x^p(n-1) = nK/L$. We hence obtain $\frac{\partial D}{\partial \sigma_\varepsilon^2} < 0$ and

$$\frac{\partial \partial p_t/\partial e_t}{\partial \sigma_\varepsilon^2} < 0.$$

■

Appendix References

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