Disagreement and Monetary Policy*

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Abstract

Time-variation in disagreement about inflation expectations is a stylized fact in survey data, but little is known on how disagreement interacts with the efficacy of monetary policy. In times of high disagreement we estimate that a 100 bps increase in the U.S. policy rate leads to a significant short-term increase in inflation and in inflation expectations of up to 1.0 percentage point, whereas in times of low disagreement we find a significant decline of close to 1.0 percentage point. We reconcile these state-dependent effects with a dispersed information New Keynesian model, where we calibrate the level of disagreement to U.S. data.

JEL: D83, E31, E32, E52.

KEYWORDS: disagreement, dispersed information, disanchoring of inflation expectations, monetary policy transmission, state-dependent effects of monetary policy, local projections.

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1 Introduction

A well-known and robust fact from survey expectations data is substantial time-variation in disagreement across individual inflation expectations (Mankiw, Reis and Wolfers, 2004, Dovern, Fritsche and Slacalek, 2012, Andrade, Crump, Eusepi and Moench, 2016). Inflation expectations crucially affect macroeconomic outcomes, such as spending choices and price-setting decisions of firms, and are a key variable for monetary policy analysis. Differences in individual inflation expectations could, therefore, be important for the transmission of monetary policy. Despite close monitoring of survey expectations by central banks and policymakers, little is known on how disagreement about inflation expectations interacts with the efficacy of monetary policy. This paper provides novel empirical evidence on the macroeconomic effects of monetary policy for high and low levels of disagreement about inflation expectations.

Why could disagreement matter for monetary policy transmission? According to the conventional view, contractionary monetary policy reduces economic activity as well as inflation and inflation expectations. This view matches the predictions of a full information New Keynesian model, where all agents share the same information and disagreement about inflation expectations is zero. Melosi (2017) shows that an additional transmission channel emerges when firms have only dispersed information and thus disagree about inflation expectations, while the central bank is more fully informed. In this case, the private sector uses the central bank's interest rate decisions to become better informed about supply and demand conditions. Firms, for example, interpret an unexpected increase in interest rates as an indicator that demand is increasing, prompting them to raise their prices, which in turn leads to a temporary increase in both inflation and short-term inflation expectations. Melosi (2017) estimates his model with Bayesian methods on U.S. data, where the signal precision and hence disagreement about inflation expectations is constant over time. He finds that the signaling channel of monetary policy *on average* mutes the response of inflation and inflation expectations. Substantial time-variation in disagreement about inflation expectations suggests that the strength of the signaling channel could in fact vary strongly over time.

In this paper, we employ the insight that the strength of the signaling effect depends on the accuracy of the information available to the private sector, which itself is reflected by the level of disagreement about inflation expectations among agents. We show that a key prediction of the model is that the effects of monetary policy shocks on inflation and inflation expectations change with the level of disagreement about inflation expectations. In our econometric approach we directly use disagreement about inflation expectations to test whether the macroeconomic effects of monetary policy shocks differ between a high- and low-disagreement regime. More precisely, we estimate state-dependent impulse responses to monetary policy shocks depending on the level of disagreement about inflation expectations in the U.S. Survey of Professional Forecasters (SPF). One advantage of our empirical strategy is that it allows us to test the existence and quantify the signaling channel of monetary policy without imposing any particular information structure.

We find significantly different state-dependent effects of monetary policy shocks. When disagreement is high, a contractionary monetary policy shock of 100 basis points leads — remarkably — to a significant temporary increase in inflation and in inflation expectations of up to 1.0 percentage point.[1] In contrast, when disagreement is low, a contractionary shock leads to a decline in inflation of close to 1.0 percentage point and a relatively less pronounced decline in output. Importantly, the state-dependent effects of monetary policy shocks on inflation and inflation expectations are highly significantly different; a finding that is undetected when estimating a linear VAR or single equation regressions without allowing for state-dependent effects.

In Section 2, we provide a theoretical background for our empirical results and derive state-dependent macroeconomic responses to monetary policy shocks for high and low levels of disagreement about inflation expectations, building on the dispersed information model of Melosi (2017).[2] Through variation in the information precision of firms, we calibrate two model specifications to match the relative difference of high and low disagreement about one-quarter-ahead inflation expectations from the U.S. SPF. Our exercise shows that the strength of the signaling channel strongly depends on the level of disagreement about inflation expectations. When disagreement is high, the model predicts that a contractionary monetary policy shock increases inflation and in-

[1] We find a delayed reduction in both inflation and in inflation expectations after two to three years.

[2] Below we refer to the model with noisy information also as *dispersed information model*, which differs from sticky information models studied, for example, in Mankiw and Reis (2002).

flation expectations for a plausible range of parameter values. Hence, the signaling channel is one potential explanation of the so-called prize puzzle. In contrast, with little or zero disagreement the conventional monetary policy channel dominates, implying that inflation and inflation expectations both decline in response to a contractionary monetary policy shock. Having established the connection between the strength of the signaling channel and disagreement about inflation expectations, we use this measure in Section 3 to test whether the signaling channel dominates the interest rate channel in the high-disagreement regime.

In Section 3, we outline the empirical methodology. In our estimation, we use U.S. data from 1970:IV to 2007:IV and employ a smooth transition local projection model. This approach has recently received much attention in examining the state-dependent effects of fiscal and monetary policy during booms and recessions (Auerbach and Gorodnichenko, 2013, Tenreyro and Thwaites, 2016, Ramey and Zubairy, forthcoming). The impulse responses to monetary policy shocks are estimated with the local projection method of Jordà (2005), which is combined with a smooth probability function to account for different disagreement regimes. The regimes are identified with a measure for disagreement, the cross-sectional standard deviation of one-quarter-ahead inflation expectations from the U.S. SPF. We map disagreement into a probability measure of being in a high-disagreement regime. The two key advantages of the empirical model are: First, we do not need to impose a specific autoregressive structure for the data generating process. Hence, we do not restrict the shape of the impulse response functions such that the responses at higher horizons remain flexible. Second, we can allow for a smooth transition between the two regimes without explicitly modeling how the transition between the regimes takes place. Our measure of exogenous monetary policy shocks is the extended Romer and Romer (2004) shock series taken from Wieland and Yang (2016). A number of studies have shown that the price puzzle, i.e. an increase in prices after contractionary monetary policy, does not occur when using narrative monetary policy shocks (Romer and Romer, 2004, Coibion, 2012, Cloyne and Hürtgen, 2016). However, when conditioning on episodes of high disagreement we document a strong price puzzle.[3]

[3]The increase in inflation and in inflation expectations is also statistically significant when we control for oil prices, a typical variable suggested to overcome the price puzzle.

Section 4 provides the main empirical results and discusses these in the context of the theoretical predictions. Our empirical results confirm the predictions of the dispersed information model when disagreement is high, according to which a contractionary monetary policy shock leads to a short-run increase in inflation and inflation expectations. In the low-disagreement regime, the empirical findings qualitatively match both, the implications of the full information model and a dispersed information model with relatively precise signals (low disagreement). The theoretical predictions of the full information model are only consistent with the empirical evidence in the low-disagreement regime. Hence, our state-dependent estimation results provide external validation on the *signaling channel* of monetary policy and, therefore, evidence in favor of a dispersed information structure with the policy rate as a public signal. Our empirical results also show that average forecast errors are more strongly autocorrelated in the high-disagreement regime. This finding is consistent with dispersed information models, but inconsistent with full information rational expectations models. Moreover, Coibion and Gorodnichenko (2012) argue that one test to differentiate between noisy and sticky information models is whether disagreement responds to structural shocks. In our empirical results we also find that disagreement itself does not respond endogenously to the monetary policy shock in both regimes. Hence, this result matches the implications of noisy information models in line with Coibion and Gorodnichenko (2012).

In Section 5, we provide an extensive robustness analysis in which we examine and confirm the empirical robustness of state-dependent effects of monetary policy on inflation and inflation expectations along multiple dimensions. These include using alternative measures of the regime-specific disagreement variable such as the interquartile range or disagreement about one-year-ahead inflation expectations. We also find that our baseline results are robust when adding several control variables that are potentially correlated with the monetary policy shock series, among these, oil prices, the fiscal stance, or aggregate uncertainty. Changing the lag length of the dependent variable or including a quadratic trend does not affect our results. Reassuringly, the distribution of monetary policy shocks is very similar in the low- and high-disagreement regime, indicating no systematic difference across the two regimes. Finally, splitting the sample in 1988, when Alan

Greenspan became the Fed's Chairman and which coincides roughly with the beginning of the Great Moderation, we also find state-dependent effects supporting the existence of a signaling channel of monetary policy in each sub-sample.

Wider literature A large empirical literature presents stylized facts on disagreement about inflation expectations and further main macroeconomic variables. Among these Mankiw et al. (2004), Dovern et al. (2012) and Andrade et al. (2016), document a number of stylized facts based on survey expectations data from different sources such as firms, professional forecasters, and households. Andrade et al. (2016) document that there is little disagreement about nominal interest rate expectations in the short-run, whereas disagreement about inflation expectations is pronounced. These empirical facts support the assumption that the nominal interest rate is observed by market participants in keeping with the information structure in the theoretical model.[4] Moreover, Romer and Romer (2000) find empirical evidence that the central bank has superior information and that U.S. market participants use the Fed's interest rate decisions to learn about the current and future state of the economy. Coibion and Gorodnichenko (2012, 2015a), Coibion et al. (2017a), and Andrade et al. (2016) present compelling evidence that dispersed information models provide a better fit to survey data compared to full information models. We derive predictions from a structural dispersed information New Keynesian model commonly used for monetary policy analysis, since our interest lies in the transmission of monetary policy shocks on the macroeconomy.

The paper builds on the literature on macroeconomic models with dispersed information (Lucas, 1972, Woodford, 2002). Within this literature, the paper is most closely related to those that have both, Calvo price stickiness and dispersed information on the firm side (Nimark, 2008, Lorenzoni, 2009) and the papers that assume that firms use the nominal interest rate as a signal (Melosi, 2017, Hoffmann and Hürtgen, 2016). Our paper adds to this literature in specifically assessing the interaction of monetary policy and disagreement about inflation expectations.

This paper also contributes to a growing empirical literature that estimates state-dependent effects of fiscal and monetary policy shocks with local projections. Auerbach and Gorodnichenko

[4] Data from the U.S. SPF indicate that forecasters closely track interest rates. The nowcast errors for the current level of the three month treasury bill rate are negligible (see Figure 17 in the Appendix). Andrade et al. (2016) also find that *Blue Chip Financial Forecasts* indicate very low disagreement about the next quarter's Federal Funds Rate.

(2013) combine the local projection method of Jordà (2005) with a smooth regime switching model to estimate the effects of fiscal policy during booms and recessions. The empirical paper closest to ours is Tenreyro and Thwaites (2016) who use the same empirical method and estimate the efficacy of U.S. monetary policy shocks during booms and recessions. Their main finding is that monetary policy is less powerful during recessions, but unlike our results the response of inflation appears very similar across regimes.

In summary, the remainder of this paper is structured as follows. Section 2 derives theoretical predictions of how the level of disagreement about inflation expectations changes the transmission of monetary policy shocks. Section 3 outlines the empirical methodology of our state dependent local projection model. Section 4 provides our main empirical results and discusses these in the context of the theoretical predictions. In Section 5, we provide an extensive robustness analysis and further results. Section 6 concludes.

2 Disagreement in a New Keynesian model

We outline a theoretical framework with the necessary ingredients to examine the interaction of disagreement and the transmission of monetary policy shocks. The goal of this section is to derive testable predictions of state-dependent effects of monetary policy shocks. Section 2.1 presents a New Keynesian model with dispersed information on the firm side. In Section 2.2 we derive theoretical predictions on how different levels of disagreement about inflation expectations change the transmission of monetary policy shocks.

2.1 The New Keynesian model: full and dispersed information

In the first part we briefly present the widely-used full information New Keynesian model, which serves as a useful benchmark to assess the transmission of monetary policy. We then describe the dispersed information model which builds on the full information New Keynesian model. The model is a simplified version of Melosi (2017) and Hoffmann and Hürtgen (2016), which build on the models studied in Nimark (2008) and Lorenzoni (2009).

2.1.1 The full information model

We present the basic full information New Keynesian model with three exogenous variables, productivity a_t, time preferences d_t, and monetary policy m_t. All exogenous variables follow an AR(1) process with a stochastic shock component ϵ_t^i and persistence $\rho_i, i = a, d, m$:

$$\begin{aligned} \hat{a}_t &= \rho_a \hat{a}_{t-1} + \epsilon_t^a, \qquad \epsilon_t^a \sim N(0, \sigma_a^2) &(1)\\ \hat{d}_t &= \rho_d \hat{d}_{t-1} + \epsilon_t^d, \qquad \epsilon_t^d \sim N(0, \sigma_d^2) &(2)\\ \hat{m}_t &= \rho_m \hat{m}_{t-1} + \epsilon_t^m, \quad \epsilon_t^m \sim N(0, \sigma_m^2)\ , &(3)\end{aligned}$$

where $\hat{x} = \log(x_t) - \log(\bar{x})$ denotes log-deviations from steady state.

We assume that household utility is additively-separable in consumption and labor.[5] A fraction of monopolistic firms can reset their prices each period. Firms produce output using a linear production technology in labor. The central bank responds to inflation and the output gap. The core equilibrium system is comprised by three linearized equations: the consumption Euler equation, the New Keynesian Phillips curve (NKPC), and a Taylor-type interest rate rule:

$$\begin{aligned} \gamma \widehat{y}_t &= \widehat{d}_t - \mathbb{E}_t \widehat{d}_{t+1} + \mathbb{E}_t \gamma \widehat{y}_{t+1} + \mathbb{E}_t \widehat{\pi}_{t+1} - \hat{r}_t &(4)\\ \widehat{\pi}_t &= \frac{(1-\theta)(1-\theta\beta)}{\theta}((\gamma+\varphi)\widehat{y}_t - (1+\varphi)\widehat{a}_t) + \beta \mathbb{E}_t \widehat{\pi}_{t+1} &(5)\\ \hat{r}_t &= \phi_\pi \widehat{\pi}_t + \phi_y \left(\hat{y}_t - \frac{1+\varphi}{\gamma+\varphi} \widehat{a}_t \right) + \widehat{m}_t\ , &(6)\end{aligned}$$

where, γ reflects the coefficient of constant relative risk aversion, φ measures the inverse Frisch elasticity, while β is the discount factor. The parameter θ is the Calvo pricing parameter. The Taylor rule coefficients on inflation and the output gap are given by ϕ_π and ϕ_y, respectively.

The key mechanism of monetary policy transmission operates through the conventional *interest rate channel*: As not all firms can reset prices, an increase in the nominal interest rate leads to

[5] For more details see Appendix A.

a sluggish response of inflation. Therefore the increase in the nominal rate leads to an increase in the real interest rate, which alters the real allocation of the economy. For a wide range of plausible model calibrations, a contractionary monetary policy shock is one that temporarily decreases economic activity. Simultaneously, due to lower demand, (expected) nominal marginal costs decrease, which leads to a decline in inflation as well as in short-run inflation expectations.

Further implications of this model and in fact any full information rational expectations model are: (i) zero disagreement among economic agents about any future macroeconomic variable, because all agents share the same information set and the same perceived law of motion, (ii) the nowcast error for every variable is zero, as agents observe all exogenous and endogenous variables, and (iii) conditional average forecast errors after any structural shock at every horizon are zero and hence not autocorrelated. These arguable restrictive implications are not shared with dispersed information models, such as the one outlined in the next subsection. In our empirical analysis, we test these and further theoretical implications.

2.1.2 The dispersed information model

In this section we embed dispersed information across firms into the basic New Keynesian model. We assume that the central bank has a different information set about the state of the macroeconomy compared to price-setting firms. For simplicity we impose that the central bank operates under full information, as do households.

Firms are heterogeneous with respect to their production technology $A_t(j)$. Each firm produces output using a linear production technology $Y_t(j) = A_t(j)N_t(j)$. The firm-specific productivity follows:

$$\log A_t(j) = a_t(j) \quad = \quad a_t + \eta_t^a(j) \; , \qquad \eta_t^a \sim N(0, \tilde{\sigma}_a^2) \; . \tag{7}$$

Hence, firm-specific productivity is the sum of the aggregate productivity level, a_t, and an idiosyncratic component, $\eta_t^a(j)$. In this respect, firm-specific productivity deviates from economic wide productivity by $\eta_t^a(j)$. The higher the variance of $\eta_t^a(j)$, the harder it is for individual firms to predict the aggregate state of the economy. In the same vein, firms observe a private signal, $d_t(j)$, about aggregate demand conditions d_t:

$$\log D_t(j) = d_t(j) \quad = \quad d_t + \eta_t^d(j) \; , \qquad \eta_t^d \sim N(0, \tilde{\sigma}_d^2) \; . \tag{8}$$

Firms also observe their own price history as well as the policy instrument R_t, i.e. the nominal interest rate, as a public endogenous signal of the central bank. The nominal interest rate follows the same policy rule as in the full information model, specified in equations (6) and (3). However, the policy decision of the central bank is based on superior information of the central bank about the output gap and the inflation rate. The central bank fully observes economic fundamentals, whereas firms have dispersed information and, hence, have to form beliefs about the true state of the economy. This assumption reflects that actual policy decisions of a central bank are based on its own assessment about its macroeconomic outlook. Therefore, the policy instrument comprises additional information that informs other market participants such as firms.[6]

To summarize, the firm j's individual information set in period t, which results in cross-sectional heterogeneity in beliefs across firms, is $\mathbb{I}_{j,t} = \{\log A_\tau(j), \log D_\tau(j), R_\tau : \tau \leq t\}$. The unobserved aggregate processes, a_t and d_t, follow the specification in equations (1) and (2). The parameters $\tilde{\sigma}_a$ and $\tilde{\sigma}_d$ measure the precision of the exogenous signals about the unobserved fundamentals. The noise-to-signal ratios, i.e. the ratio of the standard deviation of the idiosyncratic noise component and the standard deviation of the structural shock, $\tilde{\sigma}_a/\sigma_a$ and $\tilde{\sigma}_d/\sigma_d$, as well as the standard deviation of the monetary policy shock σ_m, determine how strongly agents disagree about unobserved variables. If a state variable is observed with high accuracy, i.e. if the noise-to-signal ratio approaches zero, agents perfectly observe the structural shock and their expectations are fully aligned. For intermediate degrees of signal precision, agents will not fully observe the true shock and, thus, will disagree about unobserved (future) variables. Moreover, if the idiosyncratic signals are highly imprecise, agents no longer pay attention to these signals.

[6]The assumption is in line with empirical evidence by Romer and Romer (2000), who find that market participants use monetary policy decisions to update their inflation forecasts.

The presence of dispersed information among profit-maximizing firms changes the firm's optimization problem. The resulting first-order condition is identical to the one derived in Nimark (2008) and Melosi (2017). Hence, the presence of the nominal interest rate as an endogenous public signal does not change the dispersed information New Keynesian Phillips curve. Each profit-maximizing firm takes into account that it can reset prices with probability $1-\theta$ and bases its decision on its firm-specific information set $\mathbb{I}_{j,t}$ specified above. The resulting optimality condition is the *dispersed information New Keynesian Phillips curve*:

$$\widehat{\pi}_t = (1-\theta)(1-\theta\beta)\sum_{k=1}^{\infty}(1-\theta)^{k-1}\,\widehat{mc}_{t|t}^{(k)} + \theta\beta\sum_{k=1}^{\infty}(1-\theta)^{k-1}\,\widehat{\pi}_{t+1|t}^{(k)}\,, \tag{9}$$

where real marginal costs $\widehat{mc}_{t|t}^{(k)} = (\gamma+\varphi)\hat{y}_{t|t}^{(k)} - (1+\varphi)\hat{a}_{t|t}^{(k-1)}, k > 1$ are a function of average higher-order beliefs. To fix notation, $\widehat{\pi}_{t+1|t}^{(k)}$ denotes the average k-th order expectation about the next period's inflation rate. The Appendix provides a detailed derivation of the dispersed information NKPC, which replaces the NKPC in the full information model (equation (5)). The key difference is that, in equilibrium, aggregate inflation can be expressed as a function of firms' dynamic higher-order expectations. The pass-through of higher-order expectations decreases with the order of expectations as documented in Nimark (2011). Intuitively, firms find it optimal to form beliefs about the other firms when making its own decisions (see Townsend, 1983). The reason is that firms' pricing decisions are strategic complements and each firm internalizes that the beliefs of other firms influence its decisions and, hence, aggregate outcomes.[7]

The implication of dispersed information is that firms have heterogeneous beliefs and expectations about future macroeconomic variables. We measure disagreement about future macroeconomic variables by the cross-sectional standard deviation of forecasts of individual firms. In the following we outline the general steps to obtain the model-implied cross-sectional dispersion about future macroeconomic variable. In the model we assume that the signal precision is the same for each supplier. Thus, to derive the cross-sectional standard deviation, we use the consensus forecasts $\bar{X}_t$ (which is the average expectation) and the forecast of a representative firm i, i.e. $\bar{X}_{t|t}(i)$.

[7] The dispersed information NKPC also holds when there is only dispersed information about exogenous variables without an additional endogenous public signal as shown in Nimark (2008).

