Dancing in the Dark: Sentiment Shocks and Economic Activity*

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Abstract

Expectations—some justified, some not—are widely believed to drive business cycle fluctuations. Yet, the conditions under which the economy becomes susceptible to noise-driven shifts in expectations ("sentiment shocks") remain poorly understood. We show that the macroeconomic effects of such shocks are strongly state dependent. Standard signal-extraction logic implies that expectations and their dispersion become more sensitive to noise as uncertainty increases. Consistent with this implication, U.S. time-series evidence shows that when disagreement is low, sentiment shocks have little effect on economic activity and are largely absorbed by prices, whereas when disagreement is high, they have sizable real effects with little impact on prices. We account for this state-dependent transmission in a stylized New Keynesian model with dispersed information, in which agents infer fundamentals from noisy signals—effectively dancing in the dark.

Keywords: sentiment 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 et al., 2013; Angeletos et al., 2013; Lagerborg et al., 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 likely shape their effects: when uncertainty is high—measured in our baseline by forecaster disagreement—economic activity is potentially more susceptible than when uncertainty about the state of the economy is low.

In this paper, we thus ask how such disagreement shapes the economic impact of sentiment shocks. Our identification strategy follows Enders et al. (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 effects of sentiment shocks to vary with uncertainty, measured by forecaster disagreement and other uncertainty proxies. 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—agents are "dancing in the dark"—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. That is, the weights on noise in the public signal and on idiosyncratic information increase, resulting in more dispersed expectations. In this situation, the model predicts, consistent with the evidence, that economic activity reacts more strongly to random fluctuations in the public 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 et al., 2013).

Importantly, the nowcast errors are not 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, resulting in a positive nowcast error.[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 (Benhima et al., 2021; Chahrour et al., 2021; Enders et al., 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 economic 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

[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.

high, a sentiment shock leads to a significant increase in output that persists for about four to five years. At the same time, sentiment shocks have virtually no effect on prices. 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 disagreement 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. 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. In an extension, we establish similar patterns in the responses to news shocks about future total factor productivity: they are strongly expansionary only when disagreement is high. In a robustness check, we show that our approach can be cross-validated with other measures of uncertainty, which, according to our stylized model, also rise when aggregate technology becomes more volatile.

We explain the nature of sentiment shocks and how their impact on macroeconomic outcomes varies with the prevailing level of uncertainty within 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 from either their own productivity (firms) or observed prices (households).

Assuming that prices are predetermined (rather than staggered as in the original model), the model can be solved in closed form. In the model, 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. We then 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 about aggregate technology.[2] 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.

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, developed 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, a large number of studies have 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 et al., 2017; Castelnuovo et al., 2018; Hauzenberger et al., 2021). Uncertainty, and the state of the economy more broadly, potentially also shape how expectations respond to shocks, and hence the transmission of uncertainty and TFP shocks (Ilut et al., 2014; Lhuissier et al., 2021; Gambetti et al., 2023; Bianchi et al., 2024; Antonova et al., 2026). Uncertainty also matters for price setting (Baley et al., 2019; Bachmann et al., 2019).

Like us, Ricco et al. (2016) and Falck et al. (2021) highlight state-dependent effects based on disagreement. However, their focus is on fiscal and monetary policy, and they find that lower levels of disagreement give rise to stronger effects, possibly due to more effective policy communication. In contrast, we study the conditions under which non-fundamental shocks unfold. Our contribution is to show how disagreement shapes the transmission of sentiment shocks, providing both new evidence and a theoretical account.

This question is particularly relevant in light of a second strand of the literature that seeks to assess the importance of news and "noise" for business cycle fluctuations, with partly conflicting results (Beaudry et al., 2006; Beaudry et al., 2011; Schmitt-Grohé et al., 2012; Barsky et al., 2015; Benhima et al., 2021). These differences

[2] And indeed, Benamar et al. (2020) find that investors pay more attention to (macroeconomic) data when uncertainty is high. See also Figure 1 below.

likely arise because distinguishing news from noise remains challenging (Barsky et al., 2011; Chahrour et al., 2018; Levchenko et al., 2020). Against this background, it is important to condition the effects of sentiment shocks—broadly understood—on the degree of disagreement, as disagreement reflects the severity of information frictions that give rise to sentiment shocks in the first place.

Finally, our work connects to the literature on how public signals shape coordination and welfare. Seminal work by Morris et al. (2002) and Angeletos et al. (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 et al., 2007; Cornand et al., 2008), and Angeletos et al. (2016) stress that the answer depends on the source of aggregate fluctuations. We contribute to this strand of the literature by providing evidence that coordination problems actually shape economic outcomes.

2. Fixing ideas

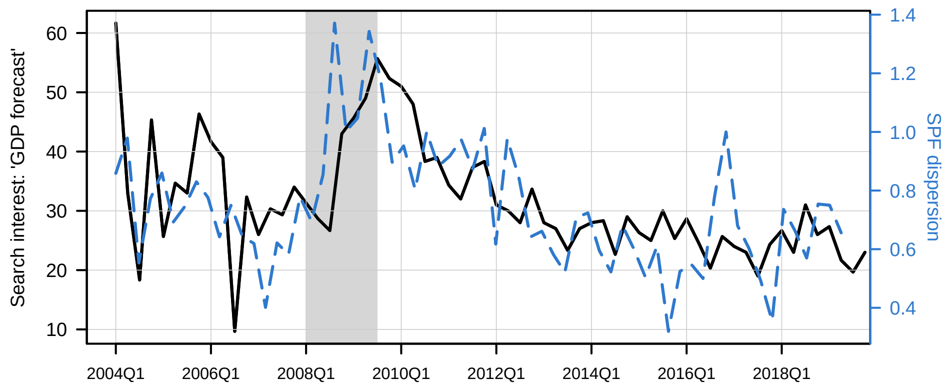
To set the stage for the empirical analysis, we fix ideas and sketch why, in theory, uncertainty matters for how sentiment shocks unfold. Specifically, we zoom in on the signal-extraction problem, which is central to the model in Section 5 below. Firm productivity features both an aggregate and an idiosyncratic 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

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

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

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 (zero in this case). This has two implications. First, the impact of noise on expectations rises—via a higher ρ. Second, the dispersion of expectations, given by $D = \delta^2\sigma_\eta^2$,

Figure 1: Attention to public signals.



Notes: Figure shows google searches for the term 'GDP forecast' (black solid line, left axis) and the interquartile range across forecasters in the SPF regarding output growth forecasts four quarters ahead (blue dashed line, right axis). Gray bars denote the NBER recession dates.

and economic uncertainty, given by the aggregate forecast error variance $FEV = \rho\sigma_e^2$, increase. This motivates our choice for the baseline state variable—expectation dispersion—and the cross-validation using other measures of economic uncertainty.

The data in Figure 1 support the notion that expectations are more susceptible to signals in times of uncertainty—reflected in forecaster disagreement. Over time, disagreement across SPF participants (measured by the interquartile range) co-moves strongly with Google searches for the term "GDP forecasts," which may proxy for public signals. This pattern lends support to conditioning the effects of sentiment shocks on disagreement in the empirical analysis below.

How expectations respond to signals matters for economic activity and prices because expectations feed back into the decisions of households and firms: In Section 5, we derive how expectations map into macroeconomic outcomes. We show formally that greater uncertainty increases the dispersion of expectations and amplifies (attenuates) the effects of sentiment shocks on output (prices).[3] The model also sheds light on the mechanisms underlying this mapping. While the signal-extraction problem is central, the key features at the heart of the New Keynesian framework turn out to be essential as well.

[3] Note that it does not matter whether this is a real or merely perceived change. In a similar vein, Gemmi et al. (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. 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.[4] We measure uncertainty as the dispersion of nowcasts by the interquartile range of the participants' forecasts for current-quarter output growth (in percentage points) in the SPF. As such, it is also a measure of disagreement.[5] Disagreement has been used as a measure of uncertainty in several studies, such as Bachmann et al. (2013), Ilut et al. (2014), and Bianchi et al. (2024). The remaining variables are relatively standard, and we provide further details in Appendix A.

3.2 Non-linear identification of sentiment shocks

In terms of identification, we build on Enders et al. (2021) and the Bayesian variant in Chahrour et al. (2021). However, we move beyond the linear VAR framework

[4] 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 before 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 et al., 2025). Using final-release data to construct nowcasts yields generally very similar results, see Enders et al. (2021).

[5] Accordingly, we construct our measure using the same dataset as the expectation data. As alternative specifications, we also consider the standard deviation across forecasts and other conventional measures of uncertainty, which are discussed in greater detail in the robustness section below.

to allow for state-dependent effects. Specifically, we estimate a bivariate Bayesian smooth-transition vector autoregressive (STVAR) model, which we identify using sign restrictions. 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. We capture state dependence using a transition function $F(z_{t-1}) \in [0, 1]$, which reflects the probability of being in the high-disagreement regime at time $t - 1$. Let the time series process $\{\boldsymbol{y}_t\}_{t=1}^T$ follow

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

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.[6] 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 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,

[6] 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.

as captured by the variable z_{t-1}.[7] Second, we specify the transition function on the basis of the empirical cumulative density function (CDF) in our sample, adopting the approach of Born et al. (2020) to our setting.[8] 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, relative to the rest of the sample. 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.

The identification of the sentiment shock builds upon nowcast errors, which are an ex-post measure of the mistakes made by market participants. Including these nowcast errors in the model provides us with an informational advantage over market participants. Identifying sentiment shocks without such an advantage is infeasible (Blanchard et al., 2013). Specifically, identification is achieved through sign restrictions (Rubio-Ramirez et al., 2010). For the nonsentiment shock, we restrict the signs such that there is a positive comovement between the nowcast error and GDP growth: In the case of a fundamental shock, the shock is generally not fully processed in real time (Coibion et al., 2012; Coibion et al., 2015), such that its effects exceed expectations. In contrast, a sentiment shock is characterized by excess movements of expectations. Since expectations overshoot actual output growth (positively or negatively), the nowcast error has the opposite sign to that of actual output growth.

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

[8] In contrast to the literature building on Auerbach et al. (2012), this allows us to avoid imposing a specific parametric transition function. Studies in this tradition (see, for instance, Auerbach et al., 2013, Caggiano et al., 2014, Tenreyro et al., 2016, or Falck et al., 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.

Hence, for the sentiment shock, we impose a negative comovement.[9] 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 unity in the second row. Sign restrictions only provide set identification, and as such, the framework inherently captures both the uncertainty regarding the imposed sign restrictions and the uncertainty regarding the estimated parameters. We generate the shocks by using the arithmetic average across both types of uncertainty. We describe the procedure in more detail in Appendix A.2.

This strategy has the advantage of allowing us to keep the identified shock fixed while examining the responses of additional variables in the state-dependent local projections framework. Otherwise, extending the STVAR with additional variables would alter the identified shock series and possibly necessitate additional identification assumptions.

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.

[9] Using a richer specification, Benhima et al. (2021) further distinguish between *supply noise* and *demand noise* shocks based on expectation errors in output growth and inflation.

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:

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

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.[10]

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 potential autocorrelation in the residuals, we apply the strategy proposed by Lusompa (2023).[11] In all specifications, we use lags of the endogenous variable in the regression as controls, which robustifies inference (Montiel-Olea et al., 2021). The specification in long differences shows considerably small sample gains when the impulse response of interest is estimated using an externally identified shock (Piger et al., 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 et al., 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

[10]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 $u_{t+h}^h \sim \mathcal{N}(0, \sigma_h^2)$.