The cross-sectional dispersion is defined as $V_t = E\left[(\bar{X}_{t|t}(i) - \bar{X}_{t|t})^2)\right]$. The firm-specific covariance matrix (which is the same for all firms) can be computed by solving the Lyapunov equation, as shown in Nimark (2011):

$$V_t = \Sigma_j = (I - KD)M\Sigma_j M'(I - KD)' + K\Sigma_{EE}K' \ . \tag{10}$$

The identity matrix is denoted by I, the Kalman gain K stems from the firms' Kalman filtering problem, while D maps the state into the firm's observation equation. The state transition matrix is M, and Σ_{EE} is the variance-covariance matrix of the shocks that enter the firm's observation equation. Based on the cross-sectional dispersion about the exogenous variables, we can directly compute the cross-sectional dispersion across endogenous variables using the policy function. Detailed derivations can be found in the Appendix. Our analysis focuses on disagreement about one-quarter-ahead inflation expectations.[8] The next section discusses the theoretical predictions after a contractionary monetary policy shock for different levels of disagreement about inflation expectations.

2.2 Theoretical predictions

The goal of this section is to illustrate that disagreement is a well-suited proxy for information dispersion, and thus, to distinguish when the signaling channel dominates the interest rate channel. We emphasize that the strength of the signaling channel correlates positively with disagreement about inflation expectations. We use this insight to inform several choices in our empirical estimation strategy (discussed below) and to provide external validation on the signaling channel of monetary policy.

To provide theoretical predictions of the dispersed information model with an endogenous signal necessitates a numerical solution method. We follow Nimark (2011) and Melosi (2017) and explicitly solve for the dynamics of higher-order expectations. The explicit solution is useful

[8]It is worth mentioning that one could extend the model by endogenising disagreement through rational inattention (Maćkowiak and Wiederholt, 2009). However, the empirical results below show that disagreement remains unchanged after a monetary policy shock, justifying our modeling approach.

to build up economic intuition on how these beliefs drive the aggregate effects. The Appendix contains all steps to solve the model. It is also worth mentioning that there are alternative solution methods for this class of model outlined in Maćkowiak and Wiederholt (2009) and Rondina and Walker (2014).

Table 1 specifies the baseline calibration of the model. Most values are commonly used in the literature and are also similar to the estimates in Nimark (2014), Melosi (2017), and Blanchard et al. (2013). Among these papers there is some disparity regarding the calibration of the signal-

Table 1: Baseline calibration

Parameter	Description	Value
β	Discount factor	0.99
γ	Relative risk aversion	1.1
φ	Inverse Frisch elasticity	0
θ	Calvo pricing	0.75
ϑ	Elasticity of substitution b/w goods	10
ϕ_π	Taylor rule coefficient: inflation	1.5
ϕ_y	Taylor rule coefficient: output gap	0.05
ρ_m	Autocorrelation monetary policy	0.5
ρ_a	Autocorrelation productivity	0.9
ρ_d	Autocorrelation preference	0.9
$100\sigma_m$	Std. dev. of monetary policy shock	0.2
$100\sigma_a$	Std. dev. productivity shock	1.0
$100\sigma_d$	Std. dev. preference shock	1.0
$100\tilde{\sigma_a}$	Std. dev. idiosyncratic productivity noise	1.0
$100\tilde{\sigma_d}$	Std. dev. idiosyncratic preference noise	1.0

to-noise ratios. The idiosyncratic variances of the shock and the precision of the public signal determine the cross-sectional standard deviation of first-order inflation expectations.[9] We target the relative mode and standard deviation of its empirical distribution in the high- and low-disagreement regime (which we later identify in our empirical model), based on the U.S. Survey of Professional Forecasters.[10] In doing so we replicate two empirical facts usually not targeted in the literature: (i) disagreement about inflation expectations in the high-regime is roughly twice the level in the low-

[9]The first-order expectation corresponds to the expectation reported in survey data, such as the U.S. SPF.

[10]Figure 18 in the Appendix shows the empirical distributions of disagreement about one-quarter-ahead inflation expectations in the two regimes. We have scaled the empirical disagreement distributions by the same factor for both regimes to illustrate that they match the shape and the relative distributions implied by the theoretical model.

disagreement regime, and (ii) disagreement in both regimes has some overlap, i.e. there is no clear-cut threshold between the low- and the high-disagreement regime. In line with the distributions of disagreement, we compare a calibration with low disagreement about inflation expectations to a high-disagreement calibration.

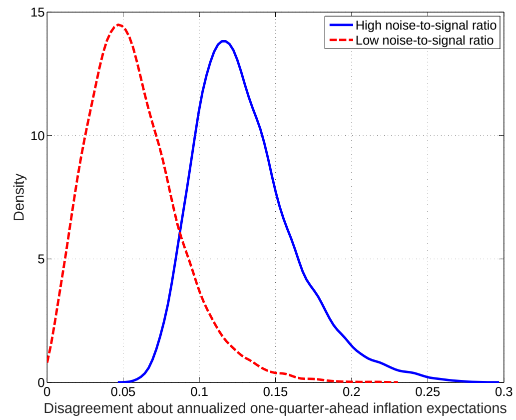
2.2.1 Prior predictive analysis

Rather than only comparing the predictions for a high and a low-disagreement calibration we check the robustness of our results across a range of parameter value. For this purpose we use prior distributions for selected parameters and compute model-implied distributions of disagreement about inflation expectations as well as the range of impulse response functions within the high- and low-disagreement regime. We simulate 20000 parameter draws for each regime separately. In the high-disagreement regime, the idiosyncratic standard deviation of shocks, $100\tilde{\sigma_a}$ and $100\tilde{\sigma_d}$, is drawn from a normal distribution with mean 1.0 and a standard deviation of 0.05. In the low-disagreement case, we set the mean of the idiosyncratic standard deviation of shocks, $100\tilde{\sigma_a}$ and $100\tilde{\sigma_d}$, to 0.01 and the standard deviation to 0.075.[11] Since we are interested in the monetary policy transmission, we also draw the Taylor rule coefficients. For the Taylor rule coefficient on inflation, ϕ_π, we draw from a normal distribution with mean 1.5 and standard deviation 0.25. For the coefficient on output gap, ϕ_y, we use a normal distribution with mean 0.05 and a standard deviation of 0.05. It is worth noting that our results are robust to keeping the Taylor rule coefficients fixed implying that the information friction is key to obtain reasonable distributions for disagreement. We also experimented with varying the size of the structural productivity and demand shock to gauge potential movements in shock uncertainty. As we discuss below the transmission of monetary policy shocks and the strength of the signaling channel is hardly affected. Later, in our empirical analysis we consider sample splits to account for potential monetary regime switches and we also purge disagreement of movements in uncertainty as robustness checks.

To examine the implied disagreement about inflation expectations in the low- and high-disagreement

[11] We choose a larger standard deviation in the low-disagreement regime to obtain a similar implied variance for disagreement about inflation expectations in the low- and high-disagreement calibration to match our empirical evidence.

Figure 1: Prior predictive: Disagreement about one-quarter-ahead inflation expectations



Notes: Kernel density estimates of disagreement (standard deviation) about annualized one-quarter-ahead first-order inflation expectations of firms based on a prior predictive simulation.

regime, Figure 1 shows kernel density estimates of the distribution of disagreement about one-quarter-ahead inflation expectations for the high- and low-disagreement regime. In the low-disagreement regime (when sampling from a range of precise signals), the mass of the standard deviation about one-quarter-ahead inflation expectations is around 0.05 and also covers the calibration that implies zero disagreement.[12] In the high-disagreement regime, the signals are less precise, which induces higher levels of disagreement about inflation expectations. As mentioned before, the model generates a reasonable relative difference in disagreement for the two regimes under consideration.[13]

Overall, we use relatively wide prior distributions for the noise variances such that disagreement about one-quarter-ahead inflation expectations has some overlap in both regimes in line with our empirical estimation results shown later (see Figure 18). Using tighter priors implies that the distributions of disagreement for the case of low and high disagreement have less overlap. In this case the confidence bands of our results in Figure 2 become even tighter.

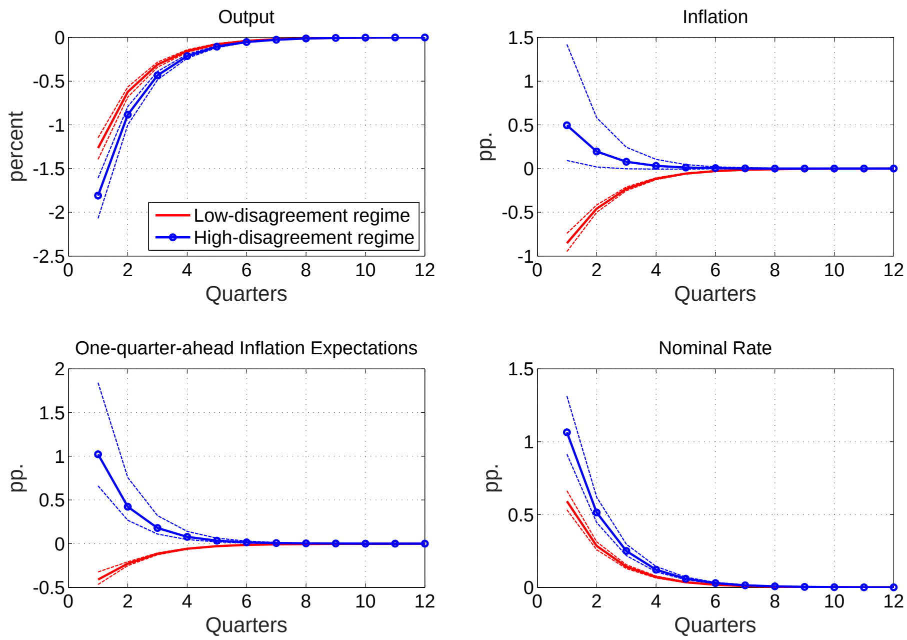
[12] The results are robust when targeting disagreement about one-year-ahead inflation expectations.

[13] When we target the empirical distribution of disagreement about real GDP growth, the model predicts that it is more difficult to separately identify the signaling and interest rate channel of monetary policy. One reason could be that real GDP growth expectations are too strongly correlated with booms and recessions and, thus, less so with information frictions.

2.2.2 State-dependent impulse response functions

Our main interest is to explore whether the distributions of high and low disagreement also imply differences in the monetary policy transmission in the two regimes. Figure 2 illustrates the median responses to a 100 basis points contractionary monetary policy shock for the low- and high-disagreement regime together with the 10^{th} and 90^{th} percentile (confidence bands). Based on

Figure 2: Macroeconomic effects of a 100 bps contractionary monetary policy shock

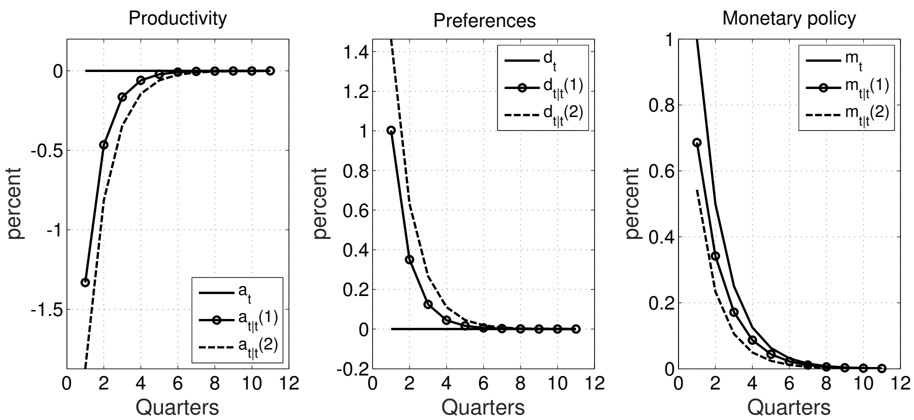


Notes: Impulse responses to a 100 basis points contractionary monetary policy shock in the low- and the high-disagreement regime. Inflation expectations are the firms' average first-order expectations. Confidence bands represent the 90^{th} and 10^{th} percentile based on prior predictive analysis.

our prior predictive simulation, the solid line shows the impulse responses when there is low disagreement, while the circled line shows the high-disagreement regime. Figure 2 shows, based on our prior predictive simulation, that the transmission of a monetary policy shock is state-dependent and strongly changes with the level of disagreement about inflation expectations.

In the case of low disagreement, the dynamics are driven by the conventional interest rate channel. A contractionary monetary policy shock increases the real interest rate (due to sticky prices) and leads to a decline in output which is accompanied by a decrease in inflation and in inflation expectations. The nominal interest rate responds by 60 basis points, as part of the contractionary shock is impaired by the systematic response of monetary policy. It is noteworthy that this monetary transmission channel is also present in a large class of representative agent medium-scale NK models such as in Smets and Wouters (2007).

Figure 3: Response of beliefs to a 100 basis points monetary policy shock



Notes: Evolution of true shocks and beliefs of up to second order in response to a 100 basis points contractionary monetary policy shock in the dispersed information New Keynesian model with high-disagreement calibration.

In the high-disagreement regime, firms partially misinterpret the contractionary monetary policy for a mix of a positive time preference shock and a negative productivity shock as visible from Figure 3. Both these shocks put upward pressure on inflation which, according to the Taylor rule, leads to an endogenous increase in the nominal rate. Firms cannot directly infer whether an increase in the nominal rate is due to a change in inflation, the output gap or due to an exogenous monetary policy shock. Therefore, the interest rate increase is perceived by firms as a mix of all three shocks.[14] As a result of misperceiving the actual policy shock, inflation increases markedly by about 0.5 percentage points on impact. The firm's first-order inflation expectations rise by about 1.0 percentage points. The perceived negative productivity shock and the contractionary monetary policy shock also lead to a mildly stronger output reaction. Hence, in the high-disagreement regime, the signaling channel of monetary policy dominates the interest rate channel such that inflation and inflation expectations change its sign conditional on a contractionary monetary policy shock.[15] The signaling channel is one potential explanation of the price puzzle found in some

[14]Note that the evolution of the higher-order beliefs determines the current inflation rate as shown by the dispersed information NKPC (see equation (9)).

[15]To trace out the relative importance of the signaling and interest rate channel in driving the aggregate macroeco-

empirical studies.

Finally, we conduct two robustness exercises to evaluate whether the connection between the signaling channel and disagreement about inflation expectations is driven by information frictions. In particular, two alternative sources that could affect disagreement and the transmission of monetary policy shocks are (i) changes in the monetary policy rule coefficients or (ii) changes in the size of aggregate supply and demand shocks. Variations in the size of productivity and demand shocks naturally change the signal-to-noise ratio and hence disagreement. Changes in the Taylor rule coefficients can affect the relative weight of the public signal and, hence, the strength of the signaling channel. To investigate the effects of these alternative sources on the transmission of monetary policy, we consider prior predictive analyses in which we vary the Taylor rule coefficients or the shock sizes and fix the value of idiosyncratic noise at the high-disagreement calibration.[16] We find that a variation in the policy parameters mildly affects disagreement, and hardly affects the transmission of monetary policy shocks. Interestingly, variations in the size of aggregate productivity and demand shocks have only minor effects on the strength of the signaling channel. In particular, the signaling channel of monetary policy is still active. Moreover, variation in aggregate volatility of productivity and demand shocks in the full information model cannot cause signaling effects. This is consistent with the view that we should not find similar state-dependent effects of monetary policy shocks on inflation and inflation expectations when we analyze regimes of high and low aggregate volatility instead of disagreement. Hence, the main source of disagreement is variation in the signal precision in line with Coibion (2012), Coibion and Gorodnichenko (2015b), Andrade et al. (2016). This implies that disagreement about short-term inflation expectations is a well-suited proxy for the information friction, and, in our setup, also constitutes a good proxy for the strength of the signaling channel.[17]

nomic dynamics, we decomposed the overall effect of a monetary policy shock into the two channels. For details and further discussion see Section A.7 in the Appendix.

[16]In the low-disagreement regime, a change the aggregate shock sizes does not affect the transmission of monetary policy. Moreover, the signaling channel is not active and within a plausible range of Taylor rule coefficients the interest rate channel does not change qualitatively.

[17]Ideally we use a direct measure of the information friction to isolate the signaling channel. However, the challenge is that no direct measures of productivity and demand signal precision are available.

3 Econometric methodology

This section presents our empirical approach for the estimation of state-dependent effects of monetary policy for different levels of disagreement about inflation expectations. In addition, we present the data sources and outline how we identify regimes of high and low disagreement.

3.1 Smooth transition local projection model

To quantify state-dependent effects, we follow a recently-applied method which combines the local projection approach by Jordà (2005) with a smooth regime-switching mechanism. Our empirical model estimates the responses of the endogenous variable, y_{t+i}, to a monetary policy shock ϵ_t depending on the probability of being in the high-disagreement, $F(z_t)$, or the low-disagreement, $1 - F(z_t)$, regime:

$$y_{t+i} = \tau_i t + (\alpha_i^H + \beta_i^H \varepsilon_t + \gamma_i^H x_t)F(z_t) + (\alpha_i^L + \beta_i^L \varepsilon_t + \gamma_i^L x_t)(1 - F(z_t)) + u_{t+i}, \tag{11}$$

where $i \in \{0, I\}$ indicates the number of periods after the shock ε_t hits the economy. Our model specification controls for a time trend (τ_i) as well as a number of regime-specific parameters. We include regime-specific constants, α_i^λ, regime-dependent effects of the monetary policy shock ϵ_t, β_i^λ, and a set of regime-specific coefficients for the vector of control variables x_t, γ_i^λ, where $\lambda = H, L$ refers to the high (H) and low (L) disagreement regime, respectively. The regression residual is denoted by u_{t+i}. The regimes are identified using the variable z_t, which measures the current level of disagreement about inflation expectations. Hence, we refer to z_t also as the *regime-indicating* variable. The function $F(z_t)$ maps the current level of disagreement into a probability measure, i.e. $F(z_t) \in [0, 1]$, and it reflects the probability to be in a high-disagreement regime at time t. The probability function $F(z_t)$ allows for a smooth transition between the states of high and low disagreement, rather than assuming distinct regimes.[18] The smooth shape of the function, therefore, takes into account that some periods cannot be clearly allocated to one of the regimes.

[18] Furthermore, in contrast to using interaction terms with disagreement (z_t), the function $F(z_t)$ simplifies the interpretation of the estimated coefficients and reduces the weight of very high and very low values of z_t.

We model the continuous function $F(z_t)$ with a logistic shape:

$$F(z_t) = \frac{exp(\theta \frac{z_t - c}{\sigma_z})}{1 + exp(\theta \frac{z_t - c}{\sigma_z})}, \tag{12}$$

where c corresponds to the median and σ_z to the standard deviation of z_t. The specification of the function is suggested by Granger and Teräsvirta (1993) for smooth transition regressions and is also used in the related literature. The function is increasing in z_t. The parameter θ determines the curvature of $F(z_t)$ and, hence, how strongly the probability function reacts to changes in disagreement z_t.[19] Previous studies parameterize rather than estimate the degree of regime-switching (Auerbach and Gorodnichenko, 2013, Tenreyro and Thwaites, 2016, Santoro et al., 2014).[20] We use a value of $\theta = 5$, but our results are robust to a wide range of values. It is noteworthy that equation (11) reduces to a linear, state-independent, model for $F(z_t)$ equal to one or zero.

To estimate impulse response functions, we use the local projection method of Jordà (2005). Local projections provide a direct estimate for the effect of a shock in period t. In particular, the coefficient β_i^λ with $\lambda \in \{H, L\}$ and $i = 0, ...I$ directly represents the impulse response of the dependent variable i periods after the shock ε_t, depending on whether the economy at the time of the shock (t) is in a high or low disagreement regime. The estimation of equation (11) is repeated for each horizon $i \in \{0, I\}$ such that the sequence $\{\beta_i\}_0^I$ corresponds to the impulse response function for y_t within the first I quarters after the shock hits.

An important property of the empirical specification is that it accounts for potential regime switches after the shock. In particular, the model controls for the probability of being in the high-disagreement regime when the shock realizes but makes no assumptions about the state of the economy in subsequent periods. If disagreement reacts to the monetary policy shock, this would implicitly be captured in the estimated coefficients. In contrast, a state-dependent vector autore-

[19]For $\theta \to \infty$, the model converges to a discrete threshold model with a clear cutoff (as in Ramey and Zubairy (forthcoming)), whereas more observations are partly allocated to both regimes for a low value of θ. Figure 20 in the Appendix illustrates the dependence of the indicator function on θ.

[20]The authors point out that it is difficult to identify the shape and location of the transition function which is due to the non-linear structure of $F(z_t)$. Moreover, the estimation would be highly sensitive towards various assumptions like the distribution of the error terms in the likelihood function.

gressive model would require the modeling of the exact transmission process for z_t.[21]

Our baseline specification includes one lag of the dependent variable and one lag of the Federal Funds Rate as controls. In the robustness section, we show that our results remain unchanged when we include more lags of the dependent variable. One advantage of the local projection method is that we do not need to model the dynamic process of the dependent variable for computing the impulse response functions. The dynamics are captured by the horizon-specific estimations. Nevertheless, including lags in the estimation is useful to control for the history of shocks. We adjust the standard errors of the estimation for correlation across time and horizons by applying the method of Driscoll and Kraay (1998). The method refines the calculation of Newey-West standard errors which are robust to heteroscedasticity and within-horizon serial correlation by controlling in addition for serial correlation across horizons.[22]

3.2 Data

Our sample is based on quarterly U.S. data and covers the period from 1970:IV until 2007:IV. The data for realized inflation, real GDP and the Federal Funds Rate stem from the FRED database provided by the St. Louis Fed. In our estimation we use the log volume of real GDP to measure real activity. Realized inflation is constructed by taking log-differences of the implicit GDP price deflator. We use the GDP deflator to construct the inflation rate because it is identical to the measure of the inflation rate in the expectations data outlined below. The Federal Funds Rate corresponds to the quarterly average of the effective rate. As common in the literature, we apply the exogenous monetary policy shock series of Romer and Romer (2004).[23] In particular, we use the updated and extended shock series by Wieland and Yang (2016) to account for the longer

[21] One possibility is to estimate a threshold VAR, but Auerbach and Gorodnichenko (2013) provide compelling evidence in favor of using a smooth local projection method compared to a regime-switching VAR.

[22] As in the former literature, the maximum lag for the correction of the autocorrelation is set to $I + 1$, the length of the impulse response function.

[23] While the narrative monetary policy shock series are itself generated regressors, we follow the related literature (Coibion et al., 2017a, Coibion and Gorodnichenko, 2012) and do not adjust the standard errors. Pagan (1984) shows that there is no need for an adjustment when testing if a coefficient is significantly different from zero.

sample.[24]

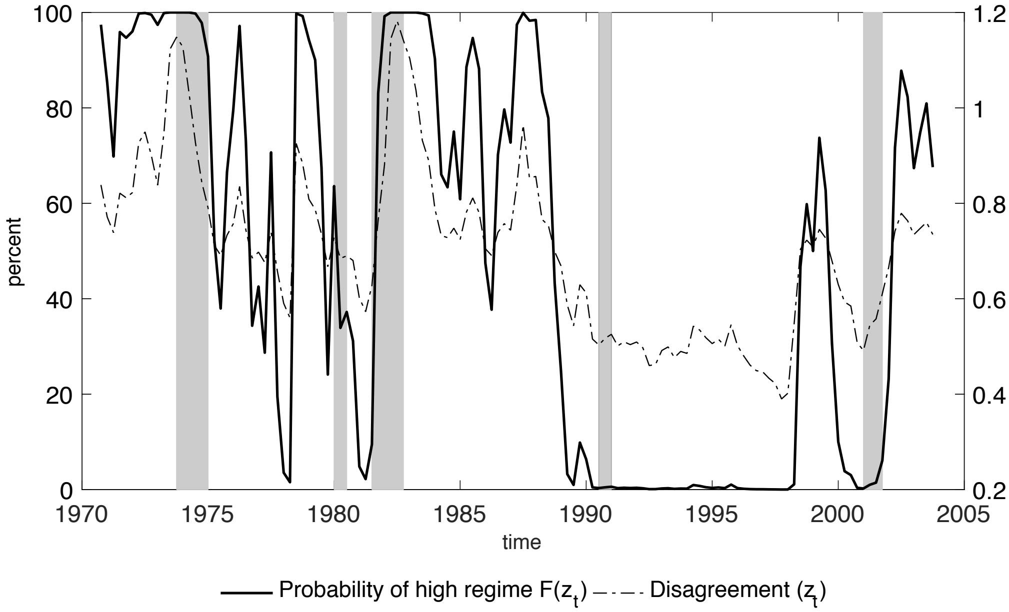
We measure inflation expectations and disagreement about inflation expectations across forecasters from the U.S. SPF. The survey is conducted quarterly and made available by the Federal Reserve Bank of Philadelphia. Data on inflation expectations are based on the mean forecasts for the level of the (seasonally adjusted) GDP price index. The forecasts for the price index are available since 1968:IV and are the only measure for price expectations in the survey that goes as far back. Based on the indices we construct the expected (annualized) inflation rate over the next quarter and over the next year by taking log differences. Moreover, disagreement across the survey participants is calculated as the standard deviation of the individual point forecasts for the price index in the next quarter. We choose the cross-sectional standard deviation to measure disagreement, since it is identical to our definition of disagreement in the theoretical model. However, other measures of disagreement as interquartile ranges evolve nearly identically and we use these alternative measures in our robustness analysis.

3.3 Periods of high and low disagreement about inflation expectations

Our sample includes the 1970s where inflation and disagreement prevailed at historically high levels (see Figure 16 in the Appendix). The correlation between disagreement about inflation expectations with the level of inflation in the data is positive and about 0.7, a finding also highlighted by Cukierman and Wachtel (1979) as well as Mankiw et al. (2004). Therefore, we scale disagreement by the expected inflation rate in the previous quarter to control for periods of relatively high inflation rates. The scaled disagreement reduces the correlation below 0.2. For comparison, Figure 19 in the Appendix shows the evolution of disagreement which is scaled and its unscaled version. The figure highlights that the scaling does not change the general pattern of the variable and only aligns the mean of disagreement in the periods before and after the Great Moderation. Later we provide robustness results, when we consider alternative scaling specifications of disagreement: (ii) excluding the first part of the sample, (iii) employing alternative measures of disagreement,

[24]We also checked the exogeneity of the shock series by regressing it on the contemporaneous value and two lags of the endogenous variable. We report results in Table 4 where we find no significant predictability of the shock series.

Figure 4: Probability of being in the high-disagreement regime



Notes: The figure shows the probability of being in the high-disagreement regime, $F(z_t)$ (*left axis*) and the regime-indicating variable z_t: disagreement scaled by one lag of the expected inflation rate (*right axis*). Disagreement is measured as the standard deviation of point forecasts about the GDP deflator in the next quarter based on the U.S. SPF. $F(z_t)$ covers the years 1970:IV to 2003:IV. The grey areas indicate NBER recessions.

and (iv) adding further control variables.

In keeping with the literature, we use a seven-period backward looking moving average to smooth our regime-indicating variable z_t.[25] In contrast to the literature, we apply a *weighted* moving average such that the highest weight is put on the current observation and the weight decreases in distance to today. This weighting strengthens the impact of the current level of disagreement. As mentioned before, the scaling and smoothing of the original function mutes the big spikes in disagreement in the late 1970s and early 1980s, but preserves the general pattern of the variable.[26]

Figure 4 shows the probability of being in a high-disagreement regime $F(z_t)$ over our sample. As expected, the probability of being in a high-disagreement regime is high at the beginning of the 1970s and in the 1980s. In contrast, the periods between 1988 and 1997 are described by a high probability of a low-disagreement regime, as $1 - F(z_t)$ is close to one. The beginning of a

[25] A smoothing of the indicator variable is applied by all related studies (Auerbach and Gorodnichenko, 2013, Tenreyro and Thwaites, 2016, Santoro et al., 2014).

[26] Our sample includes a few extreme events, for example the start of the Volcker disinflation period, that could contribute to disagreement in some particular periods. However, these events do not jeopardize that we find, on average, a significantly different effect of monetary policy shocks in time of high disagreement.

pronounced low-disagreement regime is around the time when Alan Greenspan started his term as Chairman of the Federal Reserve where he served until 2006. The prolonged episode of low disagreement also coincides largely with the *Great Moderation*.[27] During this episode business cycle fluctuations were moderate and also disagreement about short-term inflation expectations were at historically low levels. At the turn of the century the probability for the high state rises again and, after falling during 2000, increases with the 9/11 attacks and remained high until the end of the sample. Note that some disagreement is always present in the data, which implies that periods with a low value of $F(z_t)$ can be interpreted as regimes with little but non-zero disagreement. Moreover, Figure 4 reveals that the probability of being in a high-disagreement regime shows no clear pattern during NBER recessions. While it rises considerably during recessions in the early 2000s and in 1981, it drops during the downturn in the 1975 and shows no significant reaction in the economic slowdown in 1990.

4 The state-dependent effects of monetary policy

This section presents the main results of our empirical analysis. It particular, we show that the transmission of monetary policy differs strongly between the low- and high-disagreement regime. In addition, we assess the empirical results against the backdrop of the theoretical predictions derived in Section 2.

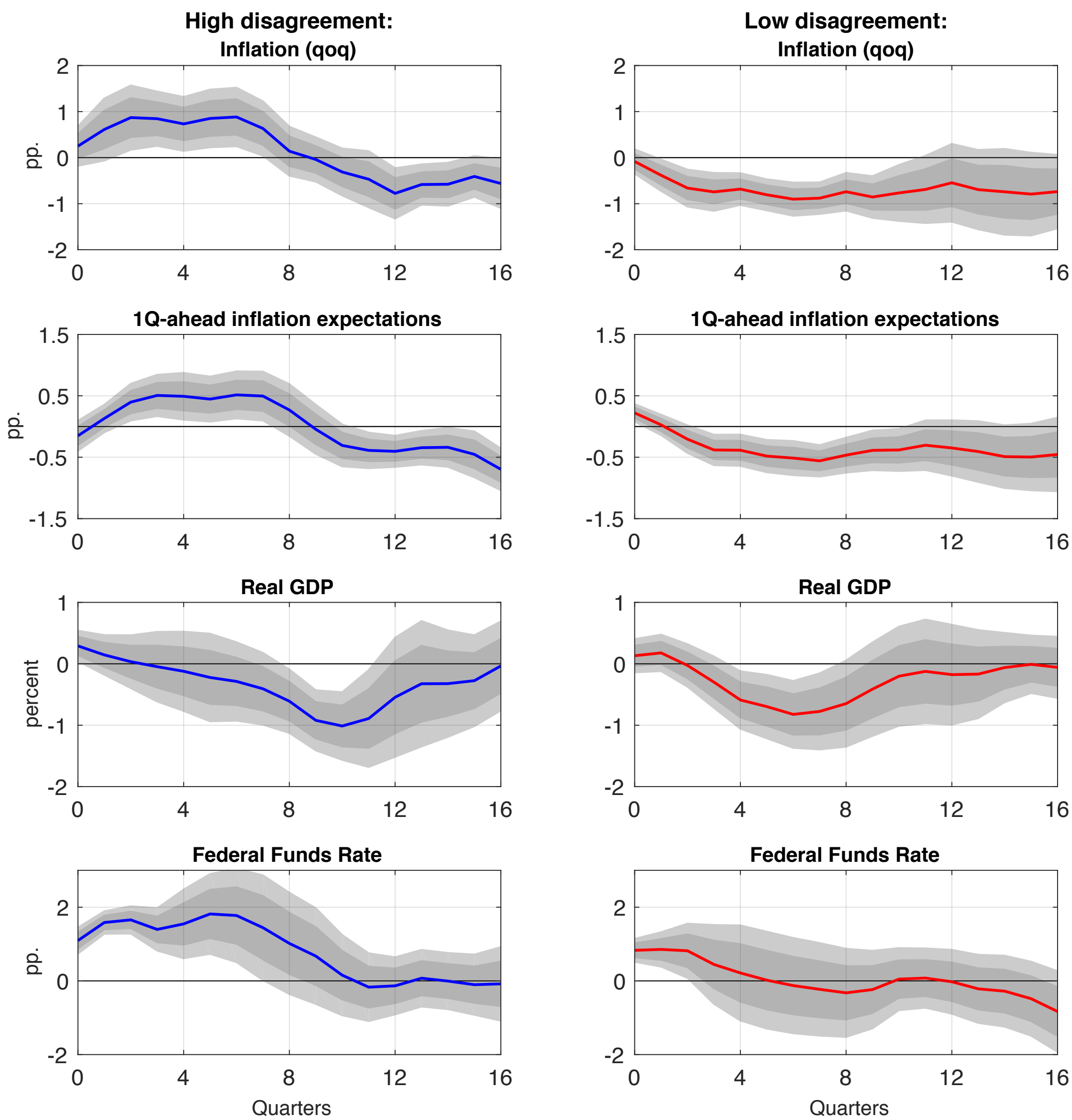
4.1 Baseline results

Figure 5 shows the impulse responses of inflation, one-quarter-ahead inflation expectations, the log of real GDP and the Federal Funds Rate to a contractionary 100 basis points monetary policy shock in the regime with high and low disagreement. The maximum horizon of the impulse response functions is set to four years ($I = 16$). The left column of the figure shows the effects of a shock that hits the economy in a high-disagreement regime (β_i^H), while the right column displays the

[27]In the U.S., this period of low aggregate volatility has been dubbed the Great Moderation in the literature (e.g. Benati and Surico, 2009, Boivin and Giannoni, 2006, Mavroeidis, 2010).

results for a shock that occurs in a regime with low disagreement (β_i^L). We display confidence bands on the 68% and 90% level. For the figures, we form a centered moving average over three consecutive periods to smooth the impulse response functions (the first and last coefficient is not smoothed). In the Appendix we also show the non-smoothed version.

Figure 5: The state-dependent effects of a 100 basis points monetary policy shock



Notes: Estimation results of equation (11) with annualized qoq-inflation and annualized qoq-inflation expectations, real GDP (log) and the Federal Funds Rate as dependent variables. The estimation covers the period 1970:IV-2007:IV. The solid lines in the left (right) column show the point estimates β_i^H (β_i^L) for horizon i (x-axes) in the high (low) disagreement regime. The coefficients reflect the response to a 100 bps monetary policy shock. Except for the end-points, the coefficients are smoothed over three consecutive periods. The light and dark grey areas display 68% and 90% confidence intervals, respectively.

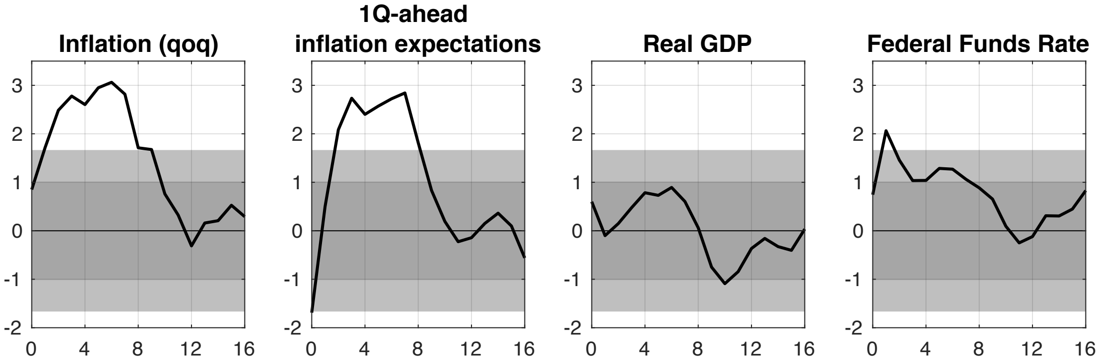
The first and second row of Figure 5 show the response of the annualized inflation rate in the current quarter and the annualized expected inflation over the next quarter, respectively. In the high-disagreement regime, both variables increase significantly after the monetary policy shock. They reach their maximum response after six quarters, where actual inflation peaks at 0.9 percentage points and the expected inflation rate amounts to 0.5 percentage points. On the contrary, inflation and inflation expectations fall in the low-disagreement regime. The actual inflation rate shows a quite fast negative response after the shock, whereas inflation expectations adjust more sluggishly. Remarkably, the impulse responses show very pronounced differences between the regimes in the first eight quarters after the shock hits the economy. Within the first two years after the shock, the response of inflation and inflation expectations in the high regime lie outside the confidence bands from the low-disagreement regime. At longer horizons, the point estimates are more similar and the responses no longer show significant differences between the regimes. In particular, inflation and inflation expectations also start to decline in the high-disagreement regime after around eight quarters. Figure 22 in the Appendix confirms these results for the actual year-on-year inflation rate and the inflation expectations over the next four quarters. As before, the state-dependent effects are present in the first two years after the shock. In addition, the impulse responses of the price index (see Figure 21 in the Appendix) are in line with the results for the realized inflation rate and confirm the existence of the state-dependent effects.

The GDP responses are displayed in the third row of Figure 5. On impact, the monetary policy shock leads to a small but insignificant output puzzle in the both regimes.[28] In the subsequent periods real GDP drops in both regimes, with a stronger and more significant response in the high-disagreement regime. The peak effect is about -1.0 percent in the high-disagreement regime, whereas it is -0.8 percent in the low-disagreement regime.

The responses of the Federal Funds Rate are shown in the fourth row of Figure 5. In the initial period, the nominal interest rate increases by 1.2 percentage points in the high-disagreement regime and by 0.8 percentage points in the low-disagreement regime. After the initial impact of

[28]The output puzzle is also found for state-dependent effects of monetary policy shocks in booms and recessions by Tenreyro and Thwaites (2016). We address the similarities and differences to their results in Section B.1 in the Appendix.

Figure 6: t-statistics of state-dependent effects



Notes: The figure shows the value of the t-statistic that tests whether the coefficients in the two regimes are significantly different from each other at horizon i: $H_0 = \beta_i^H - \beta_i^L = 0$. The estimation covers the sample 1970:IV-2007:IV. The grey areas show critical values at the 68% and 90% confidence level.

the monetary policy shock, the Federal Funds Rate increases in the following periods in the high-disagreement regime, while it declines in the low-disagreement regime. This result can be aligned to the opposing effects that we observe for inflation and inflation expectations under high and low disagreement. More precisely, to counteract the rise in inflation and in inflation expectations in the high-disagreement regime, the Federal Funds Rate rises stronger in the initial period and increases further in the subsequent periods. In the low-disagreement regime, the decline of inflation (expectations) allows for a reduction in the interest rate.

Table 2: Difference of coefficients between the regimes

Horizon	Inflation (qoq)	Inflation expectations (qoq)	Real GDP	Federal Funds Rate
0	0.333 (0.392)	-0.373 (0.221)	0.150 (0.266)	0.265 (0.355)
1	0.995 (0.581)	0.105 (0.211)	-0.033 (0.329)	0.730 (0.354)
2	1.531 (0.616)	0.604 (0.290)	0.061 (0.411)	0.839 (0.576)
3	1.589 (0.572)	0.888 (0.325)	0.252 (0.527)	0.950 (0.918)
4	1.415 (0.544)	0.878 (0.366)	0.467 (0.596)	1.331 (1.282)
5	1.658 (0.562)	0.928 (0.361)	0.474 (0.649)	1.797 (1.397)
6	1.785 (0.583)	1.029 (0.378)	0.537 (0.601)	1.902 (1.497)
7	1.513 (0.537)	1.055 (0.371)	0.369 (0.611)	1.673 (1.575)
8	0.880 (0.514)	0.735 (0.405)	0.039 (0.634)	1.342 (1.516)

Notes: The table shows the difference between the coefficients in the high- and the low-disagreement regime at horizon i. The coefficients β^H and β^L are smoothed over three consecutive periods. Standard errors are shown in the parentheses.

To validate the significance of the state-dependent effects, we investigate whether the responses in the regimes are statistically different. A key advantage of the smooth transition local projection approach is that we can directly conduct simple t-Tests for the difference between β_i^H and β_i^L at all horizons $i \in [0, 16]$. The results for the first two years are presented in Table 2. Figure 6 shows the corresponding values of the t-statistic and critical values also for longer horizons. The coefficients of inflation and inflation expectations differ significantly between the second and the eight horizon, reinforcing that the transmission of monetary policy shocks changes with the level of disagreement. The difference between the regimes becomes insignificant afterwards. The difference between the coefficients for real GDP is insignificant at most horizons, but shows a mild significance at the 68% confidence level ten periods after the shock hit. When comparing the accumulated GDP responses, the overall decline is around 20 percent stronger in the high compared to the low-disagreement regime. The responses of the Federal Funds Rate are significantly different at short horizons, which is in line with a systematic response of the nominal interest rate to the positive inflation responses in the high regime, as pointed out earlier.

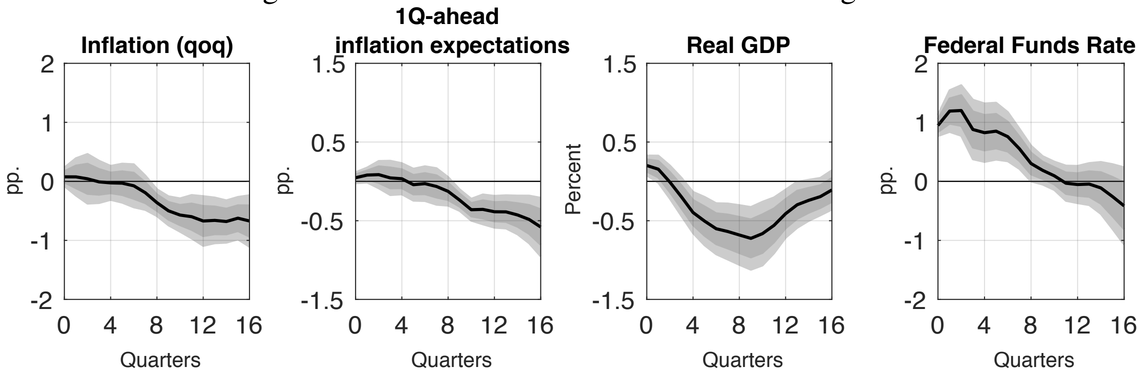
Reassuringly, our main results are robust when we re-estimate our baseline model in equation (11) for an extended sample which includes the Great Recession: 1970:IV until 2015:IV.[29] To estimate our empirical model for the extended sample, we update the monetary policy shock series until 2011:IV by re-estimating the regression of Romer and Romer (2004), using data from Coibion, Gorodnichenko, Kueng and Silvia (2017b). These additional results can be found in Figure 24 in the Appendix.[30] In particular, the responses of inflation and one-quarter-ahead inflation expectations are significantly state-dependent on the disagreement regime. We prefer the sample until 2007:IV as our baseline result, since the estimation for the extended sample is prone to potential non-linear effects through the Zero Lower Bound or the Great Recession.