[11]Lusompa (2023) shows that the autocorrelation process of LPs can be written as a vector moving average process and can be corrected using a consistent GLS estimator. This strategy exploits the fact that, at least, the horizon-1 LP residuals are not autocorrelated.

shock ε_t^s. We investigate the two polar cases in which the economy is in a low or high disagreement regime today, indexed by z_{t-1}. Formally, we have

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

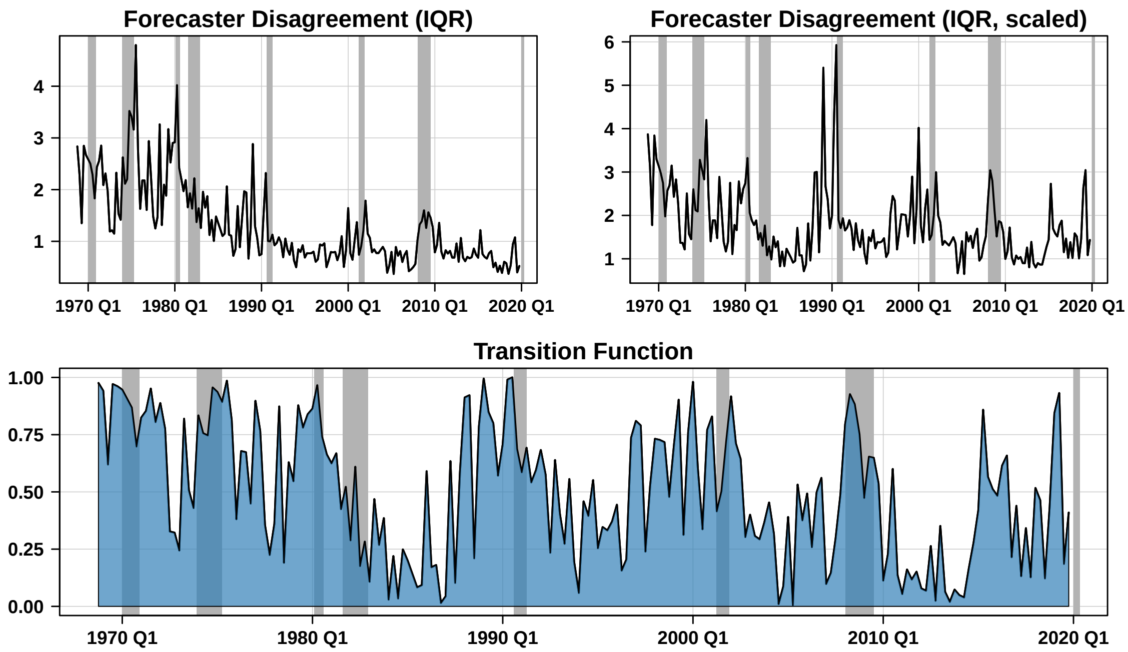
Estimation of Equation (3.4) is done for each horizon and variable separately, resulting in a sequence $\{\beta_h^r\}_{h=1}^H$ that reflects the impulse response for y_t within the first H periods. An important advantage of this approach is that it does not rule out potential regime switches after the 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 et al., 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 the 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 associated with the low and high disagreement regime. We display our measure of disagreement and the value of the transition function at each point in time in Figure 2. Forecaster disagreement is measured by the interquartile range 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 around 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

Figure 2: 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. Gray bars denote the NBER recession dates.

dispersion are elevated from the beginning of the sample until the mid 1980s. This pattern is also well documented for inflation disagreement in the SPF, which has been studied more intensively than that for GDP growth. This literature finds forecast disagreement to be positively correlated with the level and volatility of inflation.[12] However, both associations could be purely mechanical if forecast errors were assumed to be proportional to the level or volatility of the forecasted series.

Against this background, we scale the time series of forecaster disagreement by a low-frequency measure of the volatility of GDP growth for our analysis. This accounts for the possibility that a higher variance in GDP growth (and in the underlying shocks) may explain why the dispersion in professional forecasts is higher until the

[12] See, for instance, Mankiw et al. (2003) for early evidence that disagreement rises with the level and absolute change in inflation. Coibion et al. (2012) further show that disagreement was persistently higher during periods of volatile inflation, consistent with informational frictions. Dovern et al. (2012) confirm that disagreement is positively associated with both the inflation level and inflation uncertainty across time and countries.

mid-1980s. However, we verify that our results are not driven by the scaling of the series.[13] We compute the standard deviation of GDP growth using a moving window of 24 quarters.[14] We show the adjusted series in the upper right panel of Figure 2. 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.

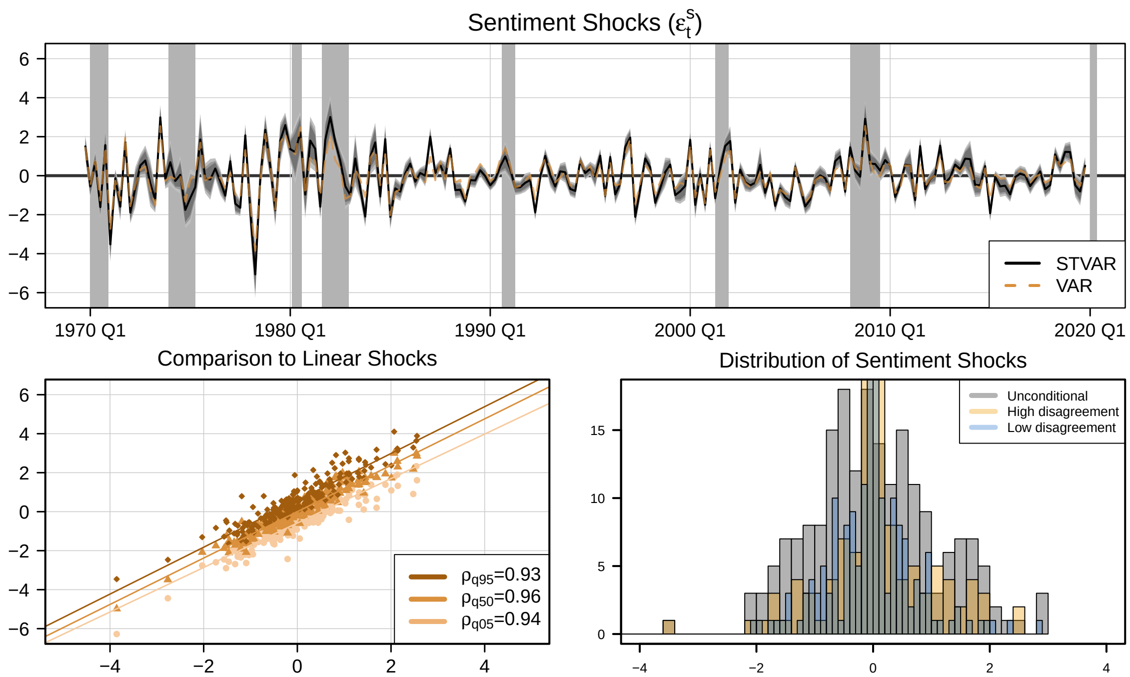
The bottom panel of Figure 2 shows the weight associated with the disagreements regime based on the scaled interquartile range. The values of the transition function are derived using Equation (3.2). We observe that we are hardly ever in one of the two polar regimes of disagreement, with much movement in the medium range. 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 for 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 et al. (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 form heterogeneous expectations, resulting in higher disagreement. For output growth, forecaster disagreement is largest for short term survey expectations (see, e.g., Coibion et al., 2012; Coibion et al., 2015; Andrade et al., 2016).

[13]Similarly, Falck et al. (2021) observe historically high levels of disagreement in inflation expectations in the 1970s. They scale disagreement by the level of expected inflation to control for periods of relatively high inflation rates.

[14]The empirical results are qualitatively and quantitatively robust to employing alternative window sizes reflecting typical business cycle frequencies of 5 to 7 years. As an alternative approach, we regress disagreement on the standard deviation of GDP growth and retain the residuals. We denote this approach as *purification*; results are also robust to this choice. We discuss these checks in more detail in the robustness section. In an additional robustness exercise, we focus on the cyclical rather than the low-frequency component of forecasters' disagreement by applying the Hodrick-Prescott filter. We report this in Figure B5 in the appendix. Again, results do not change much, neither qualitatively nor quantitatively.

Figure 3: 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 maroon lines refer to sentiment shocks estimated in a linear VAR framework. The gray shaded rectangles refer to the NBER recession dates. The lower left panel reports a scatter with the sentiment shocks from the STVAR (q05,q50,q95; y-axis) and the VAR (x-axis). The lower right panel reports the histogram of the unconditional STVAR shock series and weighted by the transition function: $F(z_{t-1})\varepsilon_t^s$ (high) and $(1 - F(z_{t-1}))\varepsilon_t^s$ (low).

4. Results

This section presents the empirical results. To set the stage, we first contrast the identified shocks with those obtained in a linear framework. We then discuss the main results and conclude with an extensive robustness analysis.

4.1 Sentiment shocks

We first show the time-series of the 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.

Figure 3 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. In the lower left panel, we compare the non-linear sentiment shock series for different quantiles to the sentiment shock series that we obtain when we abstract from state dependence. 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 within a non-linear framework but 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. In the lower right panel, we investigate whether shocks differ across regimes. We report histograms for the unconditional distribution and those conditional on the state dependence. We report $F(z_{t-1})\varepsilon_t^s$ for the high and $(1-F(z_{t-1}))\varepsilon_t^s$ for the low disagreement regime. All resulting shock series strongly reject the null hypothesis of normality (using a Shapiro-Wilk normality test). We observe a slightly higher volatility in the high disagreement regime, which is, however, not statistically significant (F-test for equality of variance yields $p = 0.058$, Levene's test for homogeneity of variance yields $p = 0.438$).

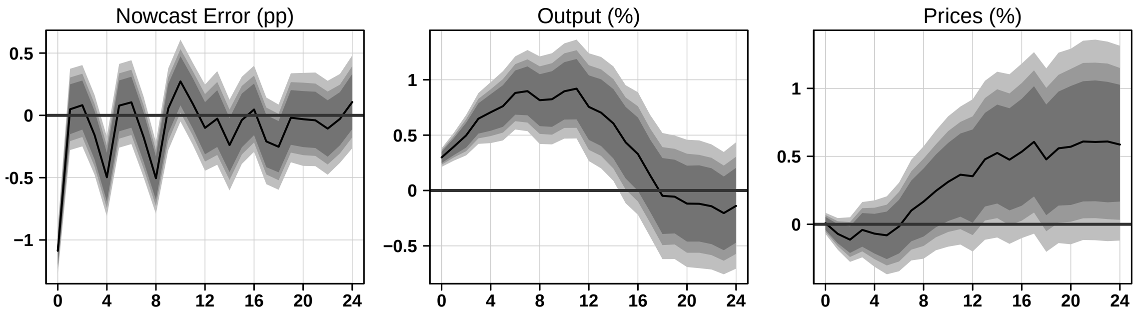
In the appendix, we report the impulse response functions of the nowcast error and output to the sentiment (and non-sentiment) shocks from the STVAR framework (see Figure B1). While the overall pattern is similar to that documented in earlier studies based on linear frameworks (Enders et al., 2021), the output response differs markedly across regimes. In the low-disagreement regime, in particular, the response of output is much weaker. In what follows, we focus on these cross-regime differences to inform the structural interpretation presented in the next section.

4.2 The effects of sentiment shocks

To flesh out the transmission mechanism of sentiment shocks under different uncertainty regimes, we rely on estimates from state-dependent local projections. Before presenting the results of the state-dependent model, however, we first show the impulse responses of the nowcast error, output, and prices in Figure 4. We obtain these estimates by suppressing the dependence on the level of disagreement in Eq. (3.4).[15] We display the sequence of $\{\beta_h\}_{h=1}^H$, which represents the dynamic causal effects of a sentiment shock. The black solid lines show the median estimates, while the shaded

[15] See footnote 10. Note that in the linear specification, the construction of the shock series, ε_t^s, is also done in a linear VAR setting.

Figure 4: The linear effects of a sentiment shock.



Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). 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).

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.[16]

The sentiment shock is normalized to unity. This translates into a negative nowcast error of one percentage point; that is, the consensus forecaster is mistakenly excessively *optimistic*: expectations exceed output. The reaction of output is positive—as imposed via the sign restrictions in the impact period to identify a sentiment shock. It is, hence, an expansionary sentiment shock, where optimism about current output growth causes actual output to increase. Prices, however, react only after some time. They increase by a maximum of 0.5 percent compared to the pre-shock level, but this effect is not statistically significant. The positive co-movement of output and prices is in line with the perception of a sentiment shock as a demand shock (Lorenzoni, 2009).

We move on to the presentation of the state-dependent effects of sentiment shocks in Figure 5. We now split the dynamic causal effects of a sentiment shock into

[16]The estimated sentiment shocks, ε_t^s, are generated regressors. Standard errors that ignore the estimation error from the first stage are asymptotically valid under the null hypothesis that the coefficients of interest (β_h^r) are zero (Pagan, 1984); see also Coibion et al. (2015), footnote 18. In the appendix, we show that results are robust once we account for the additional first stage uncertainty; see Figure B3.

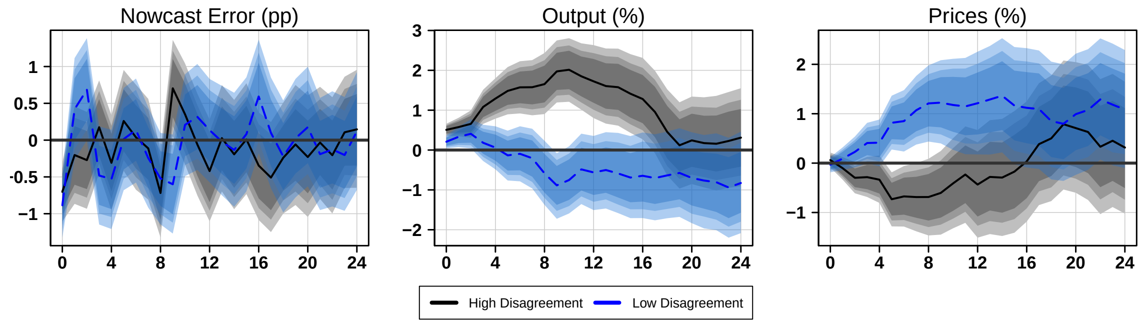
two sequences, $\{\beta_h^r\}_{h=1}^H$ for each regime $r \in \{L, H\}$. The black solid lines (gray shaded areas) show the median (68%, 80%, 90% quantiles) estimates for the high disagreement case, and the blue dashed line (blue shaded areas) shows the results for the low disagreement case. In the appendix, we report the outcomes once we take the estimation uncertainty of the first stage into account (see Figure B4).

Figure 5 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 that 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 this is 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 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, when aggregate technology is highly volatile—and, hence, uncertainty is elevated—agents rely less on their priors. Instead, they place greater weight on the signals they receive, which also makes them more susceptible to noise. Because noise in the public signal reflects sentiment shocks, their positive effects on demand and, subsequently, output become stronger. The muted inflation response follows from firms' pricing decisions: stronger sentiment shocks lead firms to (incorrectly) expect other firms to

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



Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). 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).

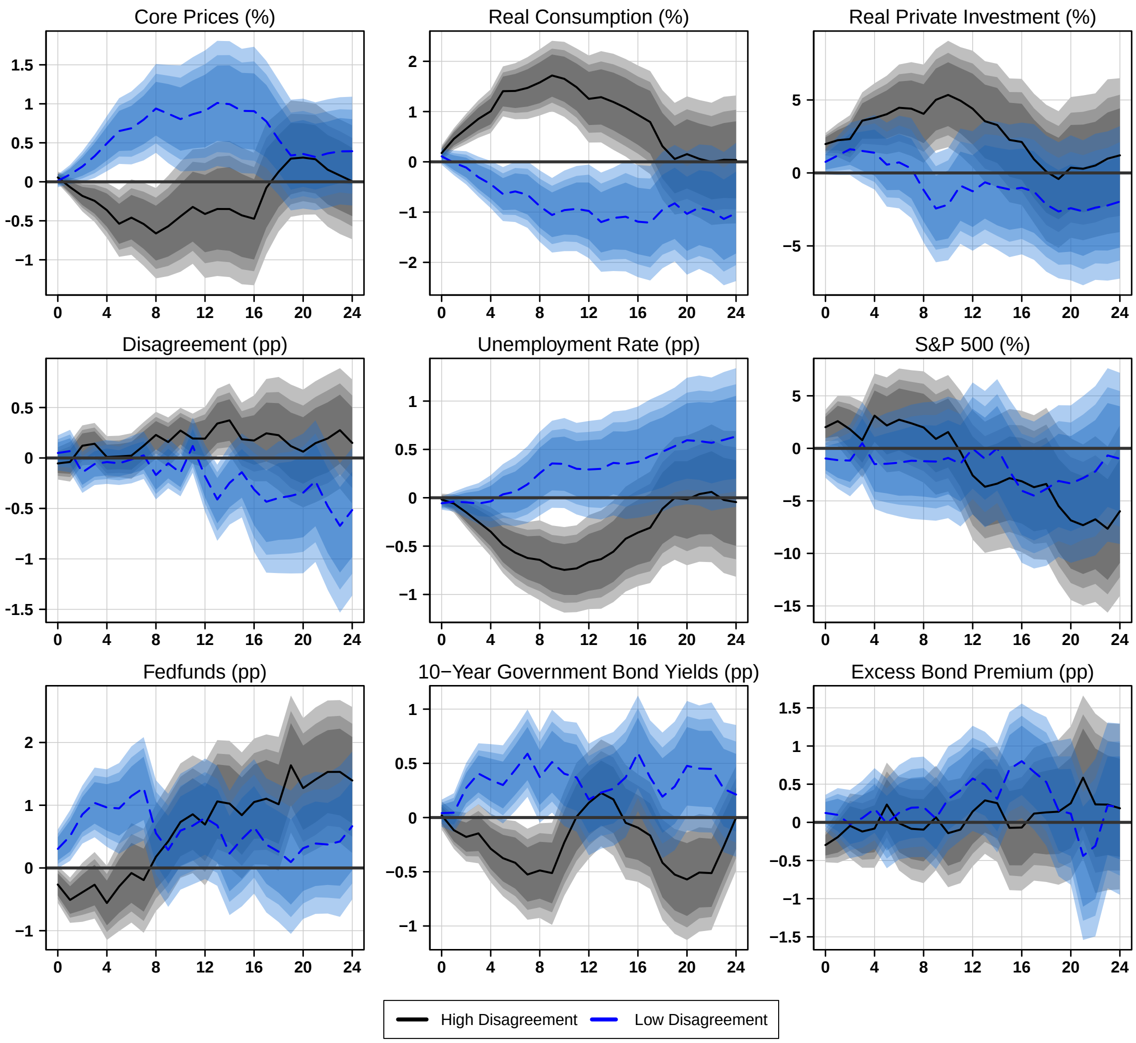
set lower prices due to better technology, which—together with strategic complementarities—dampens the price response.

In Figure 6, we report several additional state-dependent effects of a sentiment shock. We report the outcomes of core prices, dispersion, subcomponents of GDP (consumption and investment), the labor market (unemployment rate), and financial variables (stock market, federal funds rate, long-term rate, and risk premium). It is reassuring that dispersion, the threshold variable, is not reacting to the shock. The estimates are, on average, around zero, with uncertainty bands ranging from -0.2 to 0.2 on impact. Note that this variable is standardized, implying a standard deviation of one. The effects are thus far from sizable.

The shock transmits through both consumption and investment. While differences across regimes are visible for both, these differences are much more pronounced in consumption. The strong transmission through consumption underscores the demand nature of the noise shock. We use the unemployment rate to assess the transmission on the labor market. It grossly mirrors the output response: the unemployment rate decreases in the high disagreement regime, while it slightly, although not statistically significantly, increases in the low disagreement regime.

Lastly, we turn to the financial variables. We do not observe strong differences for the S&P 500 stock market index or the excess bond premium as a measure of risk,

Figure 6: Additional state-dependent effects of a sentiment shock.



Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). 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).

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, in line with the negative price response, the central bank has a (mildly) accommodative stance before turning restrictive after two to three years to prevent the economy from overheating. This behavior is mirrored in longer-term rates, using 10-year government bond yields.

4.3 Relation to (technology) news shocks

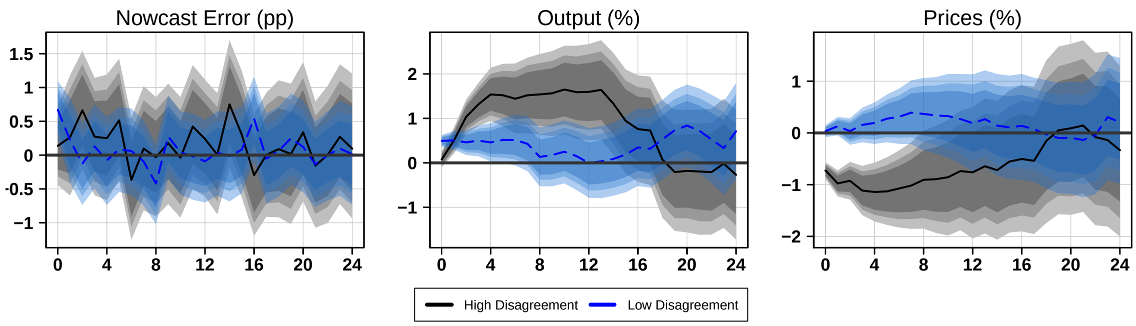
There is a tight connection between noise shocks—or "sentiment shocks"—and news shocks. In fact, Chahrour et al. (2018) show the observational equivalence between these information structures. To investigate this link more closely, we also examine the state-dependent effects of news shocks. Specifically, 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 et al. (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.

Similar to the specification of Barsky et al. (2011), the VAR features TFP, consumption, output, and hours worked.[17] All variables are in real per-capita terms (except for per-capita hours worked, which are not deflated) and enter the VAR in (log)-levels. We also use four 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.[18]

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

[18] Additionally, we do not impose zero-impact restrictions to separate anticipated from surprise shocks to technology (Kurmann et al., 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.

Figure 7: The state-dependent effects of a news shock.