For comparison with the wider literature, Figure 7 shows the results for the linear model that is estimated without accounting for state-dependent effects. This corresponds to equation (11) with $F(z_t)$ being zero (or one) in each period. Output declines by up to 0.8 percent and inflation

[29]Considering that the maximum horizon of the impulse response functions amounts to four years, the estimation uses data from 1970:IV until 2015:IV.

[30]Note that we do not report impulse response functions for real GDP for the extended sample. GDP shows a clear break in its long-run trend with the onset of the Great Recession. Therefore, we are cautious with its estimated response, even though the responses are qualitatively similar to our baseline results.

Figure 7: Estimation of linear model without regimes



Notes: Results from the linear estimation of equation (11), which corresponds to $F(z_t) = 0$ or 1. The figures show responses to a 100 bps monetary policy shock. Dependent variables are the actual annualized qoq-inflation and inflation expectations over the next quarter as well as the log level of real GDP and the level of the Federal Funds Rate. The estimation covers the sample 1970:IV-2007:IV. Except for the endpoints, the coefficients are smoothed over three consecutive periods. The light and dark grey areas display 68% and 90% confidence intervals, respectively.

declines by about 0.7 percentage points in the linear model. These results are broadly in line with former studies that document a peak effect for output and inflation between -0.5 to -1.0 percent after a 100 basis points contractionary monetary policy shock (Christiano et al., 1996, Coibion, 2012, Uhlig, 2005, Cloyne and Hürtgen, 2016). Yet, these linear estimates mask that monetary policy has significantly different effects in regimes of high and low disagreement. It is noteworthy that in line with previous studies when using the Romer and Romer shocks for the full sample we find no evidence of a significant prize puzzle (Romer and Romer, 2004, Coibion, 2012, Cloyne and Hürtgen, 2016).

4.2 Comparison with the theoretical predictions

In this section we assess whether the empirical results are in line with the theoretical predictions from Section 2. The main theoretical predictions are summarized in Table 3.

In the low-disagreement regime, the empirical impulse responses confirm that output and inflation as well as inflation expectations decline after a contractionary monetary policy shock. These results are consistent with the dispersed information model when signals are relatively precise and disagreement is low as well as the full information model. Therefore, we conclude that the monetary policy transmission mechanism of the full information New Keynesian model is consistent with the empirical results in the low-disagreement regime and, interestingly, also with the results from the estimation without regimes (see Figure 7). However, the theoretical predictions under full information can only explain the empirical findings in times of low disagreement.

Table 3: Theoretical model predictions for different information structures

	Full info	Exogenous dispersed info	Exogeneous dispersed info + endogenous signal
Monetary policy shock observed	Yes	Yes	No
Misperception of MP shock	No	No	Yes
Disagreement about exogenous variables	No	Yes	Yes
Disagreement about inflation expectations	No	Yes	Yes
Autocorrelation of forecast errors	No	Yes	Yes
Inflation response	<0	<0	>0
Inflation expectations response	<0	<0	>0
Output response	<0	<0	<0

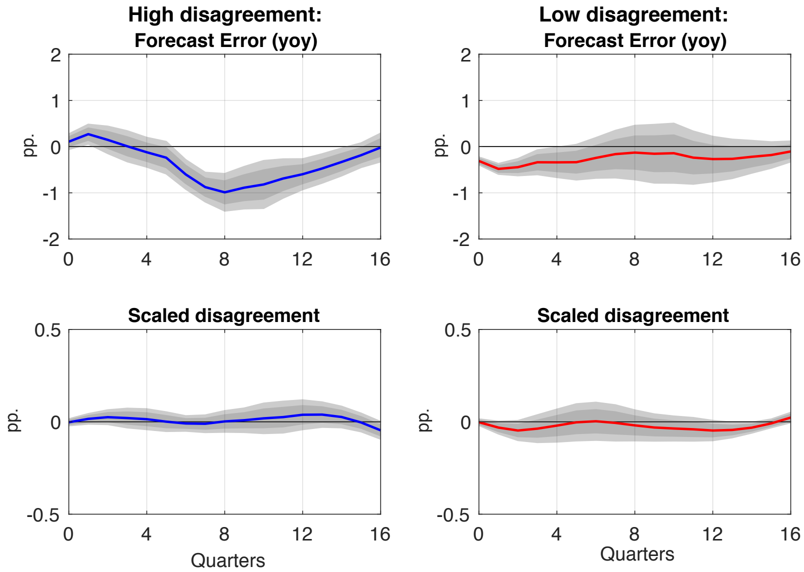
Notes: The theoretical predictions are conditional on a 100 basis points contractionary monetary policy shock based on the New Keynesian model presented in Section 2 and calibrated to the values specified in Table 1. *Full info* refers to the full information model. In the *exogenous dispersed information* model we assume that the monetary policy shock is fully observed by firms and, as a consequence, the policy rate provides no additional information. The last column summarizes the theoretical predictions of our baseline dispersed information model for the high-disagreement calibration with the policy rate as endogenous signal.

In the high disagreement regime, the empirical evidence is in line with the theoretical predictions obtained from the dispersed information model where the nominal interest rate serves as an endogenous signal. As predicted by the dispersed information model, we find that in times of high disagreement inflation and inflation expectations increase significantly. This result holds for quarter-on-quarter as well as for year-on-year inflation rates. We also find that real GDP declines slightly stronger in the high-disagreement regime, but the differences are in general not statistically significant. This result is also in line with the theoretical model predictions, as the state-dependent effects of GDP do not differ markedly.[31]

To investigate further implications of different information structures, we estimate the state-dependent effects of monetary policy shocks on forecast errors and disagreement. From this anal-

[31] As described in Section 2, the differences in the impulse responses are driven by the fact that agents misperceive the contractionary monetary policy shock partly as a negative technology or positive demand shock. While both of these shocks increase inflation and inflation expectations, they have offsetting implications for output. The insignificant statistical difference in our empirical results could therefore be driven by periods in which the belief about a positive demand shock dominated the beliefs of agents.

Figure 8: The indicator variable z_t and inflation forecast error



Notes: Empirical results from estimating equation (11) with the forecast error for next years inflation rate and the regime-indicating variable z_t disagreement as dependent variables. The estimation covers the periods 1970:IV-2007:IV. The left (right) panel show the point estimates β_i^H (β_i^L) for horizon i (x-axes) in the high (low) disagreement regime. The coefficients are smoothed over three consecutive periods. The light and dark grey areas display 68% and 90% confidence intervals, respectively.

ysis we can further distinguish between the different information assumptions that we summarized in Table 3. In Figure 8, we show the state-dependent effects of inflation forecast errors and our indicator variable disagreement to a 100 basis points contractionary monetary policy shock. In line with the theoretical predictions of dispersed information models, the forecast errors are significantly autocorrelated in the high but less so in the low-disagreement regime. Autocorrelation in average forecast errors is in fact a general property of a larger class of imperfect information models (Coibion and Gorodnichenko, 2012, 2015a). The finding that the forecast errors are also mildly autocorrelated in the low-disagreement regime highlights that this regime is also characterized by a small degree of information rigidity. This is in line with the observation that disagreement is low but not zero in the low regime. Nevertheless, the forecast errors show a much higher autocorrelation in the high regime, in which the sum of the absolute response of the forecast errors four years after the shock is about 70% higher compared to the low-disagreement regime. Overall, these additional empirical results provide further evidence for dispersed information models, especially in times of high disagreement.

Models where information is dispersed only about exogenous variables, among these Lorenzoni (2009), Nimark (2008, 2014), also imply systematic forecast errors and can account for different levels of disagreement about inflation expectations. However, these models predict that the effects of a monetary policy shock are identical (or very similar as the endogenous interest rate response can differ) for different levels of disagreement. The reason is that the monetary policy shock itself is fully revealed because the nominal interest rate is a redundant signal. Hence, in this setting, there does not exist a signaling channel of monetary policy. However, our empirical evidence supports the existence of a signaling channel in times of high disagreement, which is at odds with this class of dispersed information models.

Some papers, for example Blanchard et al. (2013) and Lorenzoni (2009), examine the properties of a New Keynesian model where information is incomplete and symmetric.[32] These models also predict correlated forecast errors. When price-setting firms have the same imprecise information about the true productivity and time preference shock there is no infinite regress problem as their information sets are all identical and firms do not need to predict the action of other firms. In this case firms know the actual prices and inflation. Hence, there is no role for a signaling channel. In addition, the incomplete and symmetric information model predicts zero disagreement about macroeconomic expectations. Hence the empirical results for the high disagreement regime cannot be reconciled with incomplete and symmetric information models.

Our econometric approach implicitly controls for endogenous movements in disagreement after the shock. In the dispersed information model, disagreement is exogenous and determined by the noise of the idiosyncratic signals. This implies that disagreement should not respond to the monetary policy shock, a fact which holds for all noisy information models with and without an endogenous signal where all agents receive noisy information with equal precision. In contrast, models with a sticky adjustment of information (Mankiw and Reis, 2002), predict a systematic response of disagreement, as only a fraction of agents are able to update their information sets. We test the endogeneity of disagreement by using it as dependent variable in equation (11). Our results confirm that disagreement does not respond significantly to the monetary policy surprise

[32] Lorenzoni (2009) also studies a model with dispersed information.

(Figure 8).[33] This finding is in line with the results in Coibion and Gorodnichenko (2012), who also find that disagreement does not respond to structural shocks. Besides the fact that disagreement does not respond significantly, the point estimates imply a slight increase in disagreement in the high and a minor drop of disagreement in the low regime at higher horizons, which therefore confirms the fact of remaining in the particular regime after the monetary policy shock. Thus, our results are more in line with a noisy information structure. Moreover, the finding that disagreement does not respond significantly to monetary policy shocks, simplifies the interpretation of the impulse response functions since they can be understood as responses within one of the two regimes. This is in line with the theoretical predictions in Figure 1, in which we do not allow for endogenous regime-switches.

5 Robustness and further results

This section shows several robustness checks for our baseline results and some additional results. In particular, we examine the robustness of our findings to alternative measures of disagreement, different scaling assumptions, sensitivity of switching regimes, the distribution of shocks, the empirical specification as well as the sub-sample stability.

5.1 Measures and scaling of disagreement

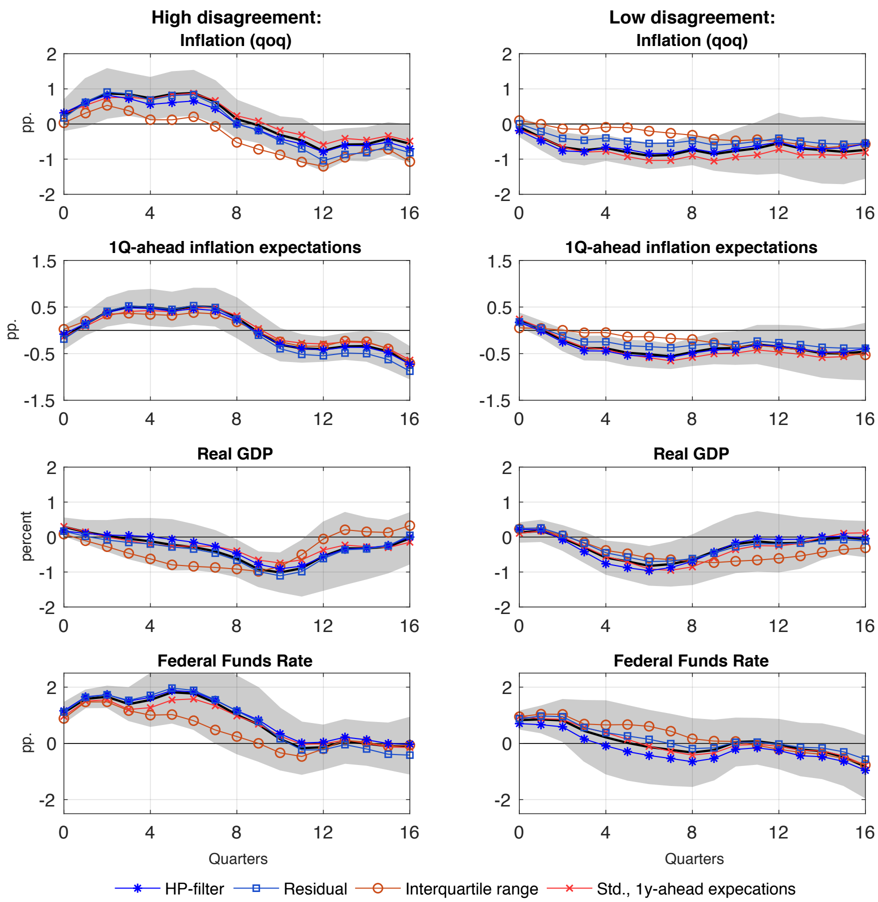
So far we have measured disagreement by the standard deviation of the individual point forecasts for the price index in the next quarter. In this section, we test the robustness of our results when we use alternative measures for disagreement. Figure 9 shows the point estimates of these alternative specifications together with our baseline results.

Our results are robust when we use disagreement about one-year-ahead price expectations instead of one-quarter-ahead expectations (see crossed red lines in Figure 9). Furthermore, it is

[33] We also find no endogenous response of z_t to the monetary policy shock when we use one lag of our regime-indicating variable z_t to define times of high and low disagreement, in order to rule out simultaneity. Hence, in this backup check we use $F(z_{t-1})$ instead of $F(z_t)$ in equation (11).

sometimes argued that measuring disagreement by the interquartile range (IQR) makes it a more robust measure against possible outliers. The circled red lines illustrate that our results do not change qualitatively when employing the IQR instead of the standard deviation of the individual point forecasts for the price index.

Figure 9: Results for various measures of disagreement



Notes: Responses to a 100 bps contractionary monetary policy shock using alternative regime-indicating variables in our baseline estimation in equation (11). The figure shows 90% confidence intervals of the baseline specification. The *HP-filter* estimation uses a HP-trend of expected inflation with a smoothing parameter of 100 to scale disagreement, whereas the specification *Residual* uses the residual from a regression of disagreement on one lag of expected inflation and one lag of the uncertainty measure of Jurado et al. (2015). In addition, the figure shows the results for disagreement measured as standard deviation over exp. inflation over the next year and the inter-quarter-range of expected inflation in the next quarter. The black solid line reflects the baseline results from Section 4. The estimation covers the period 1970:IV-2007:IV.

In our baseline results we scaled disagreement with the lagged level of inflation expectations. We confirm that our results are robust to alternative scaling specifications. In particular, we provide results for two alternative methods: (i) we either use a HP-trend of expected inflation to scale disagreement, or (ii) the alternative specification *Residual* uses the residual from a regression of disagreement on one lag of expected inflation and one lag of the uncertainty measure of Jurado et al. (2015) as regime-indicating variable. Both the HP-scaling (blue lines with stars) as well as the residual-specification (blue squared line) are well within the confidence bands of our baseline results. It is particularly noteworthy that in our second specification we intend to purge disagreement of movements in the level of aggregate uncertainty in the economy. Therefore, our findings are not driven by movements in aggregate uncertainty. Often fluctuations in aggregate uncertainty are modeled through volatility in productivity and demand shocks (Justiniano and Primiceri, 2008). Our empirical results are consistent with the theoretical results form our prior predictive analysis, where we show that the strength of the signaling channel hardly changes when we vary the size of the supply and demand shocks. When we directly use uncertainty instead of disagreement as regime-indicating variable, we find, consistent with our theoretical model, no evidence for a signaling channel of monetary policy (see Section B.1. and Figure 27 in the Appendix).

5.2 Sensitivity of regime-switching

A possible concern is that the results might be sensitive to how quickly our estimation switches between regimes. The parameter θ determines the curvature of the logistic probability function $F(z_t)$ and, hence, how strongly the probability function reacts to changes in disagreement. In our baseline specification, we follow the related literature and calibrate the curvature parameter (Auerbach and Gorodnichenko, 2013, Tenreyro and Thwaites, 2016, Santoro et al., 2014). There is no consensus on a specific parameter value. Therefore, we explore whether our results change for alternative values of θ.[34] In our baseline specification we use a value of 5.

To investigate the robustness of our results to different parameter values, we re-estimate equa-

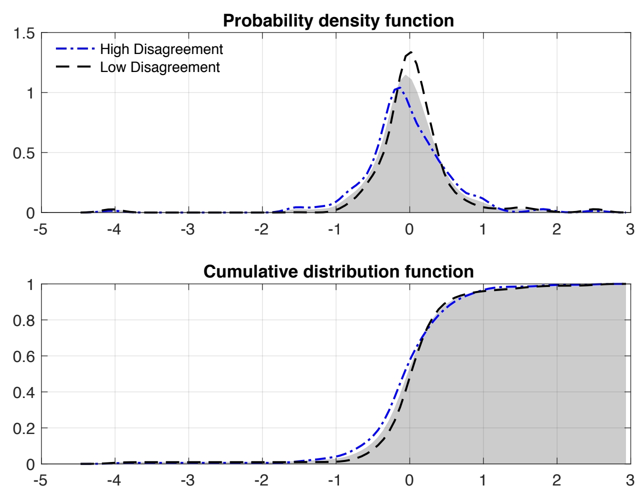
[34]Figure 20 in the Appendix illustrates how the curvature of the indicator function $F(z_t)$ changes with θ.

tion (11) for alternative values for θ. Figure 25 shows the impulse responses for $\theta = 2$ and $\theta = 10$, together with our baseline results. The results are similar to our baseline results and well within the 90% confidence interval, indicating that our findings are robust to variations in θ over a plausible range.

5.3 Distribution of shocks

A potential concern is that monetary policy shocks are larger (or systematically different) in periods of high disagreement about inflation expectations. In principle, differences in the monetary policy shocks could account for the state-dependent effects of monetary policy shocks in the regimes. To address this concern, Figure 10 shows that the distribution of monetary policy shocks is virtually identical across the high- and low-disagreement regime. Therefore, the monetary policy shocks are equally distributed across the two regimes.

Figure 10: Shock distribution



Notes: The figure shows the distribution of the realized monetary policy shocks in the two regimes (dashed lines) and on average (shaded area). The monetary policy shock series is weighted with the probability function $F(z_t)$. The derivation is based on the shock series used in our baseline estimation and covers the periods 1970:IV until 2003:IV. Note that we estimate the response of the endogenous variables within zero until 16 quarters after the respective shock, such that the last data point for the endogenous variable used in the estimations is for 2007:IV.

5.4 Empirical specification

This subsection addresses various robustness checks of our empirical specification, including changes in the lag structure as well as controlling for additional variables. In our baseline specification in equation (11), we include one lag of the Federal Funds Rate and one lag of the dependent variable as control variables. As mentioned earlier, we do not need to model the dynamics of the dependent variable due to the horizon-specific estimation of the impulse response functions.

Our baseline findings are robust to alternative specifications with more lags of the dependent variable (see Figure 11). The figure shows that the estimated impulse responses of the alternative specifications are very close to the responses of the baseline model and, in particular, lie within the 90% confidence bands of our baseline results. In addition, we find that including a quadratic trend instead of a linear time trend does not change our results.