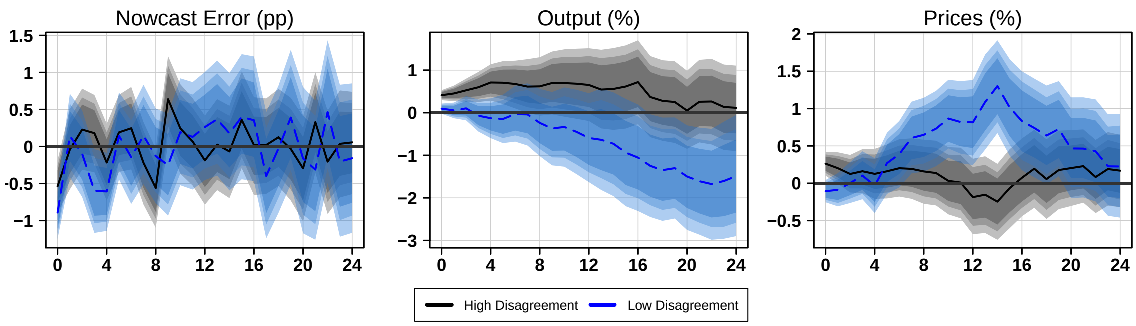
Notes: Estimates based on STLP with identified technology news shock (Kurmann et al., 2021). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines 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).

We present the results in Figure 7. 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. We note, however, that the output reaction in the low disagreement regime is significantly positive for about one year as technology factually moves eventually. 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 prices is consistent with the findings in Barsky et al. (2011) and Kurmann et al. (2021).

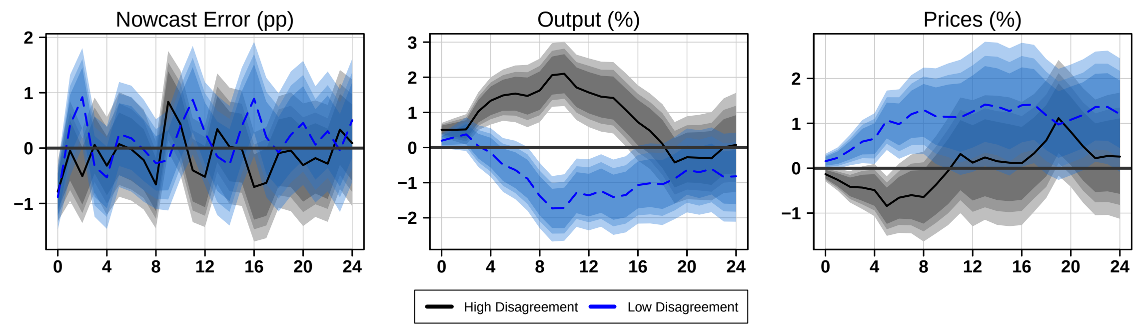
To summarize, we highlight the similar state-dependent response of output to a news shock compared to that of a sentiment shock. This underscores the tight connection between noise and news shocks. We stress that both shocks are identified using completely different setups, work through other transmission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

Figure 8: 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^s). 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).

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 8 and Figure 9.

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 8. Macroeconomic volatility was substantially heightened in the 1970s and early 1980s due to the large oil price shocks and the Volcker shock.[19] 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. Next, we turn to the second subsample reported in panel (b) of Figure 8, 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.

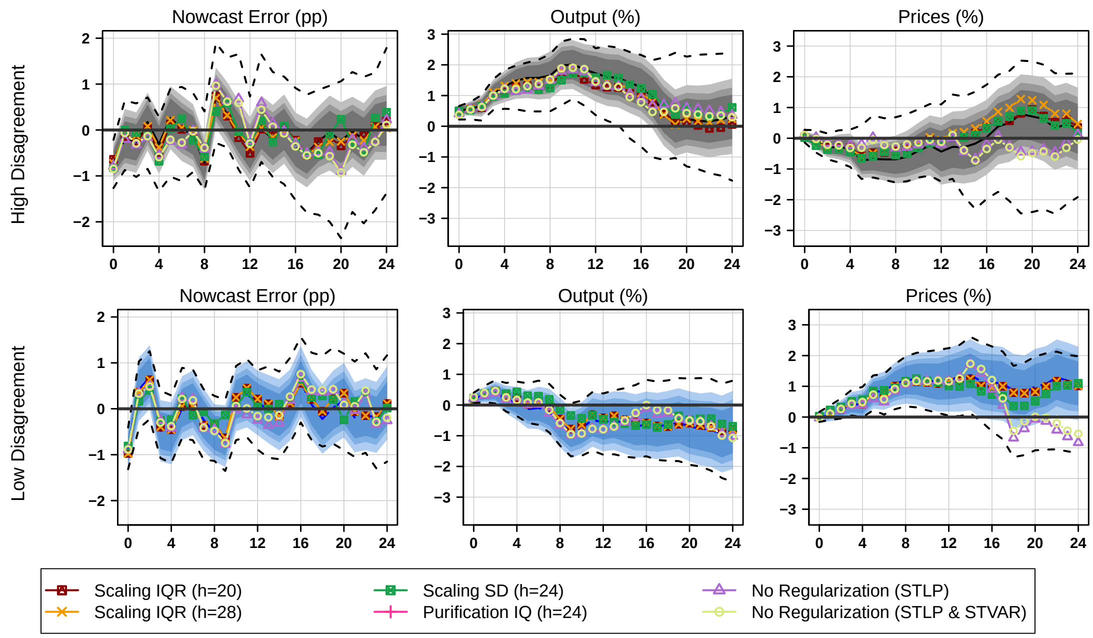
We also provide robustness to specification choices in the STLP in Figure 9.[20] In our baseline results, we scale disagreement using the moving-average standard deviation of output growth over the last 24 quarters. The window of 6 years (=24 quarters) reflects a typical business cycle frequency of 5 to 7 years. Hence, changing the window to 5 years (=20 quarters) or 7 years (=28 quarters) does not significantly change the results. 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 retain the residuals. We denote this approach as *purification*; results are again robust to this choice. As we utilize Bayesian shrinkage priors for the regularization of the controls in the empirical framework, we also perform prior sensitivity checks. Results do not change qualitatively or quantitatively when imposing no regularization in the STLP or in both the STLP and the STVAR. In these cases, no regularization means using a completely uninformative prior that resembles ordinary least squares. We report additional robustness checks concerning the number of lags and the control variables in Figure B5 in the appendix.

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

[19] This check also safeguards against concerns regarding the scaling of disagreement. Our results are robust to apply no scaling at all.

[20] We report robustness checks for the impulse response functions of the remaining variables in the appendix; see Figure B8 and Figure B9.

Figure 9: Robustness to the state-dependent effects of a sentiment shock.



Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). 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 markers 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).

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 remain unchanged, we observe that the response of prices in the high disagreement regime turns statistically insignificant. This aligns well with most median responses while also moving more towards the null line. We underscore that we tend to interpret the outcome of prices in the high disagreement regime as a null effect.

We provide two additional robustness checks in the appendix. First, we use alternative indicators for uncertainty as the state variable. Instead of disagreement, we use the financial and macroeconomic uncertainty measures provided by Jurado et al. (2015). Furthermore, we use an alternative version of the disagreement series, scaled by the real-time moving standard deviation of output growth. Second, we control for the state of the business cycle to rule out an alternative interpretation whereby our results are driven not by information frictions but by differences in capacity utilization over the business cycle. The results in Figure B6 and Figure B7 in the Appendix confirm that our findings are robust to these checks.

5. Theory

To provide a structural interpretation of the evidence, we develop a model that embeds the signal-extraction problem sketched in Section 2 in a microfounded New Keynesian framework. The model builds on the noisy and dispersed information framework of Lorenzoni (2009), which we simplify—most notably by assuming predetermined rather than staggered prices—so that the resulting model admits a closed-form solution. This setup allows us to study the macroeconomic effects of sentiment shocks. We first show that the informational friction generates nowcast errors consistent with the sign restrictions imposed above. Most importantly, we show that uncertainty amplifies the impact of sentiment shocks.

5.1 Model outline

In this section, we provide a compact description of the model; see Lorenzoni (2009) for further details of the original model.

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 $1 < n < \infty$.[21] 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,

[21] 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.

idiosyncratic component.[22] 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.

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 additionally 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 this information set, 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 private and public information, including the signals and the 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 $t+1$ onward.

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

[22] 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 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 conditionally 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

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

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 based on 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.[23] 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.

Sentiment shocks. 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 causes 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. The aggregate component x_t follows a random walk

$$\Delta x_t = \varepsilon_t.$$

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

$$s_t = \varepsilon_t + e_t,$$

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

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

[23] 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 the 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.

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 $n \to \infty$.

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.

5.2 Results

We now present the results obtained from a linear approximation of the equilibrium conditions around the symmetric steady state; see Appendix C for details. Lower-case letters denote percentage deviations from the steady state. Our first result concerns which shocks generate nowcast errors and their co-movement with output; the second establishes the state dependence—how uncertainty shapes the impact of sentiment shocks. Proofs are provided in Appendix D.

Our first result provides the underpinning for our identification strategy.

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*

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

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*

$$y_t - \mathbb{E}_{k,t} y_t = \underbrace{-\rho_x^k \left[\delta_x^h(1-\Omega) + \Omega\right]}_{<0} e_t + \underbrace{\left[\delta_x^h(1-\Omega) + \Omega\right](1 - \delta_x^k - \rho_x^k)}_{>0} \varepsilon_t, \tag{5.6}$$

with $\mathbb{E}_{k,t}$ standing for either the expectations of producers, $\mathbb{E}_{j,l,t}$, or households, $\mathbb{E}_{l,t}$, and ρ_x^k, δ_x^k correspondingly for ρ_x^p, δ_x^p or ρ_x^h, δ_x^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 in addition to the public signal. They, too, attribute this increase to adverse idiosyncratic (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.[24] Yet, as each producer and each household considers itself unlucky relative to its peers, expectations about current output are actually higher than its realization: a negative nowcast error obtains.

After a positive productivity shock, producers 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 customers expect other producers to set higher prices and consequently underestimate

[24]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.

aggregate 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 effects of shocks. Misperceptions about economic activity thus arise only after imperfectly observed shocks, such as innovations in productivity or sentiment shocks.

Our second result establishes the state dependence—how uncertainty shapes the impact of sentiment shocks.

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

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

To build intuition, recall from Section 2 that if the variance of aggregate technology—and hence uncertainty about it—increases, agents put more weight on the signals they receive. This, in turn, affects 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.[25]

[25] 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- and low-disagreement regimes documented in Figure 5. A positive signal in stage 1 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.

To see why uncertainty unambiguously reduces the impact of sentiment shocks on prices, consider the following expression, which is derived as Equation (C.14) in Appendix C:

$$\frac{\partial p_t}{\partial e_t} = \frac{1-\alpha}{\alpha}\left[(1-\Omega)\left(\rho_x^h + \delta_x^h \rho_x^p \frac{n-1}{n}\right) - \Omega(\gamma-1)\frac{n-1}{n}\rho_x^p\right], \qquad (5.7)$$

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) price 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. The term $\rho_x^p(n-1)/n$ represents an individual firm's assessment of these 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 (all) producers to the signal. Since a higher variance of aggregate technology leads households and firms to pay more attention to the signals, the whole term increases in σ_ε^2.

The second term of Equation (5.7) reflects the (negative) price 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.

Next, consider how uncertainty shapes the response of output in more detail. According to Equation (5.5) we have:

$$\frac{\partial y_t}{\partial e_t} = \rho_x^h(1-\Omega). \qquad (5.8)$$

The parameter ρ_x^h is households' optimal weight on the public signal when forming expectations about economic fundamentals (productivity) and, hence, future income, where higher expected income raises current demand. The parameter $-\Omega$ reflects the impact of a technology shock on (current and) expected future prices. Since actual prices do not fall as much 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 demand.

Whenever the variance of aggregate productivity increases, uncertainty rises and households pay closer attention to the signals. Thus, ρ_x^h and the expectations of permanent income are higher after a noise shock. Firms also place greater weight on the public signal when setting prices, which lowers $-\Omega$ and, hence, expected future prices following a perceived increase in overall technology. In principle, this would exert negative pressure on output after a noise shock. However, the demand channel dominates unless the informational content of the private signal observed by households is very large ($\sigma_\eta^2/n << \sigma_\varepsilon^2$, where σ_η^2/n is the variance of the sum of the price signals collected by households) and, in addition, contains much less noise than the public signal ($\sigma_\eta^2/n << \sigma_e^2$). In this case, $\sigma_\eta^2(\sigma_\varepsilon^{-2}+\sigma_e^{-2})/n$ can be smaller than $Q^{-1} < 1$, 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 an agency/media outlet that 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).

6. Conclusion

This paper studies the conditions under which the economy becomes susceptible to non-fundamental shocks. We focus on expectation-driven business cycle disturbances, which we label "sentiment shocks." Our main finding is that their macroeconomic effects depend critically on the degree of disagreement among forecasters. When disagreement is high, sentiment shocks have sizable effects on economic activity while leaving prices largely unaffected. When disagreement is low, their effects are mostly absorbed by prices and have little impact on output.

To interpret these findings, we rely on a New Keynesian model with dispersed information in which agents use noisy signals to infer aggregate productivity. We show that when uncertainty about fundamentals rises, agents place greater weight on these signals, amplifying the real effects of sentiment shocks. In such environments, agents must infer fundamentals from noisy signals—dancing in the dark.

References

Aastveit K A., Natvik G J., and Sola S. (2017) "Economic uncertainty and the influence of monetary policy". *Journal of International Money and Finance*, Vol. 76, pp. 50–67.

Andrade P., Crump R K., Eusepi S., and Moench E. (2016) "Fundamental disagreement". *Journal of Monetary Economics*, Vol. 83, pp. 106–128.

Angeletos G.-M., Iovino L., and La'O J. (2016) "Real rigidity, nominal rigidity, and the social value of information". *American Economic Review*, Vol. 106(01), pp. 200–227.

Angeletos G.-M. and La'O J. (2013) "Sentiments". *Econometrica*, Vol. 81 (2), pp. 739–779.

Angeletos G.-M. and Pavan A. (2007) "Efficient Use of Information and Social Value of Information". *Econometrica*, Vol. 75(4), pp. 1103–1142.

Antonova A., Matvieiev M., and Poilly C. (2026) "Supply Shocks in the Fog: The Role of Endogenous Uncertainty". CEPR Discussion Paper No. 21197.

Auerbach A J. and Gorodnichenko Y. (2013) "Fiscal Multipliers in Recession and Expansion". *Fiscal Policy After the Financial Crisis*. Ed. by A Alesina and F Giavazzi. University of Chicago Press, pp. 63–98.

Auerbach A J. and Gorodnichenko Y. (2012) "Measuring the output responses to fiscal policy". *American Economic Journal: Economic Policy*, Vol. 4(2), pp. 1–27.

Bachmann R., Born B., Elstner S., and Grimme C. (2019) "Time-varying business volatility and the price setting of firms". *Journal of Monetary Economics*, Vol. 101, pp. 82–99.

Bachmann R., Elstner S., and Sims E. (2013) "Uncertainty and economic activity: Evidence from business survey data". *American Economic Journal: Macroeconomics*, Vol. 5(2), pp. 217–249.

Baley I. and Blanco A. (2019) "Firm Uncertainty Cycles and the Propagation of Nominal Shocks". *American Economic Journal: Macroeconomics*, Vol. 11(1), pp. 276–337.

Barsky R., Basu S., and Lee K. (2015) "Whither news shocks?" *NBER Macroeconomics Annual*, Vol. 29(1), pp. 225–264.

Barsky R. and Sims E. (2011) "News shocks and business cycles". *Journal of Monetary Economics*, Vol. 58, pp. 273–289.

Basu S., Fernald J G., and Kimball M S. (2006) "Are Technology Improvements Contractionary?" *American Economic Review*, Vol. 96(5), pp. 1418–1448.

Beaudry P., Nam D., and Wang J. (2011) "Do mood swings drive business cycles and is it rational?" NBER Working Paper 17651.

Beaudry P. and Portier F. (2006) "Stock Prices, News, and Economic Fluctuations". *American Economic Review*, Vol. 96, pp. 1293–1307.

Benamar H., Foucault T., and Vega C. (2020) "Demand for Information, Uncertainty, and the Response of U.S. Treasury Securities to News". *The Review of Financial Studies*, Vol. 34(7), pp. 3403–3455.

Benhima K. and Poilly C. (2021) "Does Demand Noise Matter? Identification and Implications". *Journal of Monetary Economics*, Vol. 117, pp. 278–295.

Bianchi F., Ilut C L., and Saijo H. (2024) *Smooth diagnostic expectations*. NBER Working Paper No. 32152.

Blanchard O J., L'Huillier J.-P., and Lorenzoni G. (2013) "News, noise, and fluctuations: An empirical exploration". *American Economic Review*, Vol. 103(7), pp. 3045–3070.

Boeck M. and Pfarrhofer M. (2025) "Belief Shocks and Implications of Expectations About Growth-at-Risk". *Journal of Applied Econometrics*, Vol. 40(3), pp. 341–348.

Born B., Müller G J., and Pfeifer J. (2020) "Does austerity pay off?" *Review of Economics and Statistics*, Vol. 102(2), pp. 323–338.

Caggiano G., Castelnuovo E., and Groshenny N. (2014) "Uncertainty shocks and unemployment dynamics in US recessions". *Journal of Monetary Economics*, Vol. 67, pp. 78–92.

Carvalho C M., Polson N G., and Scott J G. (2010) "The Horseshoe Estimator for Sparse Signals". *Biometrika*, Vol. 97(2), pp. 465–480.

Castelnuovo E. and Pellegrino G. (2018) "Uncertainty-dependent effects of monetary policy shocks: A New-Keynesian interpretation". *Journal of Economic Dynamics and Control*, Vol. 93, pp. 277–296.

Chahrour R. and Jurado K. (2018) "News or noise? The missing link". *American Economic Review*, Vol. 108(7), pp. 1702–1736.

Chahrour R., Nimark K., and Pitschner S. (2021) "Sectoral Media Focus and Aggregate Fluctuations". *American Economic Review*, Vol. 111(12), pp. 3872–3922.

Coibion O. and Gorodnichenko Y. (2012) "What Can Survey Forecasts Tell Us About Information Rigidities?" *Journal of Political Economy*, Vol. 120(1), pp. 116–159.

Coibion O. and Gorodnichenko Y. (2015) "Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts". *American Economic Review*, Vol. 105(8), pp. 2644–78.

Cornand C. and Heinemann F. (2008) "Optimal Degree of Public Information Dissemination". *The Economic Journal*, Vol. 118(528), pp. 718–742.

Dovern J., Fritsche U., and Slacalek J. (2012) "Disagreement among forecasters in G7 countries". *Review of Economics and Statistics*, Vol. 94(4), pp. 1081–1096.

Ehrmann M. and Fratzscher M. (2007) *Social value of public information: testing the limits to transparency.* ECB Working Paper 821. Frankfurt a. M.

Enders Z., Kleemann M., and Müller G J. (2021) "Growth expectations, undue optimism, and short-run fluctuations". *Review of Economics and Statistics*, Vol. 103(5), pp. 905–921.

Falck E., Hoffmann M., and Hürtgen P. (2021) "Disagreement about Inflation Expectations and Monetary Policy Transmission". *Journal of Monetary Economics*, Vol. 118, pp. 15–31.

Fernald J G. (2014) "A quarterly, utilization-adjusted series on total factor productivity". Federal Reserve Bank of San Francisco Working Paper 2012-19.

Francis N., Owyang M T., Roush J E., and DiCecio R. (2014) "A flexible finite-horizon alternative to long-run restrictions with an application to technology shocks". *Review of Economics and Statistics*, Vol. 96(4), pp. 638–647.

Gambetti L., Korobilis D., Tsoukalas J., and Zanetti F. (2023) "Agreed and disagreed uncertainty". *arXiv preprint arXiv:2302.01621.*

Gemmi L. and Mihet R. (2023) "Unpacking Uncertainty in Household Expectations". Swiss Finance Institute Research Paper No. 24-20.

Gonçalves S., Herrera A M., Kilian L., and Pesavento E. (2024) "State-dependent local projections". *Journal of Econometrics*, Vol. 244(2), p. 105702.

Hauzenberger N., Pfarrhofer M., and Stelzer A. (2021) "On the effectiveness of the European Central Bank's conventional and unconventional policies under uncertainty". *Journal of Economic Behavior & Organization*, Vol. 191, pp. 822–845.

Hellwig C. (2005) *Heterogeneous Information and the Benefits of Public Information Disclosures (October 2005)*. UCLA Economics Online Papers 283. UCLA Department of Economics.

Ilut C L. and Schneider M. (2014) "Ambiguous business cycles". *American Economic Review*, Vol. 104(8), pp. 2368–2399.

Jordà Ò. (2005) "Estimation and inference of impulse responses by local projections". *American Economic Review*, Vol. 95(1), pp. 161–182.

Jurado K., Ludvigson S C., and Ng S. (2015) "Measuring Uncertainty". *American Economic Review*, Vol. 105(3), pp. 1177–1216.

Keynes J M. (1936) *The General Theory of Employment, Interest, and Money.* Orlando, Florida: Edition Harvest/Harcourt Brace 1964.

Kurmann A. and Sims E. (2021) "Revisions in utilization-adjusted TFP and robust identification of news shocks". *Review of Economics and Statistics*, Vol. 103(2), pp. 216–235.

Lagerborg A., Pappa E., and Ravn M O. (2023) "Sentimental Business Cycles". *The Review of Economic Studies*, Vol. 90(3), pp. 1358–1393.

Levchenko A A. and Pandalai-Nayar N. (2020) "TFP, news, and "sentiments": The international transmission of business cycles". *Journal of the European Economic Association*, Vol. 18(1), pp. 302–341.

Lhuissier S. and Tripier F. (2021) "Regime-dependent effects of uncertainty shocks: A structural interpretation". *Quantitative Economics*, Vol. 12(4), pp. 1139–1170.

Lorenzoni G. (2009) "A Theory of Demand Shocks". *American Economic Review*, Vol. 99, pp. 2050–2084.

Lusompa A. (2023) "Local projections, autocorrelation, and efficiency". *Quantitative Economics*, Vol. 14(4), pp. 1199–1220.

Mankiw N G., Reis R., and Wolfers J. (2003) "Disagreement about Inflation Expectations". *NBER Macroeconomics Annual 2003, Volume 18.* Ed. by M Gertler and K Rogoff. MIT Press, pp. 209–248.

Montiel-Olea J L. and Plagborg-Møller M. (2021) "Local projection inference is simpler and more robust than you think". *Econometrica*, Vol. 89(4), pp. 1789–1823.

Morris S. and Shin H S. (Dec. 2002) "Social Value of Public Information". *American Economic Review*, Vol. 92(5), pp. 1521–1534.

Pagan A. (1984) "Econometric issues in the analysis of regressions with generated regressors". *International Economic Review*, pp. 221–247.

Patton A J. and Timmermann A. (2010) "Why do forecasters disagree? Lessons from the term structure of cross-sectional dispersion". *Journal of Monetary Economics*, Vol. 57(7), pp. 803–820.

Piger J. and Stockwell T. (2023) *Differences from Differencing: Should Local Projections with Observed Shocks be Estimated in Levels or Differences?* Working Paper Available at SSRN 4530799.