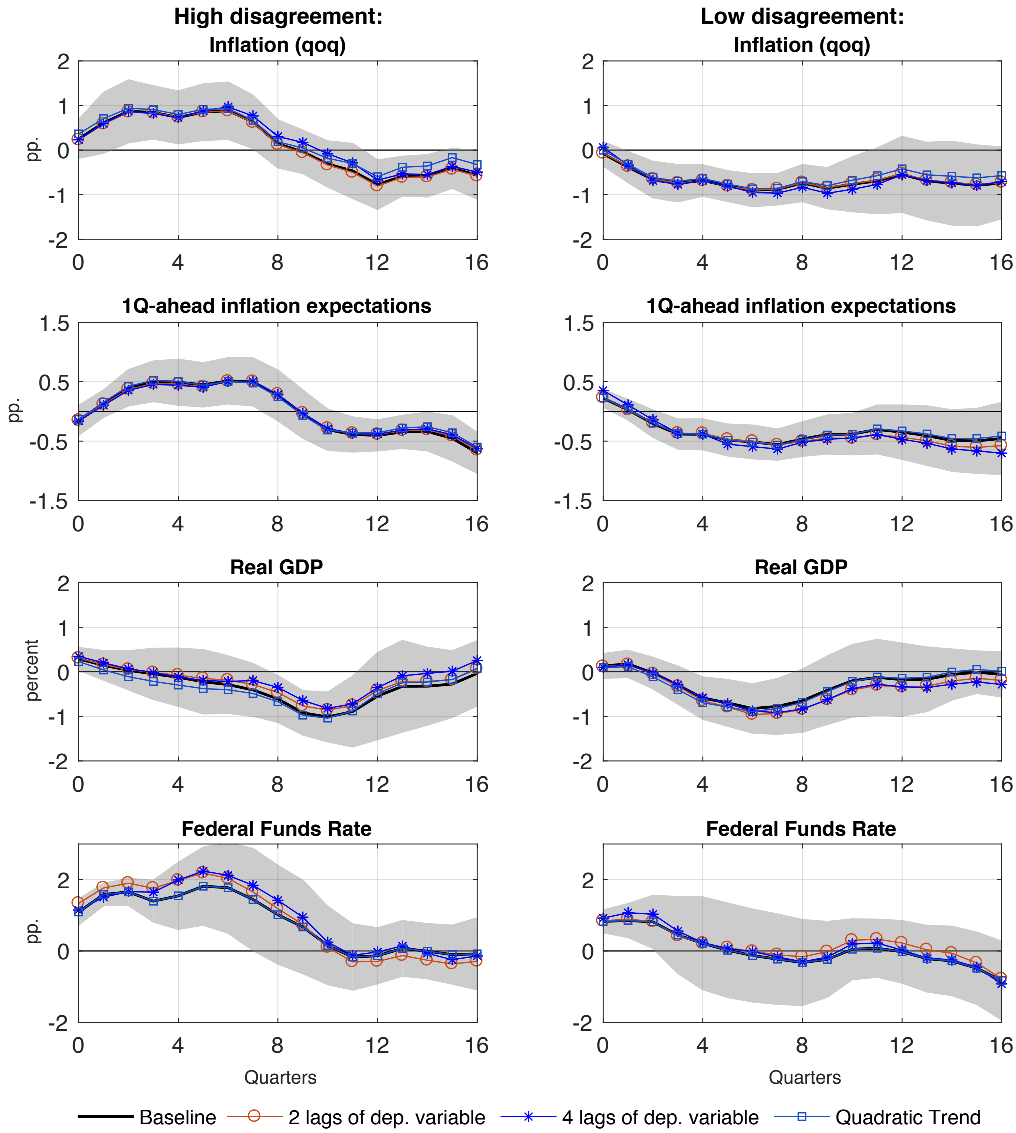
We confirm that our monetary policy shock series cannot be predicted by movements in the dependent variables (see Table 4 in the Appendix). In addition, to control for the possibility that the monetary policy shock series might be correlated with other factors, we explore whether adding the following variables affects our results: oil prices, lags of the debt-to-GDP ratio and the fiscal stance, measured as primary deficit divided by private debt holdings as in Sims (2011), and aggregate uncertainty.

It is argued, that controlling for oil prices might mitigate the positive response of inflation to a contractionary monetary policy shock as they allow the central bank to better predict future inflation (Sims, 1992). The reason is that oil prices (being a financial market variable) indicate more quickly future inflationary pressures to the central bank. However, our baseline results are robust to the inclusion of this control variable and, thus, oil prices do not resolve the price puzzle in periods of high disagreement (see Figure 12).

Previously we argued that aggregate uncertainty is not a good proxy for disagreement about short-term inflation expectations, and thus, for identifying state-dependent effects of monetary policy on inflation and inflation expectations.[35] As an additional test we estimate whether our

[35] See Section B.1. in the Appendix for a detailed discussion.

Figure 11: Results for different empirical model specifications

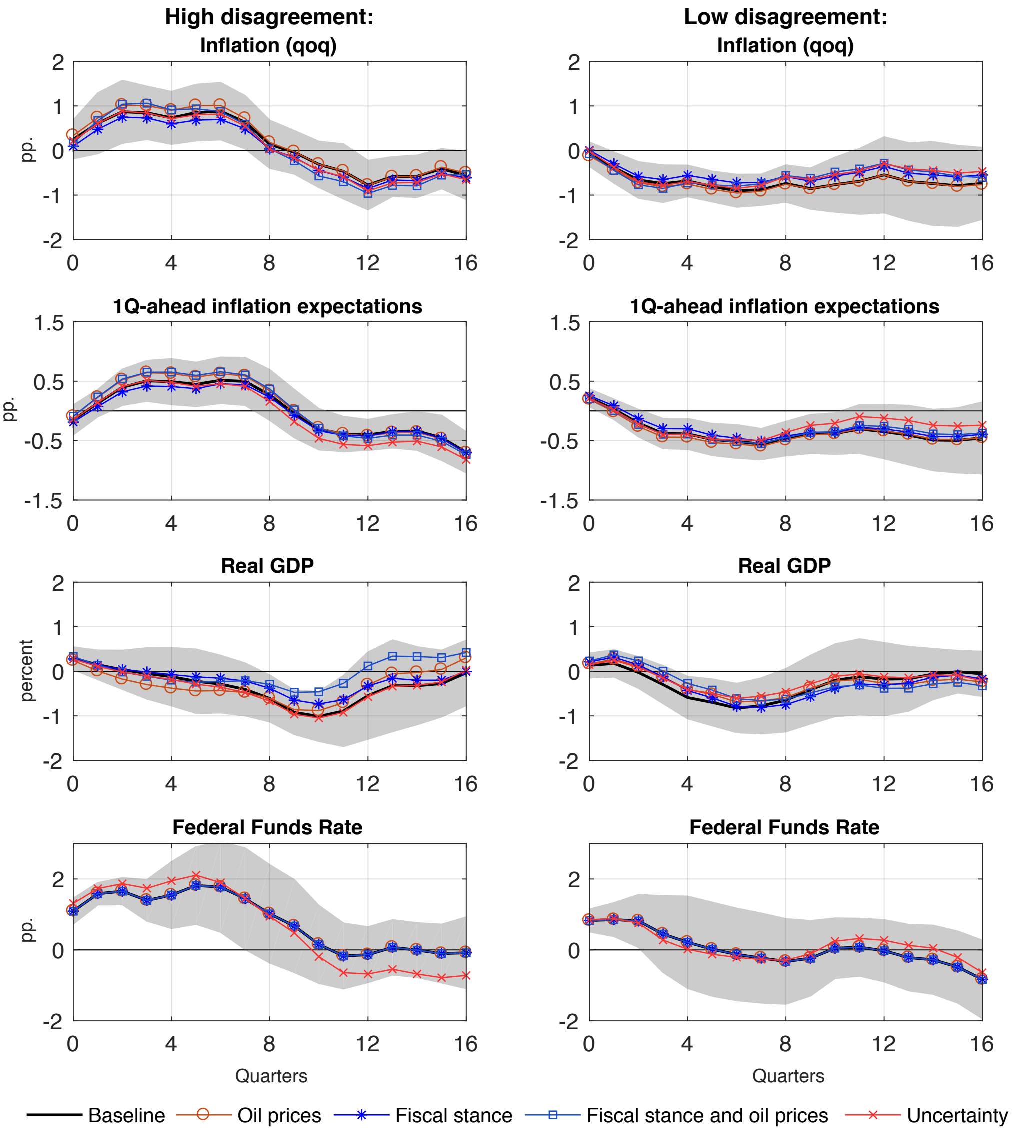


Notes: Responses to a 100 bps contractionary monetary policy shock using alternative numbers of lags or a quadratic trend in our estimation of equation (11). The figure shows 90% confidence intervals of the baseline specification. The dotted- and star-line show results for a specification with two or four lags of the dependent variable, respectively. The black solid line reflects the baseline results from Section 4. The estimation covers the period 1970:IV-2007:IV.

baseline results change when we also control for aggregate uncertainty using both stock market volatility and the Jurado et al. (2015) uncertainty measure in our baseline model specification. Reassuringly, when controlling for movements in aggregate volatility, we find the impulse responses are well within the 90% confidence bands of our baseline results (see Figure 12).

There is an ongoing debate about the interaction between fiscal and monetary policy. To account for the stance of fiscal policy, we control both for the change in the debt-to-GDP ratio as

Figure 12: Results with additional control variables



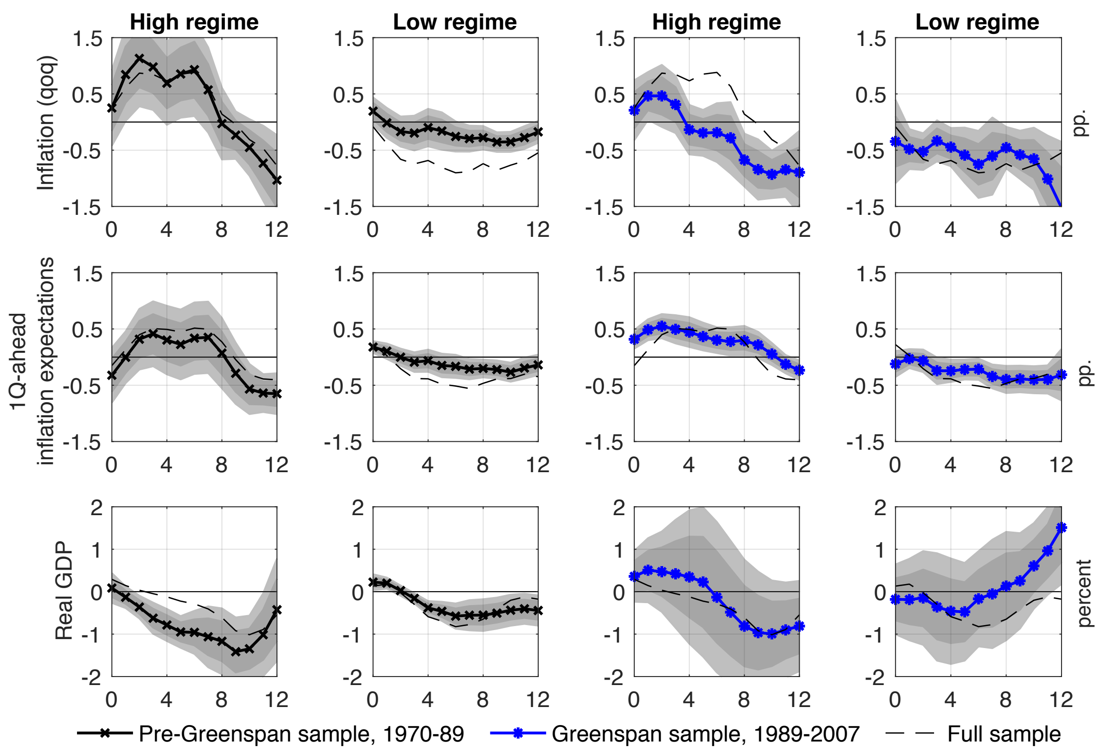
Notes: Responses to a 100 bps contractionary monetary policy shock using lags of oil prices and/or measures for fiscal stance (changes in debt-to-GDP ration and primary deficit over private debt holdings) as controls in equation (11). The *uncertainty* specification controls for one lag of stock market volatility and the uncertainty measure of Jurado et al. (2015). The figure shows 90% confidence intervals of the baseline specification. The black solid line reflects the baseline results from Section 4. The estimation covers the period 1970:IV-2007:IV.

well as the ratio of the primary deficit over total private debt holdings in a robustness estimation. To avoid endogeneity of the variables, we include the variables with a lag of one year. Reassuringly, our results for inflation and inflation expectations remain unchanged when including these additional control variables (Figure 12).

5.5 Sub-sample stability

Disagreement about inflation expectations was exceptionally high in the 1970s. Therefore, a possible concern is whether the empirical finding of state-dependent monetary policy effects only holds when including this period in our analysis. We address this concern and re-estimate our baseline results for the periods pre- and post-1988.[36] Figure 4 shows that also the post-1988 contains a few episodes of high disagreement. Our precise sample split corresponds to the start of the Greenspan-era, which coincides with the beginning of the *Great Moderation*. To increase the sample size in the two sub-samples, the estimation is employed for a horizon of 12 instead of 16 quarters.

Figure 13: Sub-sample stability



Notes: Responses to a 100 bps contractionary monetary policy shock in the two sub-samples. For reference we also show the point estimate from our baseline estimation. The coefficients are smoothed over three consecutive periods. The x-axes indicates quarters after the shock hits the economy. The light and dark grey areas display 68% and 90% confidence intervals, respectively. The dashed line shows the point estimates from the baseline (full sample) estimation.

Reassuringly, Figure 13 shows that our baseline results are qualitatively unchanged for the two

[36]For example, Davig and Leeper (2011) identify the late 1960s and 1970s as a regime of passive monetary policy and more active fiscal policy. Under an active fiscal and passive monetary policy, inflation could rise in response to a contractionary monetary policy shock, due to a positive wealth effect, as discussed in Woodford (1995).

samples. The response of inflation in the two regimes remains statistically significantly different from each other at the 90% confidence level at small horizons in both sub-samples. For short-term inflation expectations the responses are significantly different from each other at the 90% level in the Greenspan sample. However, the difference is not statistically significant in the pre-Greenspan sample, possibly due to a fewer number of observations. We conclude that our findings are consistent with signaling effects of monetary policy in each sub-sample, which are, as expected, less pronounced in the more recent sample.

Previous literature also argues that monetary policy transmission may have changed over time, for example, because monetary policy has become more forward-looking over time or due to switches in the policy regimes. Our findings are also consistent with this strand of the literature in that the macroeconomic effects are less pronounced in the post-1988 sample similar to Barakchian and Crowe (2013), Ramey and Zubairy (forthcoming). Coibion (2012) also documents that the effects are less pronounced when omitting the pre-Volcker period using Romer-Romer monetary policy shocks.

6 Conclusion

Survey data display a considerable degree of time-variation in disagreement about inflation expectations. This paper provides novel empirical evidence showing that the transmission of monetary policy shocks changes significantly with the level of disagreement about inflation expectations in the U.S. economy. Remarkably, when disagreement is high, a contractionary monetary policy shock leads to an increase in both inflation and inflation expectations. When disagreement is low, we find a decline in inflation, inflation expectations, and economic activity, which can be easily reconciled with the interest rate channel in the standard New Keynesian model. Hence, we provide empirical evidence for a strong non-linear interaction between disagreement and monetary policy.

Our estimates for the high-disagreement regime are consistent with a dispersed information New Keynesian model, where the policy rate set by the central bank reveals additional information to firms about the state of economy. When disagreement is high, firms cannot infer whether an increase in the nominal rate is due to a contractionary monetary policy shock or an endogenous response to inflation or output. As a consequence, the rise in the nominal interest rate is perceived by firms to be partly the consequence of negative supply or positive demand conditions, which puts upward pressure on inflation and inflation expectations. Therefore, taking into account the role of disagreement in the New Keynesian model is crucial to obtain theoretical predictions consistent with our novel empirical evidence.

Our results indicate that the transmission of monetary policy is significantly impaired when disagreement is high, a fact that we think should be taken into consideration by policymakers. A recent example: after an extensive period of unconventional monetary policy the U.S. Fed has initiated the process of policy normalization and raised the interest rate by 25 basis points in December 2015, followed by two further rises of 25 basis points until March 2017. In April 2017, Stanley Fischer, the Fed's vice chairman, commented on the U.S. experience "...favorable reaction partly reflects a view by market participants that the rate hikes are a signal of the FOMC's confidence in the underlying prospects for the US economy...". This statement nicely summarizes the predictions of the theoretical model when disagreement is high and the central bank's signal is particularly important to firms. Since December 2015 short-term inflation expectations have increased in the U.S., despite several interest rate hikes. Even though there are several potential channels, our theoretical and empirical results support the vice chairman's assessment. More generally, tightening monetary policy when disagreement about inflation expectations is at a high level, is likely to lead to the potentially unintended effect of raising inflation and inflation expectations. In further research we plan to address the question how optimal monetary policy should be conducted when the economy can switch between regimes of low and high disagreement as well as the role of central bank communication about the state of the economy.

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A Theoretical model

This section provides a detailed description on solving the dispersed information New Keynesian model. This material heavily draws on Melosi (2017) and Hoffmann and Hürtgen (2016).

A.1 Timing of events

At stage 1 shocks are realized and the central bank sets the interest rate for the current period. At stage 2 firms update their information set by observing (i) idiosyncratic productivity, (ii) idiosyncratic preference and (iii) the interest rate set by the central bank. Firms then set their prices based on their information set. At stage 3 households become perfectly informed about the realization of shocks and decide about consumption, demand for assets and labour supply. At this stage firms hire domestic labour to produce the goods demanded by households, given the price they have set at stage 2. At stage 3 the fiscal authority collects either lump-sum taxes or pays transfers to households and goods, labour and financial markets clear.

A.2 Households

Households have perfect information and maximize the following utility function

$$U_t = \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s D_{t+s} \left[\frac{C_{t+s}^{1-\gamma}}{1-\gamma} - \frac{N_{t+s}^{1+\varphi}}{1+\varphi} \right] , \tag{13}$$

where $\mathbb{E}_t$ is the households' full information rational expectations operator, $\gamma > 0$ is the relative risk aversion parameter, and $\varphi \geq 0$ is the inverse Frisch elasticity. Households face demand shocks D_t and they optimally choose consumption C_t, labor N_t and bond holdings B_t subject to their budget constraint

$$P_t C_t + B_t = W_t N_t + R_{t-1} B_{t-1} + \Pi_t - T_t , \tag{14}$$

where P_t is the aggregate price index, W_t is the nominal wage, R_t is the gross return on bonds, Π_t are profits rebated to the household, and T_t are lump-sum taxes.

A.3 Derivation of dispersed information New Keynesian Phillips curve

Firm j which re-optimizes prices solves the problem as stated by equation (8) in the main text:

$$\max_{\widetilde{P}_t} E_t(j) \left[\sum_{s=0}^{\infty} (\theta\beta)^s \lambda_{t,t+s} \left(\overline{\pi} \widetilde{P}_t(j) - MC^n(j)_{t+s} \right) Y_{t,t+s}(j) \right],$$

subject to the firm's resource constraint, where $\lambda_{t,t+s} = \beta \left(\frac{C_{t+s}}{C_t} \right)^{-\gamma} \frac{D_{t+s}}{D_t} \frac{P_t}{P_{t+s}}$ denotes the stochastic discount factor and MC^n the nominal marginal costs. $E_t(j)$ is the expectation operator conditional on firm j's information set $\mathbb{I}_{j,t} = \{\log A_\tau(j), \log D_\tau(j), R_\tau, P_\tau(j) : \tau \leq t\}$. In the main text we set the gross steady state inflation rate $\overline{\pi} = 1$. We substitute the following equations:

$$\begin{aligned} Y_t(j) &= C_t(j), \\ Y_t(j) &= \left(\frac{P_t(j)}{P_t} \right)^{-\nu} C_t, \end{aligned}$$

so that

$$\max_{\widetilde{P}_t} E_t(j) \left[\sum_{s=0}^{\infty} (\theta\beta)^s \lambda_{t,t+s} \left(\overline{\pi} \widetilde{P}_t(j) - MC^n(j)_{t+s} \right) \left(\frac{\widetilde{P}_t(j)}{P_{t+s}} \right)^{-\nu} C_{t+s} \right]. \tag{15}$$

From the Calvo (1983) price setting we have that

$$p_t = \theta \left(p_{t-1} + \log \overline{\pi} \right) + (1-\theta) \int_0^1 \widetilde{p}_t(j)\, dj. \tag{16}$$

Then using the following definitions

$$\begin{aligned} \widehat{\widetilde{p}}_t(j) &= \widetilde{p}_t(j) - p_t \\ \widehat{\pi}_t &= p_t - p_{t-1} - \log \overline{\pi}, \end{aligned}$$

the linearized price index becomes

$$\begin{aligned} \frac{\widehat{\pi}_t}{1-\theta} &= -p_{t-1} - \log \overline{\pi} + \int_0^1 \widetilde{p}_t(j)\, dj \\ \Leftrightarrow \frac{\widehat{\pi}_t}{1-\theta} &= p_t - p_{t-1} - \log \overline{\pi} + \int_0^1 \widehat{\widetilde{p}}_t(j)\, dj \end{aligned}$$

so that

$$\int_0^1 \widehat{\widetilde{p}}_t(j)\, dj = \frac{\theta}{1-\theta} \widehat{\pi}_t. \tag{17}$$

In addition, the linearized real marginal costs are given by

$$\widehat{mc}_t(j) = \widehat{w}_t - \widehat{p}_t - \widehat{a}_t(j).$$

Using equation (5) of the main text we have

$$\widehat{mc}_t(j) = \widehat{w}_t - \widehat{p}_t - (\widehat{a}_t + \eta_t^a(j)).$$

Using the labour-leisure condition we obtain

$$\widehat{mc}_t(j) = \varphi\widehat{n}_t + \gamma\widehat{y}_t - \widehat{a}_t - \eta_t^a(j).$$

Integrating across firms the average expectations of real marginal costs are yields:

$$\begin{aligned} \widehat{mc}_{t|t}^{(1)} &= \varphi\widehat{n}_{t|t}^{(1)} + \gamma\widehat{y}_{t|t}^{(1)} - \widehat{a}_t \\ \widehat{mc}_{t|t}^{(1)} &= (\varphi+\gamma)\widehat{y}_{t|t}^{(1)} + \varphi\hat{a}_t^{(1)} - \hat{a}_t \end{aligned} \tag{18}$$