Pigou A C. (1927) *Industrial Fluctuations*. Macmillan.

Ramey V A. and Zubairy S. (2018) "Government spending multipliers in good times and in bad: evidence from US historical data". *Journal of Political Economy*, Vol. 126(2), pp. 850–901.

Ricco G., Callegari G., and Cimadomo J. (2016) "Signals From the Government: Policy Disagreement and the Transmission of Fiscal Shocks". *Journal of Monetary Economics*, Vol. 82, pp. 107–118.

Rubio-Ramirez J F., Waggoner D F., and Zha T. (2010) "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference". *The Review of Economic Studies*, Vol. 77(2), pp. 665–696.

Schmitt-Grohé S. and Uribe M. (2012) "What's news in business cycles". *Econometrica*, Vol. 80(6), pp. 2733–2764.

Tenreyro S. and Thwaites G. (2016) "Pushing on a string: US monetary policy is less powerful in recessions". *American Economic Journal: Macroeconomics*, Vol. 8(4), pp. 43–74.

Walsh C E. (2007) "Optimal economic transparency". *International Journal of Central Banking*, Vol. 3(1).

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, which include 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
GDP deflator	$100 \log x_t$	`GDPDEF`	FRED
Real consumption	$100 \log x_t$	`PCE`	FRED
Real private investment	$100 \log x_t$	`GPDI`	FRED
Unemployment rate	x_t	`UNRATE`	FRED
Federal funds rate	x_t	`FEDFUNDS`	FRED
10-year government bond yields	x_t	`GS10`	FRED
Excess bond premium	x_t	`EBP`	Favara et al. (2016)
S&P 500	$100 \log x_t$	`P`	Robert Shiller's website
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. Real private consumption and real investment is deflated by the GDP deflator.

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

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

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 a 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

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

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. 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 et al., 2012; Caggiano et al., 2014; Tenreyro et al., 2016; Falck et al., 2021). Therefore, we specify the transition function based on the logistic function, following Granger et al. (1993). We assume that the alternative $\tilde{F}(z_{t-1})$ follows

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

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 is identified using sign restrictions. We impose our set of sign restrictions using the methods in Rubio-Ramirez et al. (2010). The reduced-form innovations, $\boldsymbol{u}_t$, are related to the structural innovations, $\boldsymbol{\varepsilon}_t$, by the linear combination $\boldsymbol{u}_t = \boldsymbol{S}_t \boldsymbol{\varepsilon}_t$, where structural shocks are, by assumption, orthogonalized, such that $\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$ and $\boldsymbol{S}_t$ is an 2×2 nonsingular matrix. The time variation in the impact matrix $\boldsymbol{S}_t$ arises from the time variation in the covariance matrix, as $\boldsymbol{\Sigma}_t = \boldsymbol{S}_t \boldsymbol{S}_t'$. Given that this time variation is exclusively driven by two states, we get $\boldsymbol{\Sigma}_r = \boldsymbol{S}_r \boldsymbol{S}_r'$, where $\boldsymbol{S}_r$ is the regime-specific structural impact matrix with $r \in \{1, 2\}$. To implement the sign-restrictions, we proceed as follows. The regime-specific covariance matrix can be rewritten as $\boldsymbol{\Sigma}_r = \boldsymbol{C}_r \boldsymbol{Q} \boldsymbol{Q}' \boldsymbol{C}_r'$, where $\boldsymbol{C}_r$ denotes the lower Cholesky factor of $\boldsymbol{\Sigma}$ and $\boldsymbol{Q} \in \mathcal{O}(2)$, which is the set of all 2×2 orthonormal matrices ($\boldsymbol{Q}\boldsymbol{Q}' = \boldsymbol{I}$ holds). We use the algorithm of Rubio-Ramirez et al. (2010) to independently draw from the uniform distribution over $\mathcal{O}(2)$. We search for a $\boldsymbol{Q}$ such that the sign-restrictions on the structural impact matrix $\boldsymbol{S}_r = \boldsymbol{C}_r \boldsymbol{Q}$ are satisfied. This methodology takes into account both the uncertainty inherent to sign restrictions and the uncertainty of the estimated parameters.

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 et al. (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 et al. (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 et al., 1984, and

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 et al. (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 distributions of the VAR coefficients and the covariance matrix are standard, we use the auxiliary sampler of Makalic et al. (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 that 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 using 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 LP with horizon $h = 0$, $\eta_t = u_{t+h}^{(h)}$ 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 LPs being standard linear regressions, we elicit well-known independent priors for linear regressions. For both coefficient vectors, $\boldsymbol{\beta}_h$ and $\boldsymbol{\gamma}_h$, we impose independent Gaussian priors. Note that we are interested in the 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 $\boldsymbol{\gamma}$. For each element of $\boldsymbol{\beta}$, we do not impose any form of regularization and instead 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 in 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 et al. (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 et al. (2015) to sample from the corresponding 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 et al., 2023). For the deterministic terms, we do not impose any shrinkage and assume a zero mean and a large variance, i.e., 10^5. Regarding 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.

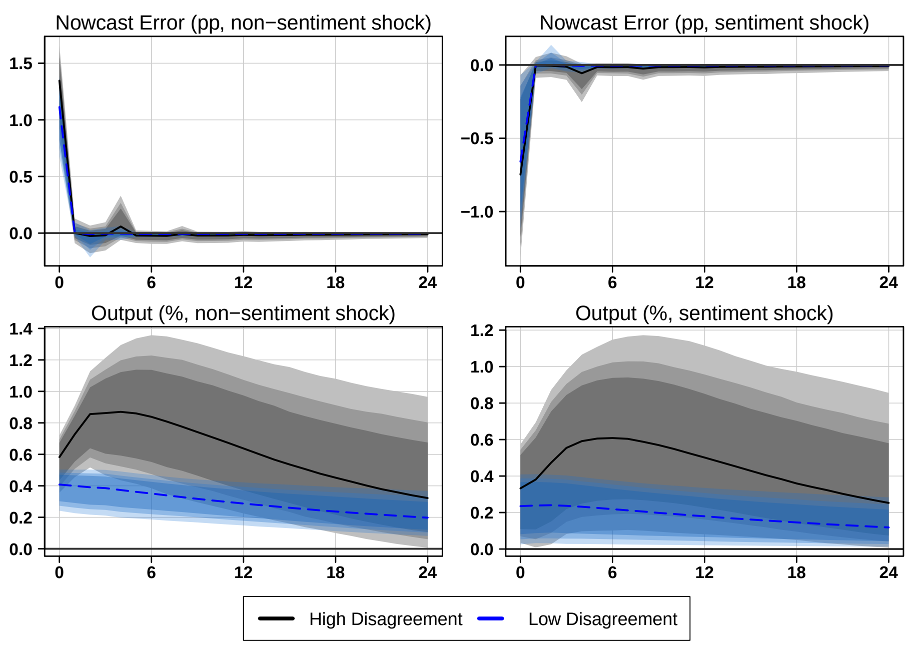
Similarly to the sampler of the STVAR, we briefly discuss the posterior simulation within an MCMC algorithm. Conditional on the regime indicator function $F(z_{t-1})$ the model is fully linear, and all conditional posterior distributions are available in closed-form, rendering a Gibbs sampler convenient. Although the conditional posterior distributions of the VAR coefficients and the covariance matrix are standard, we use the auxiliary sampler of Makalic et al. (2015) to sample from the conditional posterior densities for the HS prior. Lastly, 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 is 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.

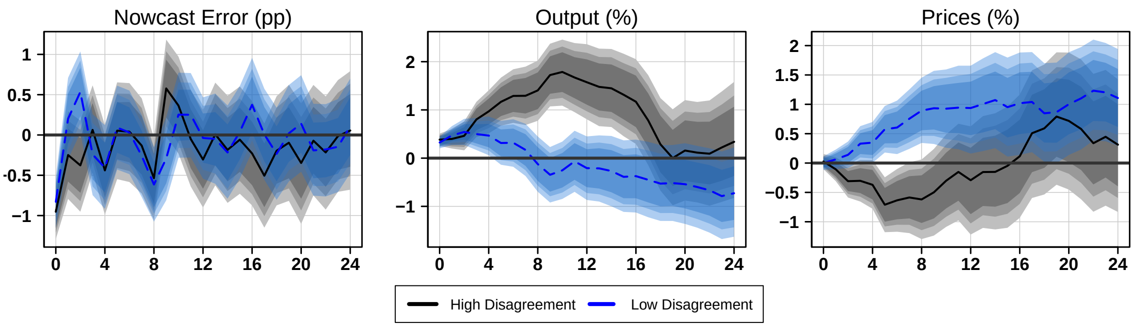


Notes: Estimates based on STVAR model. Identification based on sign-restrictions. The estimation covers the period 1969Q4-2019Q4. Black solid (blue dashed) line refers to the median response, while gray (blue) shaded areas indicates the 68%/80%/90% credible sets. The horizontal axis measures the impulse 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 a negative comovement on impact between the nowcast error and output to identify a sentiment shock. In terms of differences across regimes, we find stronger effects on output in the high disagreement regime. However, the impulse response function is much more hump-shaped, obscuring the effects we observe in the local projections framework. This is due to the relatively small number of lags in the STVAR model, which may introduce a bias in the impulse responses beyond the horizon of the number of lags introduced in the STVAR.

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

Figure B2: Using the logistic function as transition function.

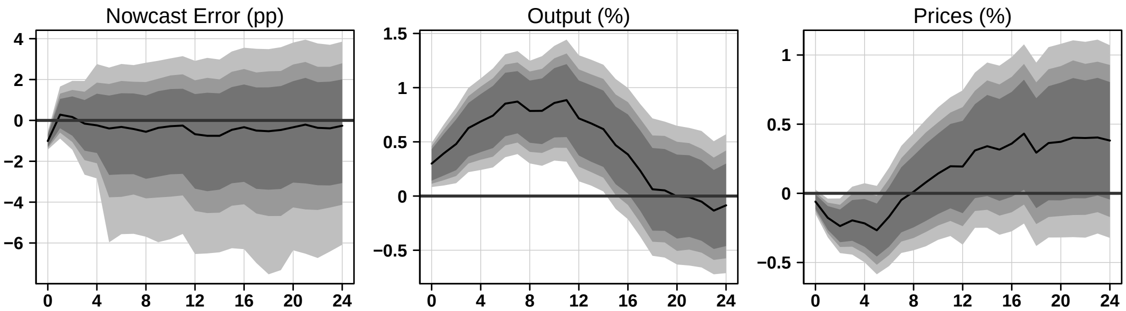


Notes: Estimates based on STLP with identified sentiment shock (ε_t^s) using a logistic transition function. Dependent variables are the nowcast error, output (log), prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates of β_h^H (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 by using the logistic function as the transition function. Therefore, we specify the transition function based on the logistic function, as discussed in Equation (A.4). We follow several previous studies that 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 from the main outcomes in Figure 5.