Solving the price setting problem (15) leads to the following first-order condition:

$$E_t(j)\left[\sum_{s=0}^{\infty}(\theta\beta)^s\lambda_{t,t+s}\left((1-\nu)\overline{\pi} + \nu\frac{MC_{t+s}^n(j)}{\widetilde{P}_t(j)}\right)Y_{t+s}(j)\right] = 0.$$

We can rewrite this equation in the following way:

$$\begin{gathered} E_t(j)\left[\lambda_{t,t}\left((1-\nu)\overline{\pi} + \nu\frac{MC_t^n(j)}{\widetilde{P}_t(j)}\right)Y_t(j) + \right. \\ \left.\sum_{s=1}^{\infty}(\theta\beta)^s\lambda_{t,t+s}\left((1-\nu)\overline{\pi} + \nu\frac{MC_{t+s}^n(j)}{\widetilde{P}_t(j)}\{\textstyle\prod_{\tau=1}^{s}\pi_{t+\tau}\}\right)Y_{t+s}(j)\right] = 0. \end{gathered}$$

In steady state the terms in round brackets are zero. Consequently, the terms outside the round brackets are not relevant for the following derivation:

$$\begin{gathered} E_t(j)\left[\left((1-\nu)\overline{\pi} + \nu\overline{MC}(j)\exp\left(\widehat{mc}_t(j) - \widehat{\widetilde{p}}_t(j)\right)\right) + \right. \\ \left.\sum_{s=1}^{\infty}(\theta\beta)^s\left((1-\nu)\overline{\pi} + \nu\overline{MC}(j)\exp\left(\widehat{mc}_{t+s}(j) - \widehat{\widetilde{p}}_t(j) + \textstyle\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau}\right)\right)\right] = 0\ , \end{gathered}$$

for $\widehat{\widetilde{p}}_t(j) = \widetilde{p}_t(j) - p_t$. Differentiating this expression gives:

$$E_t(j)\left(\widehat{mc}_t(j) - \widehat{\widetilde{p}}_t(j) + \sum_{s=1}^{\infty}(\theta\beta)^s\left(\widehat{mc}_{t+s}(j) - \widehat{\widetilde{p}}_t(j) + \sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau}\right)\right) = 0\ ,$$

which we can rewrite as

$$\widetilde{p}_t(j) = (1-\theta\beta)\, E_t(j) \left(\widehat{mc}_t(j) + \frac{1}{1-\theta\beta} p_t + \sum_{s=1}^{\infty} (\theta\beta)^s \left(\widehat{mc}_{t+s}(j) + \sum_{\tau=1}^{s} \widehat{\pi}_{t+\tau} \right) \right). \tag{19}$$

Forwarding the equation by one period gives:

$$E_t(j)\left(\widetilde{p}_{t+1}(j)\right) = (1-\theta\beta)\, E_t(j) \left(\frac{1}{1-\theta\beta} p_{t+1} + \frac{1}{\theta\beta} \sum_{s=1}^{\infty} (\theta\beta)^s\, \widehat{mc}_{t+s}(j) + \sum_{s=1}^{\infty} (\theta\beta)^s \sum_{\tau=1}^{s} \widehat{\pi}_{t+\tau+1} \right).$$

The equation can be written as

$$\sum_{s=1}^{\infty} (\theta\beta)^s\, E_t(j)\left(\widehat{mc}_{t+s}(j)\right) = \frac{\theta\beta}{(1-\theta\beta)} \left[E_t(j)\left(\widetilde{p}_{t+1}(j)\right) - E_t(j)\left(p_{t+1}\right) \right] - \theta\beta \sum_{s=1}^{\infty} (\theta\beta)^s \sum_{\tau=1}^{s} E_t(j)\left(\widehat{\pi}_{t+\tau+1}\right). \tag{20}$$

Rewriting equation (19) yields

$$\begin{aligned} \widetilde{p}_t(j) &= (1-\theta\beta) \left(E_t(j)\left(\widehat{mc}_t(j)\right) + \frac{1}{1-\theta\beta} E_t(j)\left(p_t\right) + \sum_{s=1}^{\infty} (\theta\beta)^s\, E_t(j)\left(\widehat{mc}_{t+s}(j)\right) \right) \\ &\quad + (1-\theta\beta) \sum_{s=1}^{\infty} (\theta\beta)^s\, E_t(j) \sum_{\tau=1}^{s} \widehat{\pi}_{t+\tau}. \end{aligned}$$

Substituting in (20), yields

$$\begin{aligned} \widetilde{p}_t(j) &= (1-\theta\beta) \left(E_t(j)\left(\widehat{mc}_t(j)\right) + \frac{1}{1-\theta\beta} E_t(j)\left(p_t\right) \right) \\ &\quad + \theta\beta \left[E_t(j)\left(\widetilde{p}_{t+1}(j)\right) - E_t(j)\left(p_{t+1}\right) \right] - \theta\beta(1-\theta\beta) \sum_{s=1}^{\infty} (\theta\beta)^s \sum_{\tau=1}^{s} E_t(j)\left(\widehat{\pi}_{t+\tau+1}\right) \\ &\quad + (1-\theta\beta) \sum_{s=1}^{\infty} (\theta\beta)^s\, E_t(j) \sum_{\tau=1}^{s} \widehat{\pi}_{t+\tau}. \end{aligned}$$

This can be written as

$$\begin{aligned} \widetilde{p}_t(j) &= (1-\theta\beta) \left(E_t(j)\left(\widehat{mc}_t(j)\right) + \frac{1}{1-\theta\beta} E_t(j)\left(p_t\right) \right) \qquad (21) \\ &\quad + \theta\beta \left[E_t(j)\left(\widetilde{p}_{t+1}(j)\right) - E_t(j)\left(p_{t+1}\right) \right] - (1-\theta\beta) \sum_{s=1}^{\infty} (\theta\beta)^{s+1} \sum_{\tau=1}^{s} E_t(j)\left(\widehat{\pi}_{t+\tau+1}\right) \\ &\quad + (1-\theta\beta) \sum_{s=1}^{\infty} (\theta\beta)^s\, E_t(j) \sum_{\tau=1}^{s} \widehat{\pi}_{t+\tau}. \end{aligned}$$

Rewrite the last term:

$$\begin{aligned}
(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau} &= (1-\theta\beta)\left((\theta\beta)E_t(j)\widehat{\pi}_{t+1}+\sum_{s=2}^{\infty}(\theta\beta)^{s}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau}\right)\\
(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau} &= (1-\theta\beta)\left((\theta\beta)E_t(j)\widehat{\pi}_{t+1}+\sum_{s=1}^{\infty}(\theta\beta)^{s+1}E_t(j)\widehat{\pi}_{t+1}\right.\\
&\qquad\left.+\sum_{s=1}^{\infty}(\theta\beta)^{s+1}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau+1}\right),
\end{aligned}$$

and

$$\begin{aligned}
(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau} &= (1-\theta\beta)(\theta\beta)E_t(j)\widehat{\pi}_{t+1}+(\theta\beta)^{2}E_t(j)\widehat{\pi}_{t+1}\\
&\quad+(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s+1}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau+1}\\
(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau} &= (\theta\beta)E_t(j)\widehat{\pi}_{t+1}+(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s+1}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau+1}.
\end{aligned}$$

Plug this into (21), we have

$$\begin{aligned}
\widetilde{p}_t(j) &= (1-\theta\beta)\left(E_t(j)(\widehat{mc}_t(j))+\frac{1}{1-\theta\beta}E_t(j)(p_t)\right)\\
&\quad+\theta\beta\left[E_t(j)(\widetilde{p}_{t+1}(j))-E_t(j)(p_{t+1})\right]-(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s+1}\sum_{\tau=1}^{s}E_t(j)(\widehat{\pi}_{t+\tau+1})\\
&\quad+(\theta\beta)E_t(j)\widehat{\pi}_{t+1}+(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s+1}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau+1}.
\end{aligned}$$

which becomes

$$\widetilde{p}_t(j)=(1-\theta\beta)E_t(j)(\widehat{mc}_t(j))+E_t(j)(p_t)+\theta\beta\left[E_t(j)(\widetilde{p}_{t+1}(j))-E_t(j)(p_{t+1})\right]+(\theta\beta)E_t(j)\widehat{\pi}_{t+1}.$$

Given our definition of inflation as $\widehat{\pi}_t=p_t-p_{t-1}-\log\overline{\pi}$, we have that

$$\begin{aligned}
\widetilde{p}_t(j) &= (1-\theta\beta)E_t(j)(\widehat{mc}_t(j))+E_t(j)(p_t)+\theta\beta\left[E_t(j)(\widetilde{p}_{t+1}(j))-E_t(j)(p_{t+1})\right]\\
&\quad+(\theta\beta)E_t(j)(p_{t+1}-p_t-\log\overline{\pi}),
\end{aligned}$$

$$\Leftrightarrow \widetilde{p}_t(j)=(1-\theta\beta)E_t(j)(\widehat{mc}_t(j))+(1-\theta\beta)E_t(j)(p_t)+\theta\beta E_t^{j}(\widetilde{p}_{t+1}(j))-(\theta\beta)\log\overline{\pi}. \quad (22)$$

Then integrating (22) across firms, we obtain the average reset price:

$$\widetilde{p}_t = (1-\theta\beta)\,\widehat{mc}^{(1)}_{t|t} + (1-\theta\beta)\,p^{(1)}_{t|t} + \theta\beta\widetilde{p}^{(1)}_{t+1|t} - (\theta\beta)\log\overline{\pi}. \tag{23}$$

Combine equation (16) with the following relationship:

$$\widetilde{p}_t = \int_0^1 \widetilde{p}_t\,(j)\,dj, \tag{24}$$

yields:

$$p_t = \theta\,(p_{t-1} + \log\overline{\pi}) + (1-\theta)\,\widetilde{p}_t. \tag{25}$$

Next, we substitute the following equation into equation (25)

$$p_t = \widehat{\pi}_t + p_{t-1} + \log\overline{\pi}, \tag{26}$$

and we obtain

$$\widehat{\pi}_t + p_{t-1} + \log\overline{\pi} \;\; = \;\; \theta\,(p_{t-1} + \log\overline{\pi}) + (1-\theta)\,\widetilde{p}_t \text{ and, forwarding by one period:}$$

$$\widetilde{p}_{t+1} \;\; = \;\; \frac{\widehat{\pi}_{t+1}}{(1-\theta)} + p_t + \log\overline{\pi}. \tag{27}$$

Plug (23) into equation (25) gives

$$p_t \;\; = \;\; \theta\,(p_{t-1} + \log\overline{\pi}) + (1-\theta)\,\widetilde{p}_t \tag{28}$$

$$\begin{aligned} p_t \;\; = \;\; & \theta\,(p_{t-1}) + (\theta - (1-\theta)\,(\theta\beta))\log\overline{\pi} \\ & + (1-\theta)\left((1-\theta\beta)\,\widehat{mc}^{(1)}_{t|t} + (1-\theta\beta)\,p^{(1)}_{t|t} + \theta\beta\widetilde{p}^{(1)}_{t+1|t}\right) \end{aligned} \tag{29}$$

Next, we substitute (26) and (27) into equation (29)

$$\begin{aligned} \widehat{\pi}_t \;\; = \;\; & -(1-\theta)\,(p_{t-1} + \log\overline{\pi}) + (1-\theta)\,(1-\theta\beta)\,\widehat{mc}^{(1)}_{t|t} \\ & + (1-\theta)\,p^{(1)}_{t|t} + \theta\beta\widehat{\pi}^{(1)}_{t+1|t}, \end{aligned}$$

and for $p_t = \widehat{\pi}_t + p_{t-1} + \log\overline{\pi}$, we have

$$\widehat{\pi}_t = (1-\theta)\,(1-\theta\beta)\,\widehat{mc}^{(1)}_{t|t} + (1-\theta)\,\widehat{\pi}^{(1)}_{t|t} + \theta\beta\widehat{\pi}^{(1)}_{t+1|t}. \tag{30}$$

Under full information we obtain $\widehat{\pi}_t = \frac{(1-\theta)(1-\theta\beta)}{\theta}\widehat{mc}_t + \beta\widehat{\pi}_{t+1|t}$, the well known Phillips curve. However, under imperfect information we have to take expectations of (30) and averaging across firms to get

$$\widehat{\pi}_{t|t}^{(k)} = (1-\theta)(1-\theta\beta)\,\widehat{mc}_{t|t}^{(k+1)} + (1-\theta)\,\widehat{\pi}_{t|t}^{(k+1)} + \theta\beta\widehat{\pi}_{t+1|t}^{(k+1)}.$$

Repeatedly substituting equation (30) for $k \geq 1$ yields the dispersed information Phillips curve, which is equation (9) in the main text. To fix notation, $\widehat{\pi}_{t+1|t}^{(k)}$ denotes the average k-th order expectation about the next period's inflation rate $\widehat{\pi}_{t+1|t}^{(k)} = \underbrace{\int E_t^j ... \int E_t^j ... \int E_t^j}_{k} \widehat{\pi}_{t+1} dj...dj.$

A.4 The equilibrium system

A general representation of the dispersed information model is given by:

$$\begin{aligned}
\Gamma_0 s_t &= \Gamma_1 E_t s_{t+1} + \Gamma_2 X_{t|t}^{(0:k)} \\
X_{t|t}^{(0:k)} &= M X_{t-1|t-1}^{(0:k)} + N\varepsilon_t \\
s_t &= [\widehat{y}_t, \widehat{\pi}_t, \widehat{r}_t, \widehat{\pi}_{t+1|t}, \widehat{\pi}_{t+2|t+1}, \widehat{\pi}_{t+3|t+2}, \widehat{\pi}_{t+4|t+3}, \widehat{\pi}_{t+4|t}]' \\
X_{t|t}^{(0:k)} &= \left[\widehat{a_{t|t}^{(s)}}, \widehat{m_{t|t}^{(s)}}, \widehat{d_{t|t}^{(s)}} : 0 \leq s \leq k\right]',
\end{aligned}$$

where $\widehat{\pi}_{t+ik|t+ij} = \frac{P_{t+ik}}{P_{t+ij}}$. The core equilibrium system is comprised by three linearized equations: the consumption Euler equation, the dispersed information Phillips curve, and the interest rate rule:

$$\begin{aligned}
\gamma\widehat{y}_t &= \hat{d}_t - E_t\hat{d}_{t+1} + E_t\gamma\widehat{y}_{t+1} + E_t\widehat{\pi}_{t+1} - \hat{r}_t \\
\widehat{\pi}_t &= (1-\theta)(1-\beta\theta)\sum_{k=1}^{\infty}(1-\theta)^{k-1}\left((\gamma+\varphi)\hat{y}_{t|t}^{(k)} - (1+\varphi)\hat{a}_{t|t}^{(k-1)}\right) + \beta\theta\sum_{k=1}^{\infty}(1-\theta)^{k-1}\,\widehat{\pi}_{t+1|t}^{(k)} \\
\hat{r}_t &= \phi_\pi E_t\widehat{\pi}_t + \phi_y E_t\left(\hat{y}_t - \frac{1+\varphi}{\gamma+\varphi}\hat{a}_t\right) + \widehat{m}_t\ .
\end{aligned}$$

The remaining five equations are definitions for inflation expectations at various horizons.

Following Melosi (2017), we rewrite the Phillips curve as a function of exogenous state variables $X_{t|t}^{(0:k)}$:

$$
\begin{aligned}
&\hat{\pi}_t = \mathbf{a_0} X_{t|t}^{(0:k)} \\
&\Leftrightarrow \hat{\pi}_t = (1-\theta)(1-\beta\theta) \sum_{s=0}^{k-1} (1-\theta)^s 1_1^T (\gamma+\varphi) \left(v_0 T^{(s+1)} X_{t|t}^{(0:k)} \right) \\
&- (1-\theta)(1-\beta\theta) \sum_{s=0}^{k-1} (1-\theta)^s (1+\varphi) \left(\gamma_a^{(s)\prime} X_{t|t}^{(0:k)} \right) \\
&+ \beta\theta \sum_{s=0}^{k-1} (1-\theta)^s 1_2^T \left(v_0 M T^{(s+1)} X_{t|t}^{(0:k)} \right) \\
&\Leftrightarrow \hat{\pi}_t = \left[(1-\theta)(1-\beta\theta) \left((\gamma+\varphi) \varpi m_1 - (1+\varphi) \left(\sum_{s=0}^{k-1} (1-\theta)^s \gamma_a^{(s)\prime} \right) \right) + \beta\theta\varpi m_2 \right] X_{t|t}^{(0:k)} ,
\end{aligned}
$$

where we use the following definitions:

$$
\begin{aligned}
1_1^T &= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
1_2^T &= \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\
\varpi &= 1_{1xk} \\
m_1 &= \begin{bmatrix} 1_1^T v_0 T^{(1)} \\ (1-\theta) 1_1^T v_0 T^{(2)} \\ \vdots \\ (1-\theta)^{k-1} 1_1^T v_0 T^{(k)} \end{bmatrix}, m_2 = \begin{bmatrix} 1_2^T v_0 M T^{(1)} \\ (1-\theta) 1_2^T v_0 M T^{(2)} \\ \vdots \\ (1-\theta)^{k-1} 1_2^T v_0 M T^{(k)} \end{bmatrix} .
\end{aligned}
$$

Furthermore, we use $\gamma_a^{(s)} = \begin{bmatrix} 0_{1x3s} & (1,0,0) & 0_{1x3(k-s)} \end{bmatrix}'$ and $T^{(s)}$, which is an operator that truncates the order of beliefs such that $s_{t|t}^{(s)} = v_0 T^{(s)} X_{t|t}^{(0:k)}$ and is defined as follows:

$$
T^{(s)} = \begin{bmatrix} 0_{3(k-s+1)x3s} & I_{3(k-s+1)} \\ 0_{3sx3s} & 0_{3sx3(k-s+1)} \end{bmatrix} .
$$

Using $\hat{\pi}_t = \mathbf{a_0} X_{t|t}^{(0:k)}$ allows us to cast the equilibrium system into a set of first-order difference equations in the following form:

$$
\Gamma_0 s_t = \Gamma_1 E_t s_{t+1} + \Gamma_2 X_{t|t}^{(0:k)} \tag{31}
$$

$$\Gamma_0 = \begin{bmatrix} 1 & 0 & \gamma^{-1} & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ -\phi_y & -\phi_\pi & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 & -1 \end{bmatrix}, \Gamma_1 = \begin{bmatrix} 1 & \gamma^{-1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & = & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$\Gamma_2 = \begin{bmatrix} 0_{1x2} & \frac{1-\rho_d}{\gamma} & 0_{1x3k} \\ a_{0,11} & a_{0,12} & a_{0,13} \\ -\phi_y \frac{1+\varphi}{\gamma+\varphi} & 1 & 0_{1x3k+1} \\ 0_{5x1} & 0_{5x1} & 0_{5x3k+1} \end{bmatrix}_{8x(3k+3)}$$

A.5 Solution algorithm

We solve the dispersed information model following Nimark (2011) and Melosi (2017). Note that alternative methods to solve dispersed information models have been proposed by Maćkowiak and Wiederholt (2009) and Rondina and Walker (2014). As shown in Appendix A.4 we cast the structural model into the form:

$$\begin{aligned} \Gamma_0 s_t &= \Gamma_1 E_t s_{t+1} + \Gamma_2 X_{t|t}^{(0:k)} && (32) \\ X_{t|t}^{(0:k)} &= M X_{t-1|t-1}^{(0:k)} + N\epsilon_t && (33) \end{aligned}$$

The solution algorithm is based on four steps:

1. Set $i = 1$ and guess the matrices $M^{(i)}$, $N^{(i)}$, and $v_0^{(i)}$.

2. Use a rational expectations solver on equation (32) and (33) to solve for the policy function matrix $v_0^{(i+1)}$ where $s_t = v_0^{(i+1)} X_{t|t}^{(0:k)}$. We truncate the order of the average expectation at $k = 10$.

3. Update the endogenous policy signal

$$\hat{r}_t = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} v_0^{(i+1)} X_{t|t}^{(0:k)}$$

and solve for the firm‘s signal extraction problem using the Kalman filter to obtain the matrices $M^{(i+1)}$ and $N^{(i+1)}$ as specified in Appendix A.6.

4. We iterate on steps $2-4$ until convergence:

$$\left\| M^{(i)} - M^{(i+1)} \right\| < \varepsilon, \left\| N^{(i)} - N^{(i+1)} \right\| < \varepsilon, \left\| v_0^{(i)} - v_0^{(i+1)} \right\| < \varepsilon$$

for $\varepsilon < 1e-6$.