In the 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

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

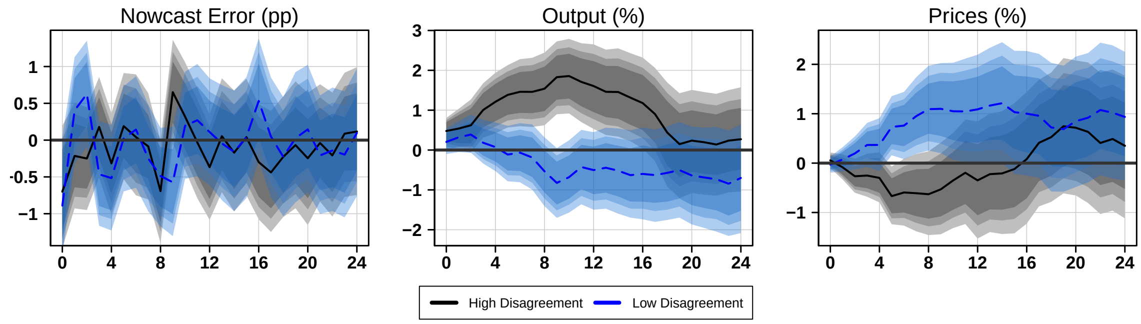


Notes: Estimates based on LP with identified sentiment shock (ε_t^s) accounting also for the uncertainty around the sentiment shock. Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. 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).

of the sentiment shock, which we denote as $p(\varepsilon_t^s)$. 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: $(\varepsilon_t^s)^{(m)} \sim p(\varepsilon_t^s)$, where (m) denotes the m-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 still indicate significant results, as in 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 report some additional robustness checks concerning the specification in Figure B5: We detrend the disagreement series by using the Hodrick-Prescott filter (instead of relying on scaling with the volatility of GDP growth), which is another approach to remove the low-frequency movement in the series. We have estimated the STLP also with a lower ($p = 2$) and higher ($p = 6$) number of lags. Lastly, we

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

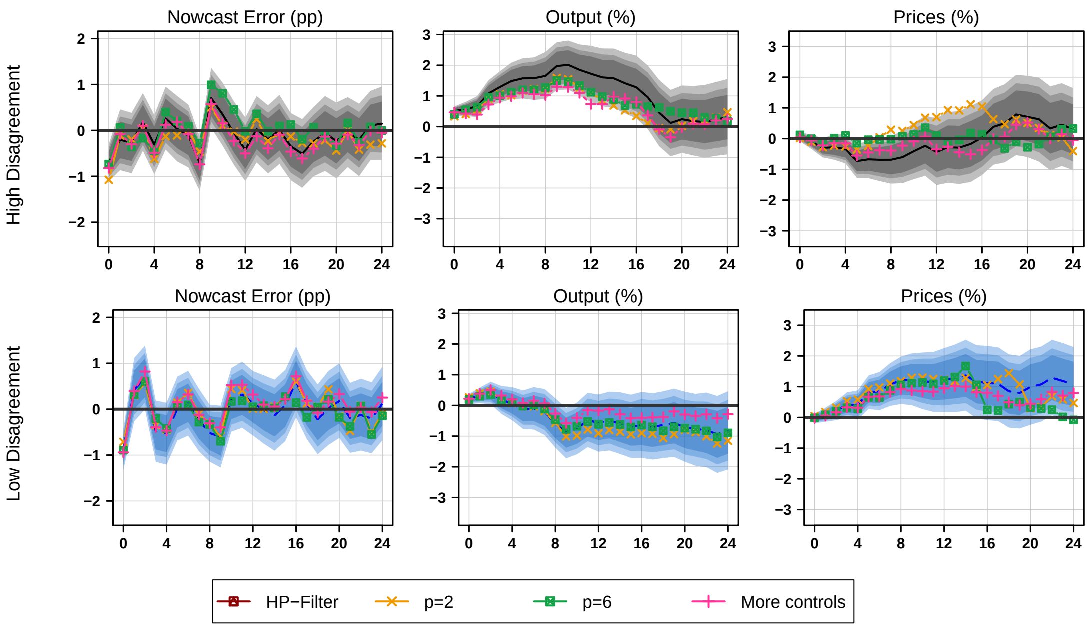


Notes: Estimates based on STLP with identified sentiment shock (ε_t^s) accounting also for the uncertainty around the sentiment shock. Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. 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).

add more control variables to the STLP: we include the nowcast error, output, and prices in the set of controls. Our results are robust to these additional modifications.

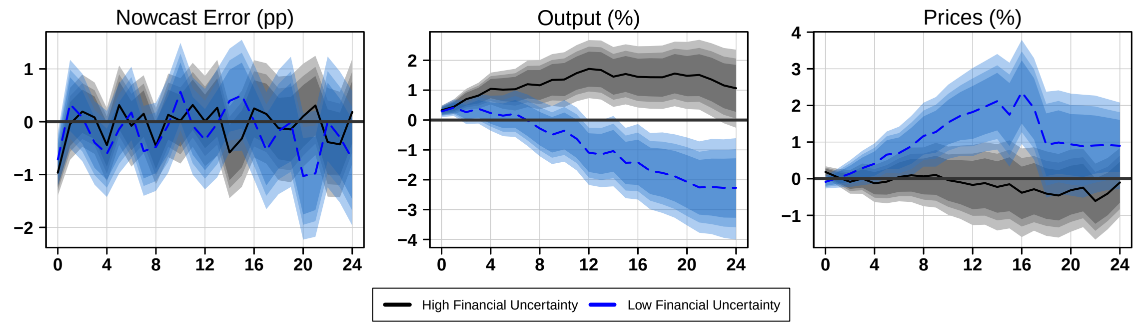
We perform some additional robustness checks regarding the threshold variable. In the baseline, we use the interquartile range of the forecasters' forecasts in the SPF regarding output growth as a measure of disagreement. Additionally, we scale the series using the moving standard deviation of output 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 et al., 2023; Gambetti et al., 2023). We thus provide a robustness check in which we use the financial and macro uncertainty measures provided by Jurado et al. (2015). These measures are statistically significantly correlated with 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.

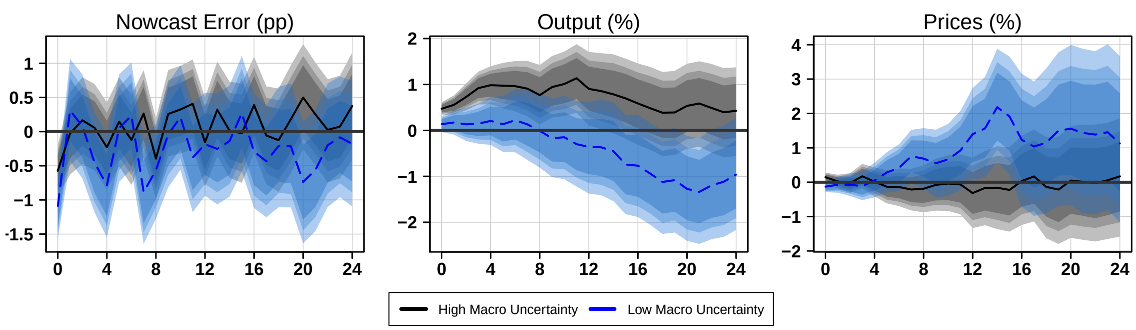


Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates 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: detrending disagreement with the Hodrick-Prescott filter, using less ($p = 2$) and more ($p = 6$) lags, and using more control variables. 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).

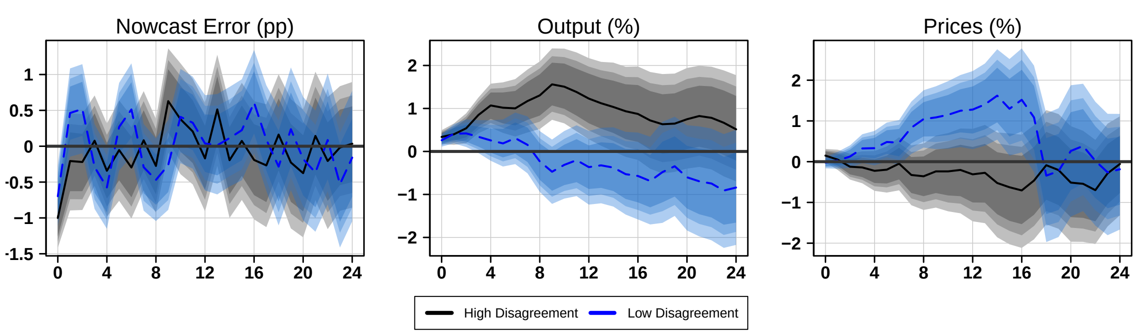
Figure B6: Additional robustness checks: uncertainty and real-time threshold variable.



(a) Threshold variable: Financial uncertainty.



(b) Threshold variable: Macro uncertainty.



(c) Threshold variable: Real-time disagreement.

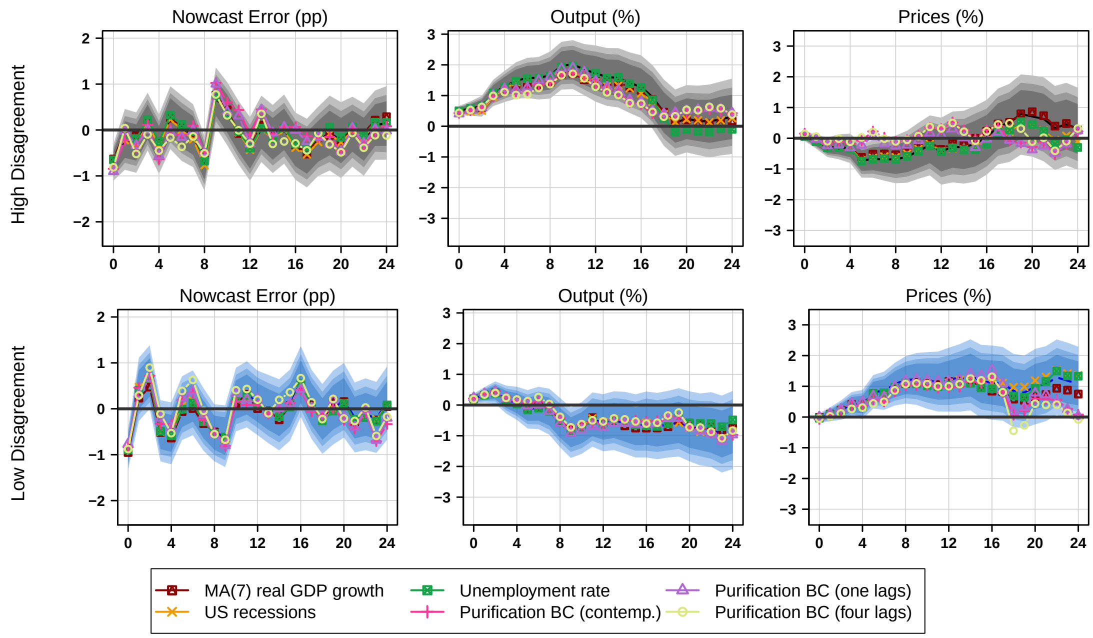
Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates 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 B6. Our main findings are robust to these alternative indicators of uncertainty and 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 that quickly becomes 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 consistently use the same survey, which asks the same respondents. This allows us to investigate the effect of sentiment shocks conditional on the level of disagreement under which 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 respect to the state of the business cycle. As disagreement is correlated with the business cycle (Dovern et al., 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 et al. (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 analysis, we re-estimate the baseline version of the model while additionally controlling 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 effects of the business cycle. In the second exercise, we off-project the information contained in the business cycle from the disagreement series before constructing the state indicator (*purification)*. This orthogonalizes the disagreement series with respect to the business cycle.

Figure B7: Controlling for the state of the business cycle.