A.6 Evolution of higher-order expectations

Following Melosi (2017), this section shows how to obtain the evolution of the hierarchy of expectations described by

$$X_{t|t}^{(0:k)} = MX_{t-1|t-1}^{(0:k)} + N\epsilon_t \ , \tag{34}$$

where $\left[\begin{array}{ccc} \epsilon_t^a & \epsilon_t^m & \epsilon_t^d \end{array} \right]'$. For brevity we define $X_t = X_{t|t}^{(0:k)}$. The general form of the firms' state space model with the state and measurement equation, respectively, is given by:

$$X_t = MX_{t-1} + N\epsilon_t \tag{35}$$

$$Z_t(j) = DX_t + Q\eta_{j,t} \ , \tag{36}$$

where $D = \left[\begin{array}{ccc} d_1 & d_2 & \left(1_3^T v_0\right)' \end{array} \right]'$, with

$d_1{}' = \left[\begin{array}{cc} 1 & 0_{1x3(k+1)-1} \end{array} \right], d_2{}' = \left[\begin{array}{cccc} 0 & = & 1 & 0_{1x3(k)} \end{array} \right], 1_3^T = \left[\begin{array}{cccc} 0 & 0 & 1 & 0_{1x5} \end{array} \right], \eta_{j,t} = \left[\begin{array}{cc} \eta_{j,t}^a & \eta_{j,t}^d \end{array} \right]'$
and

$$\text{Q} = \left[\begin{array}{cc} \tilde{\sigma}_a & 0 \\ 0 & \tilde{\sigma}_d \\ 0 & 0 \end{array} \right].$$

We solve the firms' filtering problem by applying the Kalman filter. Firm j's first-order expectation about the state vector is denoted $X_{t|t}(j)$ and the conditional covariance matrix is $P_{t|t}$:

$$X_{t|t}(j) = X_{t|t-1}(j) + P_{t|t-1}D'F_{t|t-1}^{-1}\left(Z_t(j) - Z_{t|t-1}(j)\right) \tag{37}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}D'F_{t|t-1}^{-1}DP_{t|t-1}' \ , \tag{38}$$

where

$$P_{t|t-1} = MP_{t-1|t-1}M' + NN' \ , \tag{39}$$

and the matrix $F_{t|t-1} = E(Z_t Z_t' | Z^{t-1})$ is obtained from:

$$F_{t|t-1} = D P_{t|t-1} D' + QQ' \ . \tag{40}$$

Thus, from combining these equations we obtain:

$$P_{t+1|t} = M \left[P_{t|t-1} - P_{t|t-1} D' F_{t|t-1}^{-1} D P_{t|t-1}' \right] M' + NN' \ . \tag{41}$$

Therefore, the evolution of higher-order expectations of firm j about the unobserved state vector $X_{t|t}(j)$ is:

$$\begin{aligned} X_{t|t}(j) &= X_{t|t-1}(j) + K_t \left[DX_t + Q\eta_{j,t} - DX_{t|t-1}(j) \right] && (42) \\ K_t &= P_{t|t-1} D' F_{t|t-1}^{-1} \ , && (43) \end{aligned}$$

where K_t denotes the Kalman-gain matrix. Using that $X_{t|t-1}(j) = MX_{t-1|t-1}(j)$ we can rewrite the hierarchy of higher-order expectations:

$$X_{t|t}(j) = (M - KDM) X_{t-1|t-1}(j) + K_t \left[DMX_{t-1} + DN\epsilon_t + Q\eta_{j,t} \right] \ . \tag{44}$$

Integrating over all firms we obtain the law of motion of the average expectation about $X_{t|t}^{(1)}$:

$$X_{t|t}^{(1)} = (M - KDM) X_{t-1|t-1}^{(1)} + K_t \left[DMX_{t-1} + DN\epsilon_t \right] \ . \tag{45}$$

Note, that $X_t = X_{t|t}^{(0:k)} = \left[X_t^{(0)}, X_{t|t}^{(1:k)} \right]'$ and, therefore, the evolution of the true states is given by:

$$X_t = \underbrace{\begin{bmatrix} \rho_a & 0 & 0 & 0 \\ 0 & \rho_m & 0 & 0 \\ 0 & 0 & \rho_d & 0 \end{bmatrix}}_{R_1} X_{t-1|t-1}^{(0:k)} + \underbrace{\begin{bmatrix} \sigma_a & 0 & 0 \\ 0 & \sigma_m & 0 \\ 0 & 0 & \sigma_d \end{bmatrix}}_{R_2} \varepsilon_t \ .$$

Assuming common knowledge in rationality, i.e. agents form model consistent rational expectations (see Nimark (2008)), we construct matrices M and N:

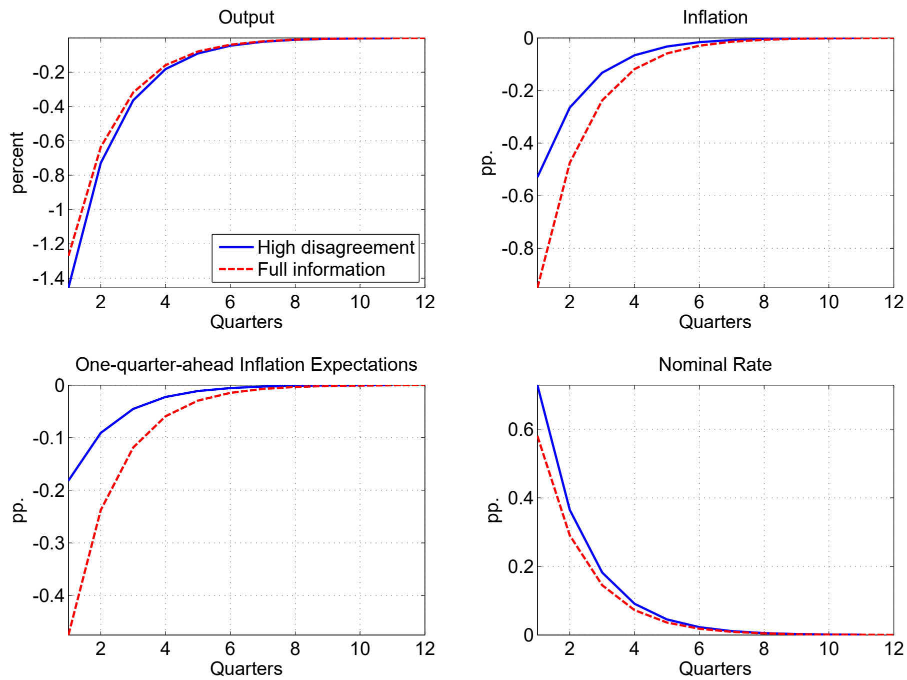
$$\begin{aligned} M &= \begin{bmatrix} R_1 \\ 0 \end{bmatrix} + \begin{bmatrix} 0_{3x3} & 0_{3x3k} \\ 0_{3kx3} & (M - KDM)_{(1:3k,1:3k)} \end{bmatrix} + \begin{bmatrix} 0 \\ KDM_{(1:3k,3(k+1))} \end{bmatrix}, \\ N &= \begin{bmatrix} R_2 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ KDN_{(1:3k,1:3)} \end{bmatrix} \end{aligned}$$

Following Nimark (2011), the last row and/or column of the matrices have been cropped to make the matrices conformable (i.e. implementing the approximation that expectations of order $k > \bar{k}$ are redundant). The steady-state Kalman gain matrix is denoted K.

A.7 Dissecting the signaling and the interest rate channel

To isolate the interest channel, we compute the endogenous responses only attributed to beliefs about monetary policy shocks (right panel in Figure 3) and we shut-off the effect of higher-order beliefs about productivity and preferences. Figure 14 illustrates the effects of the pure interest rate channel in the high-disagreement case and compares them to the full-information model.

Figure 14: The interest rate channel

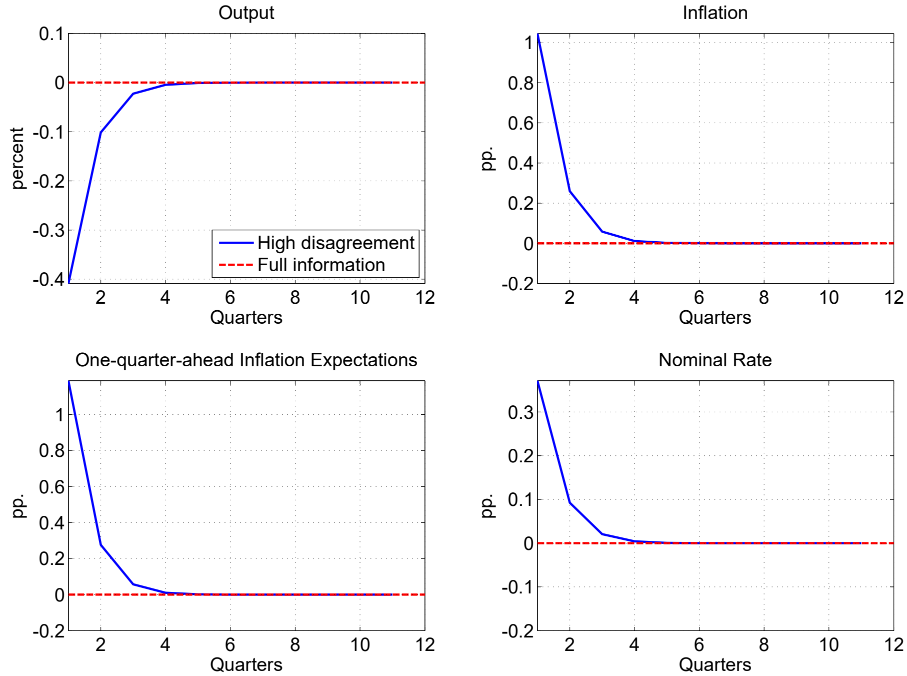


Notes: Impulse responses to a 100 basis points contractionary monetary policy shock in the dispersed information (high-disagreement) New Keynesian model only attributed to the response of beliefs stemming from an actual monetary policy shock. The dashed line is the response to the monetary policy shock in the full-information model.

In the high-disagreement case, the belief of being hit by a monetary policy shock is smaller compared to the full information model. As a result, inflation and inflation expectations respond much weaker, triggering a smaller systematic response of the nominal rate. Therefore, the real interest rate responds stronger, which leads to a stronger negative output response as households increase saving and reduce spending.

To back out the effect of the signaling channel, Figure 15 shows the macroeconomic effects in response to beliefs about the productivity and preference shock. In this experiment we shut-off the evolution of beliefs about monetary policy shocks. As argued before, it is the signaling channel that

Figure 15: The signaling channel



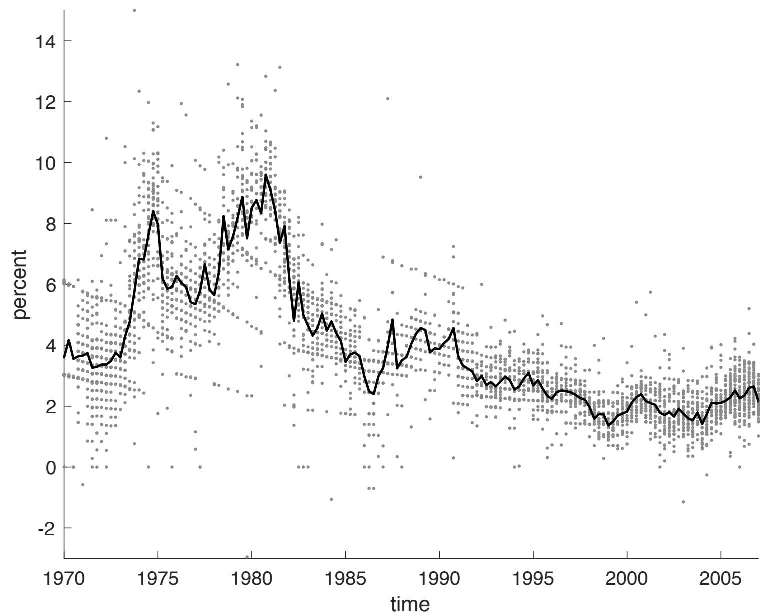
Notes: Impulse responses to a 100 basis points contractionary monetary policy shock in the dispersed information (high-disagreement) New Keynesian model only attributed to the response of beliefs stemming from productivity and time preference shocks. Inflation expectations are the firms' average first-order expectations. The dashed line is the response to the monetary policy shock in the full-information model.

drives the strong increase in inflation and in inflation expectations. The intuition is that when firms respond to a negative perceived productivity shocks and a perceived positive preference shock they increase prices today and thus also inflation expectations. At the same time the negative productivity shock beliefs dominate the positive preference shock beliefs such that output declines in equilibrium. Naturally, in the full-information model there is no signaling channel and hence the economy does not respond to beliefs about a productivity and a time preference shock, as illustrated by the dashed line in Figure 15.

To investigate the relative importance of noisy information about supply and demand conditions we have also experimented with only using one idiosyncratic private signal. In theory, one noisy private and one noisy public signal are sufficient to invoke the signaling channel. We find that the strength of the signaling channel is more strongly driven by noisy information about demand conditions as compared to supply side conditions. In particular, we obtain a similar result to our baseline results when we have a more precise signal about productivity and a less precise signal about demand conditions. In his estimated model, Melosi (2017) also finds that the signal precision for demand shocks is smaller compared to that for productivity shocks.

B Further empirical results

Figure 16: Individual inflation forecasts



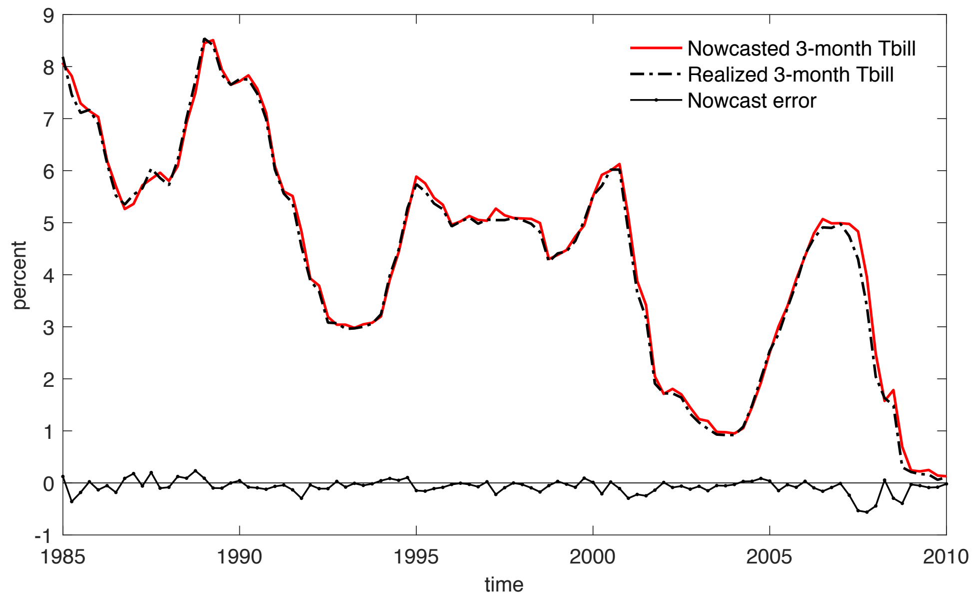
Notes: The figure shows the annualized one-quarter-ahead inflation expectation, measured as the difference of the (log) mean forecast of the price index in the next quarter across agents minus the log of the mean nowcast of the price index. The dots reflect the individual forecasts of the inflation rate. The data stems from the U.S. SPF. For visibility, very extreme individual forecasts (above 14% and below -2.5%) are disregarded in the figure. These extreme values are occasionally observed between 1971 and 1987.

Table 4: Predictability of the monetary policy shock series

	L = 2 lags	
Dependent variable	F-statistics	P-values
Inflation rate	0.20	0.90
One-quarter-ahead inflation expectations	0.03	0.99
Real GDP	0.34	0.80
Disagreement about inflation expectations	1.33	0.27
Aggregate uncertainty (Jurado et al., 2015)	0.54	0.65

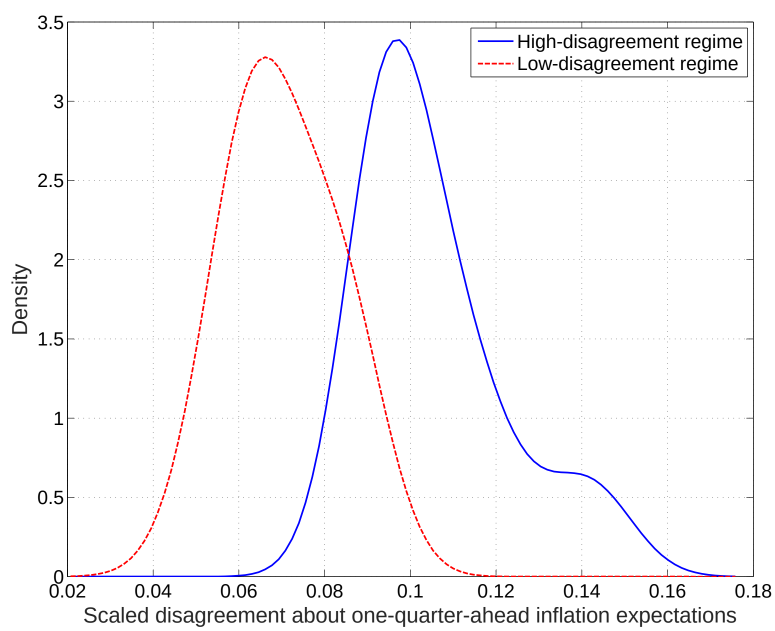
Notes: We run the following regression for each variables: $\epsilon_t = c + \sum_{l=0}^{I} \beta_l y_{t-1} + u_t$. The table reports F-statistics and P-values for the null hypothesis that all coefficients β_l are equal to zero. The estimation covers the baseline sample from 1970:IV to 2007:IV. The standard errors are corrected for the possible presence of serial correlation and heteroscedasticity using a Newey-West variance covariance matrix.

Figure 17: The nowcasted nominal interest rate



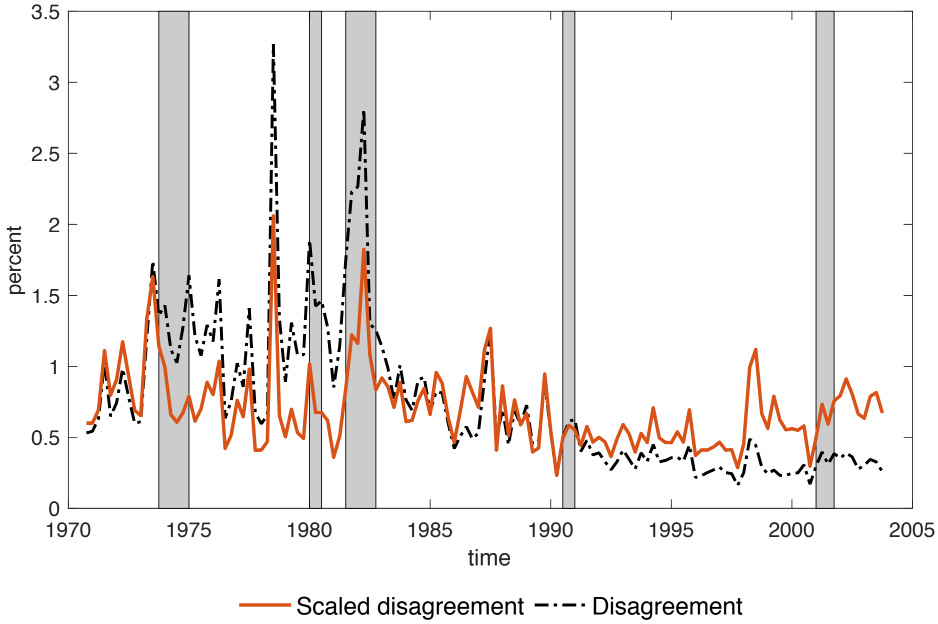
Notes: The figure shows the mean point forecasts for the current value of the three-month T-Bill from the U.S. SPF and the actual level of the current period three-month T-Bill (from St.Louis FRED database). Both series are on quarterly basis. The nowcast error (solid black line) is the difference between the two series. Forecasts for the T-Bill in the SPF start in 1981:III.

Figure 18: Kernel density estimates of disagreement in the two regimes



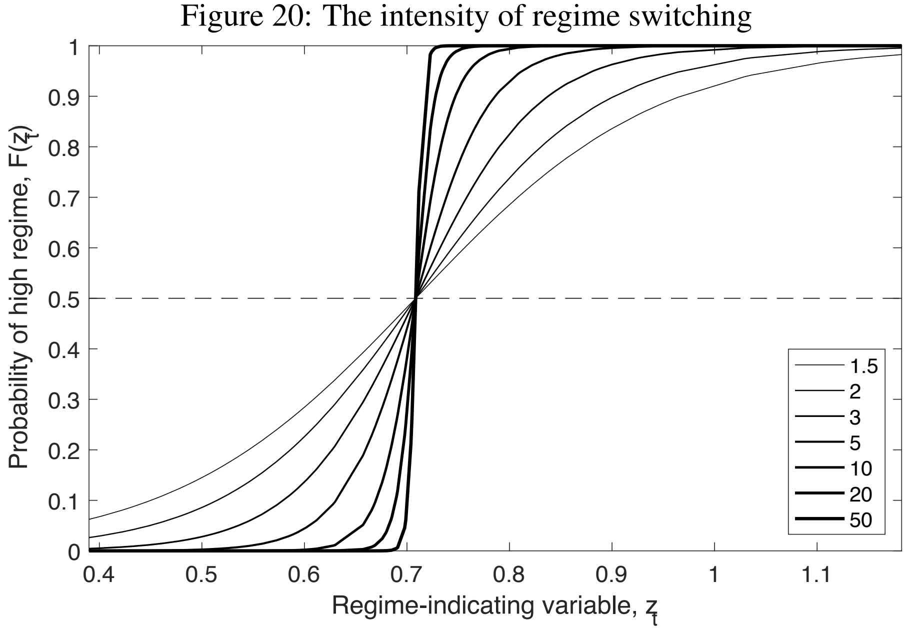
Notes: Kernel density estimate of disagreement about one-quarter-ahead inflation expectations in the high- (solid line) and low-disagreement regime (dashed line) based on the U.S. SPF data. Disagreement in each regime is scaled by a factor of eight to normalize with the theoretical distributions in Figure 1.