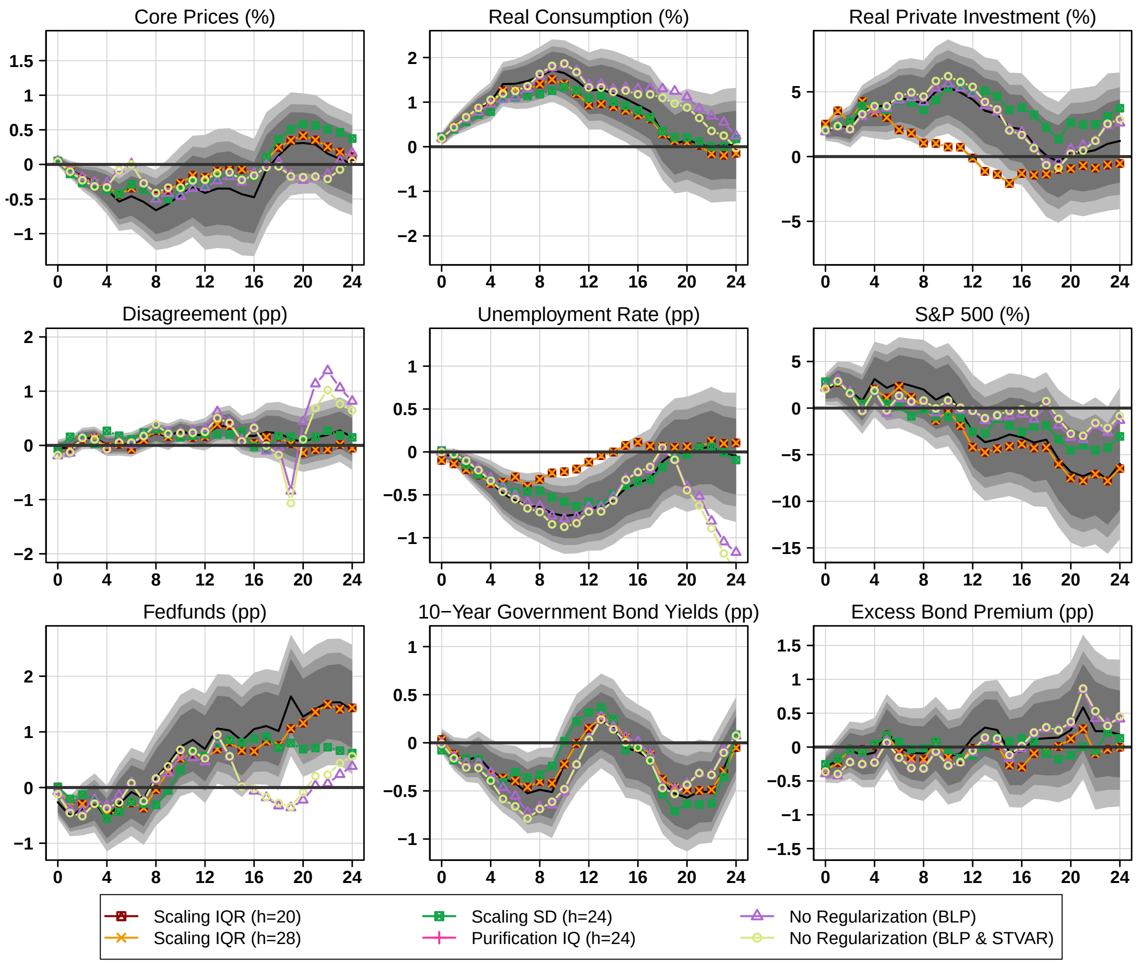


Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). Dependent variables are the nowcast error, output measured by real GDP (log), and prices measured by consumer prices (log). The estimation covers the period 1969Q4-2019Q4. The black solid (blue dashed) lines refer to the median estimates 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 B7 reports the results, showing the median estimate and credible sets of the baseline model, as well as the median estimates of the alternative specifications. The baseline model is both robust to the level 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.

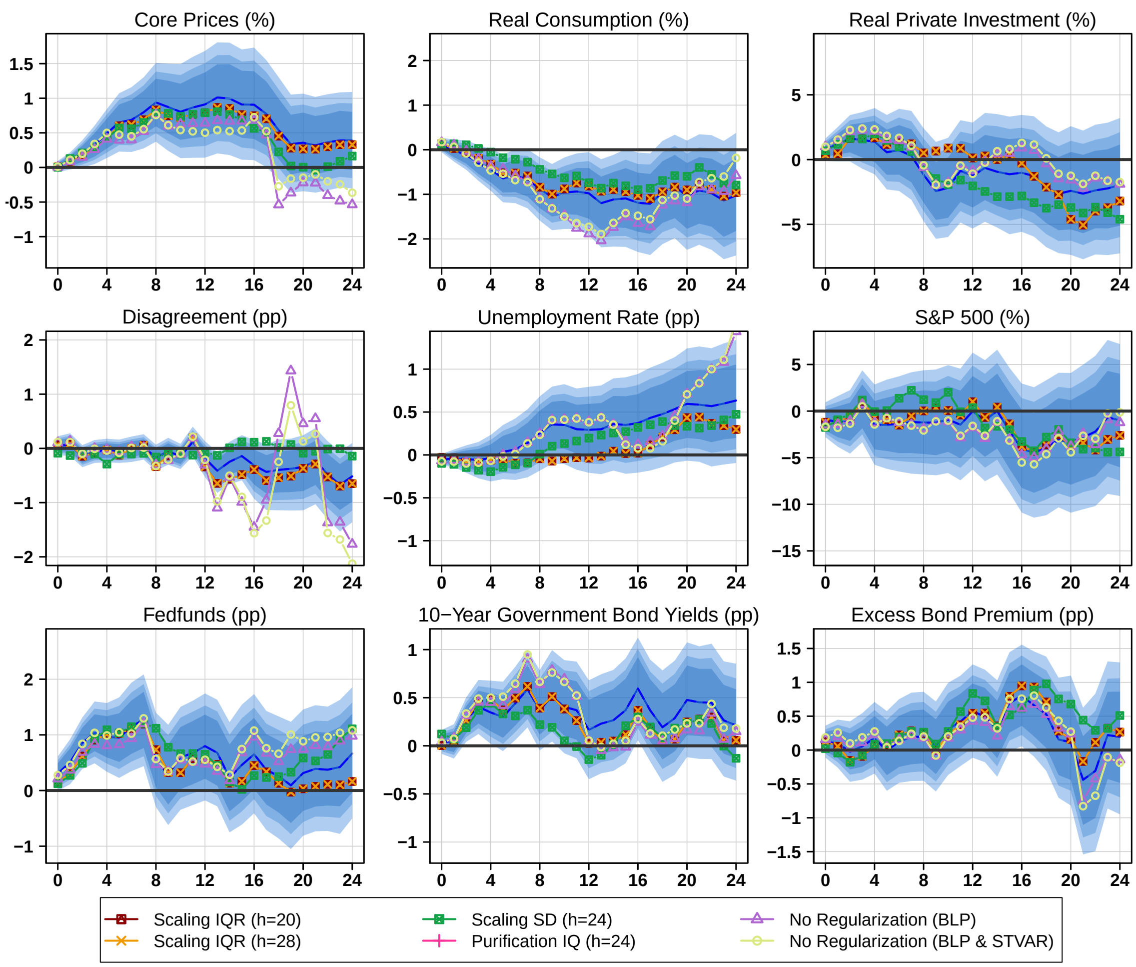
In Figure 9, we report robustness regarding the window size by using the standard deviation instead of the interquartile range or by performing purification. We refer to purification as off-projecting the information contained in the moving standard deviation via a linear regression. Additionally, we report robustness checks for using different prior distributions that impose no regularization 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 B8 and Figure B9.

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



Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). 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 B9: Robustness to the state-dependent effects of a sentiment shock (low disagreement).



Notes: Estimates based on STLP with identified sentiment shock (ε_t^s). 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:

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

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 $\overline{E}_t p_t = \iint \mathbb{E}_{j,l,t}p_t \; dj dl$ 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),

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

Inserting the insights from (C.10) yields

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

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

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

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),

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

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:

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

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

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

where

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

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

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

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

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

Given that $Q > 1$, this inequality holds in realistic cases, particularly 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 signals' informational content. 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 when 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

Auerbach A J. and Gorodnichenko Y. (2012) "Measuring the output responses to fiscal policy". *American Economic Journal: Economic Policy*, Vol. 4(2), pp. 1–27.

Born B., Dovern J., and Enders Z. (2023) "Expectation dispersion, uncertainty, and the reaction to news". *European Economic Review*, Vol. 154, p. 104440.

Caggiano G., Castelnuovo E., and Groshenny N. (2014) "Uncertainty shocks and unemployment dynamics in US recessions". *Journal of Monetary Economics*, Vol. 67, pp. 78–92.

Carvalho C M., Polson N G., and Scott J G. (2010) "The Horseshoe Estimator for Sparse Signals". *Biometrika*, Vol. 97(2), pp. 465–480.

Doan T., Litterman R., and Sims C. (1984) "Forecasting and conditional projection using realistic prior distributions". *Econometric Reviews*, Vol. 3(1), pp. 1–100.

Dovern J., Fritsche U., and Slacalek J. (2012) "Disagreement among forecasters in G7 countries". *Review of Economics and Statistics*, Vol. 94(4), pp. 1081–1096.

Falck E., Hoffmann M., and Hürtgen P. (2021) "Disagreement about Inflation Expectations and Monetary Policy Transmission". *Journal of Monetary Economics*, Vol. 118, pp. 15–31.

Favara G., Gilchrist S., Lewis K F., and Zakrajšek E. (2016) *Updating the recession risk and the excess bond premium.* FEDS Notes. Board of Governors of the Federal Reserve System.

Ferreira L N., Miranda-Agrippino S., and Ricco G. (2023) "Bayesian Local Projections". *The Review of Economics and Statistics*, Vol. forthcoming.

Gambetti L., Korobilis D., Tsoukalas J., and Zanetti F. (2023) "Agreed and disagreed uncertainty". *arXiv preprint arXiv:2302.01621.*

Granger C. and Teräsvirta T. (1993) *Modelling Non-Linear Economic Relationships.* Oxford University Press.

Hahn P R., Carvalho C M., Puelz D., and He J. (2018) "Regularization and confounding in linear regression for treatment effect estimation". *Bayesian Analysis*, Vol. 13 (1), pp. 163–182.

Jurado K., Ludvigson S C., and Ng S. (2015) "Measuring Uncertainty". *American Economic Review*, Vol. 105(3), pp. 1177–1216.

Kadiyala K R. and Karlsson S. (1997) "Numerical Methods for Estimation and Inference in Bayesian VAR Models". *Journal of Applied Econometrics*, Vol. 12(2), pp. 99–132.

Litterman R. (1986) "Forecasting with Bayesian vector autoregressions—five years of experience". *Journal of Business & Economic Statistics*, Vol. 4(1), pp. 25–38.

Lusompa A. (2023) "Local projections, autocorrelation, and efficiency". *Quantitative Economics*, Vol. 14(4), pp. 1199–1220.

Makalic E. and Schmidt D F. (2015) "A Simple Sampler for the Horseshoe Estimator". *IEEE Signal Processing Letters*, Vol. 23(1), pp. 179–182.

Pagan A. (1984) "Econometric issues in the analysis of regressions with generated regressors". *International Economic Review*, pp. 221–247.

Rubio-Ramirez J F., Waggoner D F., and Zha T. (2010) "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference". *The Review of Economic Studies*, Vol. 77(2), pp. 665–696.

Tenreyro S. and Thwaites G. (2016) "Pushing on a string: US monetary policy is less powerful in recessions". *American Economic Journal: Macroeconomics*, Vol. 8(4), pp. 43–74.

Wooldridge J M. (2002) *Econometric analysis of cross section and panel data MIT press*. Cambridge University Press.