Figure 19: Scaled disagreement



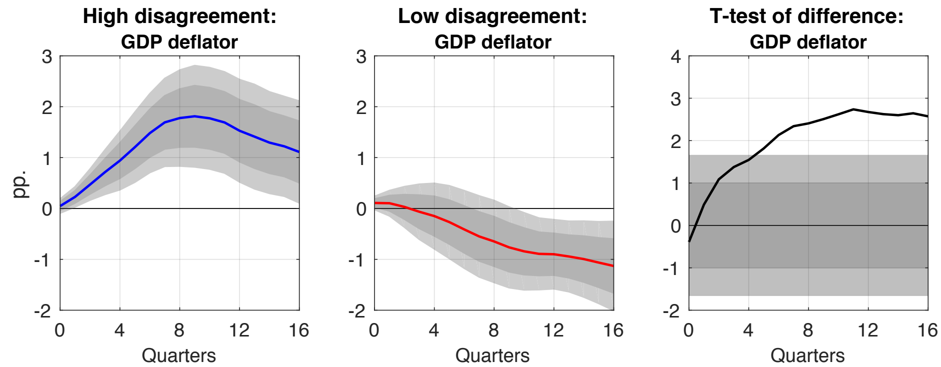
Notes: The dashed line shows *disagreement* measured as the standard deviation of the point forecasts about the price level (GDP deflator) in the next quarter, based on U.S. SPF data. The solid line shows the previous variable scaled by the expected inflation rate in the previous quarter. The latter is used as regime-indicating variable (z_t) in our baseline estimation. The shaded areas reflect NBER recessions.

Figure 20: The intensity of regime switching



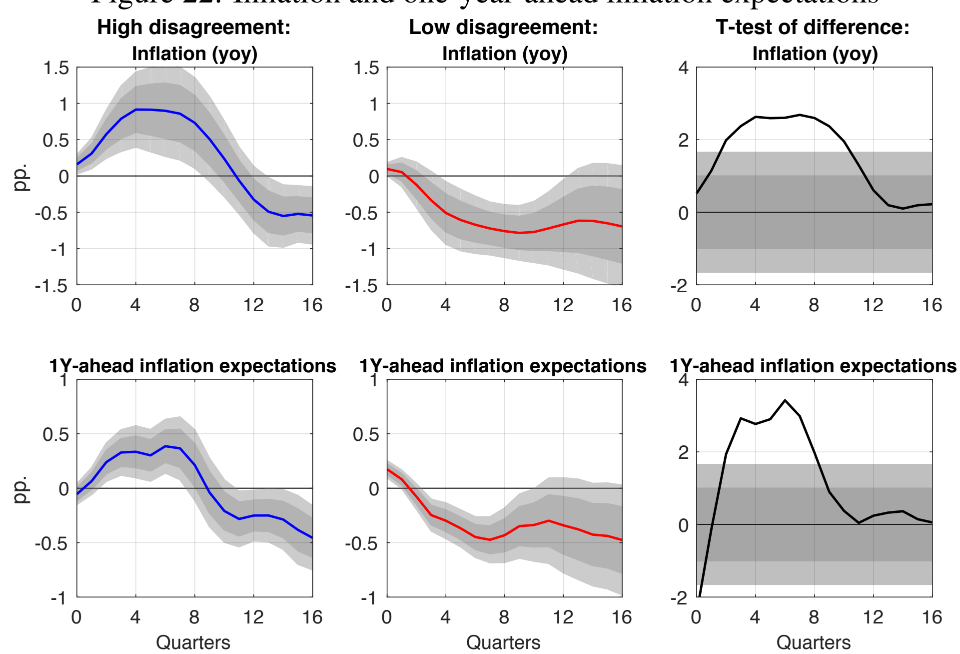
Notes: The figure shows the value of the probability function $F(z_t)$ for different values of the regime-switching intensity θ over the whole range of values of the regime-indicating variable z_t, i.e. the scaled disagreement. The intersection point of the dashed line and the functions indicates the median of the regime-indicating variable z_t.

Figure 21: Impulse response of GDP deflator



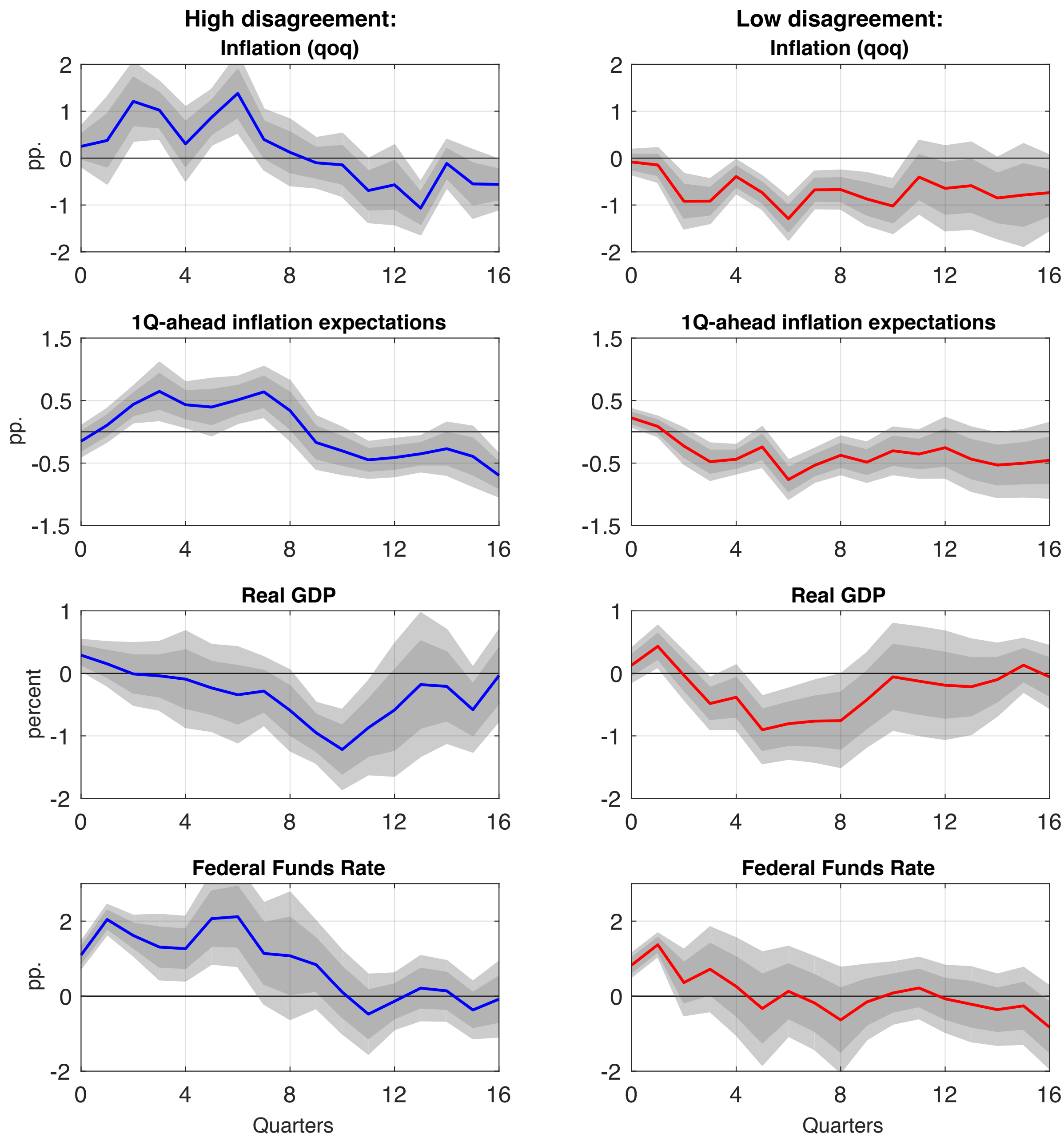
Notes: Results for the estimation with the level of the (log) GDP deflator (minus the level in period $t-1$) as dependent variable. We estimate the following equation: $y_{t+i} - y_{t-1} = \tau_i t + (\alpha_i^H + \beta_i^H \varepsilon_t + \gamma_i^H x_t)F(z_t) + (\alpha_i^L + \beta_i^L \varepsilon_t + \gamma_i^L x_{t-2})(1 - F(z_t)) + u_{t+i}$. The estimation covers the sample 1970:IV-2007:IV. The solid lines in the left (middle) column show the point estimates for the high-disagreement regime β_i^H (low-disagreement regime β_i^L) for horizon i (x-axes). The right column shows the result of a t-Test for the difference between the high and low-disagreement regime. The grey areas show 68% and 90% confidence intervals and critical test values, respectively.

Figure 22: Inflation and one-year-ahead inflation expectations



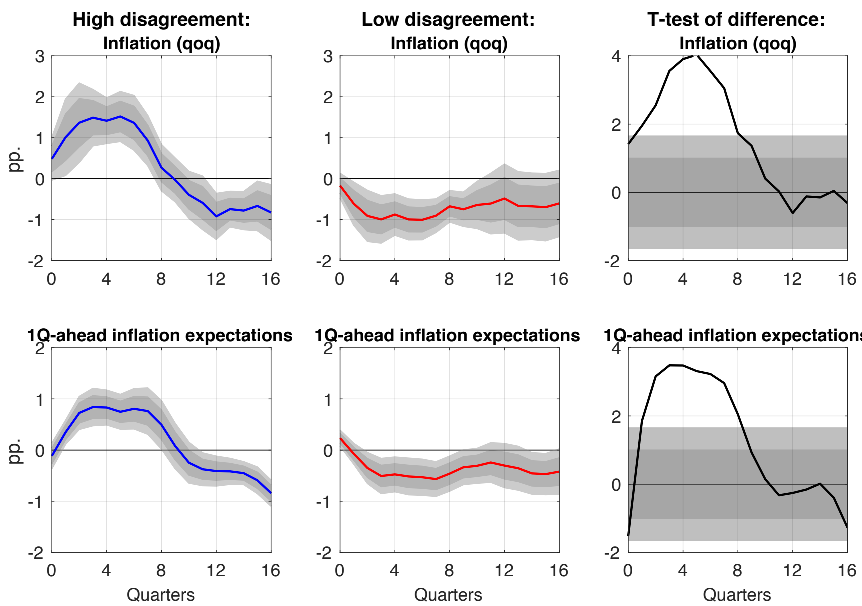
Notes: Results from the estimation of equation (11) with the actual yoy-inflation and inflation expectations over the next year as dependent variables. The estimation covers the sample 1970:IV-2007:IV. The solid lines in the left (middle) column show the point estimates β_i^H (β_i^L) for horizon i (x-axes). The right column shows the result of a t-Test for the difference between the high and low-disagreement regime. The grey areas show 68% and 90% confidence intervals and critical test values, respectively.

Figure 23: Baseline results, non-smoothed estimates



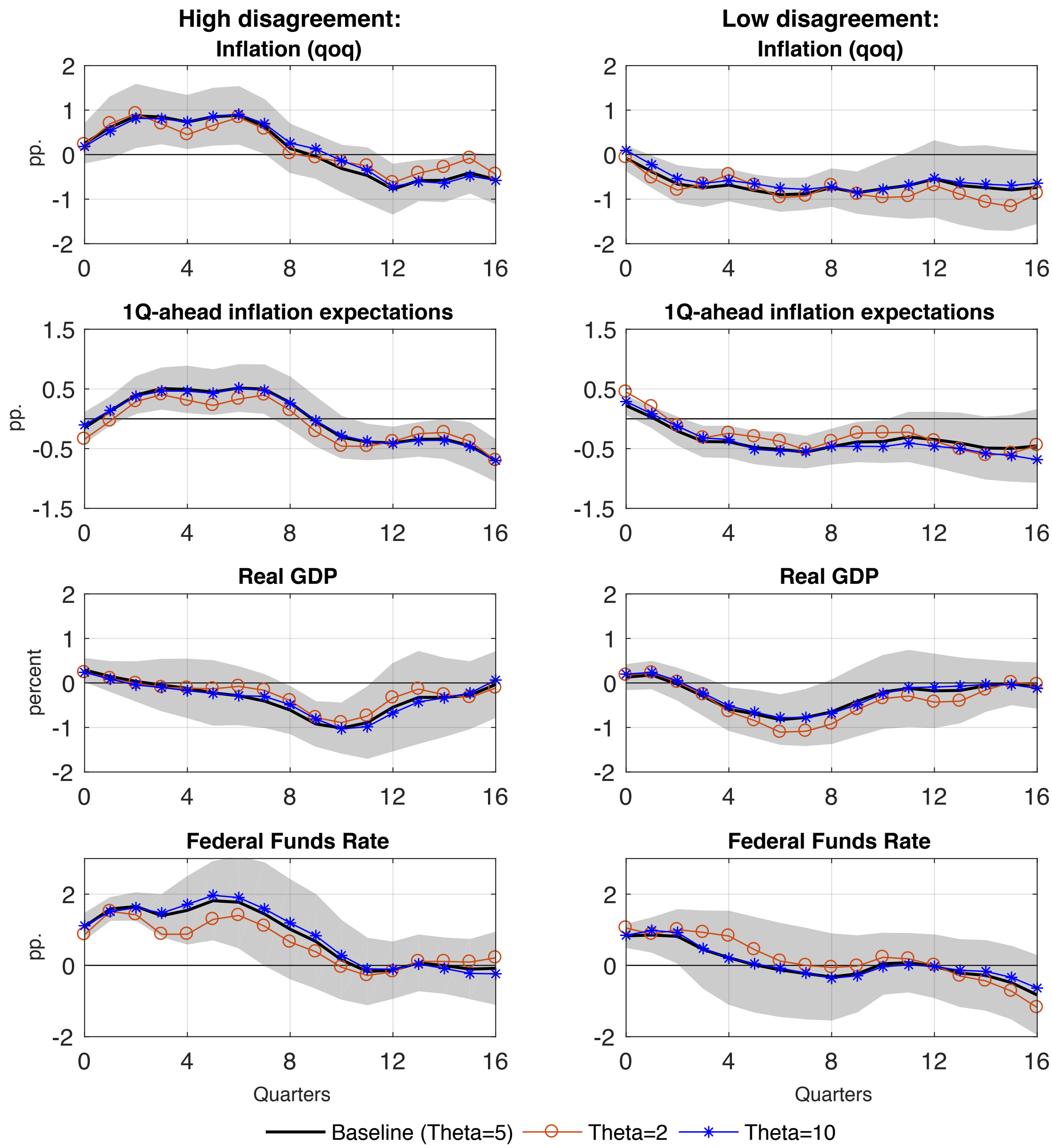
Notes: Non-smoothed results from the estimation of equation (11) with the Federal Funds Rate (FFR), real GDP (log), annualized qoq-inflation and annualized one-quarter-ahead inflation expectations as dependent variables. The estimation covers the sample 1970:IV-2007:IV. The solid lines in the left (right) column show the point estimates β_i^H (β_i^L) for horizon i (x-axes) in the high (low) disagreement regime. The coefficients are *not* smoothed over three consecutive periods. The grey areas display 68% and 90% confidence intervals.

Figure 24: Results for sample including the Great Recession



Notes: Results from estimation of equation (11) for the extended sample, 1970:IV-2015:IV, for annualized qoq-inflation and annualized one-quarter-ahead inflation expectations as dependent variables. We include two lags of the Federal Funds Rate and the dependent variable as controls. The solid line in the left (middle) column show the point estimates in the high-disagreement regime β_i^H (low-disagreement regime β_i^L) for horizon i (x-axes). The right column shows the result of a t-Test for the difference between the high and low-disagreement regime. The grey areas show 68% and 90% confidence intervals and critical test values, respectively.

Figure 25: Results for different regime-switching parameters



Notes: Responses to a 100 bps contractionary monetary policy shock using alternative values for θ in our baseline estimation in equation (11). The figures show 90% confidence intervals of the baseline specification. The black solid line reflects the baseline results from Section 4. The estimation covers the period: 1970:IV-2007:IV.

B.1 Disagreement and aggregate uncertainty

Some papers investigate whether the transmission of monetary policy changes with aggregate volatility and we contrast our results to this strand of the literature. In doing so we also shed new light on the connection between disagreement and aggregate uncertainty or volatility. As discussed in Section 2 the theoretical predictions of the full information model for different levels of productivity and demand shock volatility do not suggest state-dependent effects of monetary policy shocks on inflation and on inflation expectations. Therefore, we expect that the state-dependent results for times of high and low uncertainty differ from our baseline findings when using disagreement as regime-indicating variable.

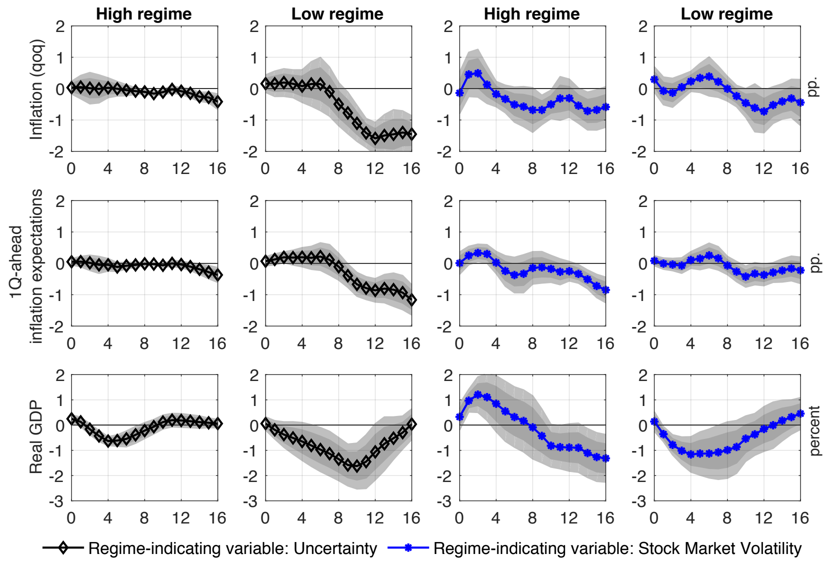
From a theoretical perspective disagreement and uncertainty are two distinct concepts. On the one hand, disagreement measures the cross-sectional standard deviation about heterogeneous but certain expectations of market participants. On the other hand, uncertainty is triggered by the volatility of aggregate shocks, which does not imply that individuals disagree in their expectations about the future (see Justiniano and Primiceri, 2008, Born and Pfeifer, 2014, Fernández-Villaverde et al., 2015). For example, periods with large aggregate shocks but no noise in the idiosyncratic signals are characterized by high uncertainty and no disagreement. To examine this issue, we re-estimate our baseline model using measures for uncertainty as regime-indicating variables instead of disagreement. In particular, we use the uncertainty measure of Jurado et al. (2015) and stock market volatility as implied by the S&P 500 Index as regime-indicating variables.[37] In our sample, disagreement about inflation expectations and measures of aggregate uncertainty do not co-move strongly.[38] For comparison, Figure 27 in the Appendix shows the evolution of the series, together with our measure for disagreement

When we use the uncertainty measure or stock market volatility as regime-indicating variable, we do not find significantly different inflation (expectations) responses across both regimes as shown in Figure 26. Interestingly, we find a significant initial increase in output in the high-uncertainty regime. This initial increase is particularly pronounced in the results for stock market volatility, but there is also a slightly significant initial increase when using the uncertainty measure of Jurado et al. (2015) (0.25 percent). Such a response cannot be observed in the low-uncertainty regime. Our estimated state-dependent responses in periods of high and low uncertainty or stock market volatility are in line with the results of previous studies, which show that the effect of monetary policy shocks are muted in times of high aggregate volatility, among these Aastveit et al. (2017), Pellegrino (2017), Caggiano et al. (2017), Eickmeier et al. (2016). Therefore, using uncertainty measures instead of disagreement in the regime-switching estimation do not, as expected,

[37]In detail, the stock market volatility reflects the quarterly sum of squared (daily) returns (S&P 500 Index), as suggested by Eickmeier et al. (2016).

[38]Disagreement and the uncertainty measure of Jurado et al. (2015) are mildly positively correlated (0.32).

Figure 26: The effects of monetary policy shocks for uncertainty and stock market volatility as regime-indicating variable



Notes: The figure shows the responses of the endogenous variables from a state-dependent estimation of equation (11) for different levels of stock market volatility and the uncertainty measure of Jurado et al. (2015). The stock market volatility is measured by the variance of the S&P 500 Index. The light and dark grey areas display 68% and 90% confidence intervals, respectively. The figure shows the smoothed IRFs and the estimation covers the period from 1970:IV to 2007:IV.

appear to be suitable proxies. This result is also supported by the finding that our baseline results do not change when we control for uncertainty in our baseline estimation. In particular, including lags of the uncertainty measure of Jurado et al. (2015) or lags for stock market volatility in equation (11) leaves the results unchanged (see Figure 12).[39]

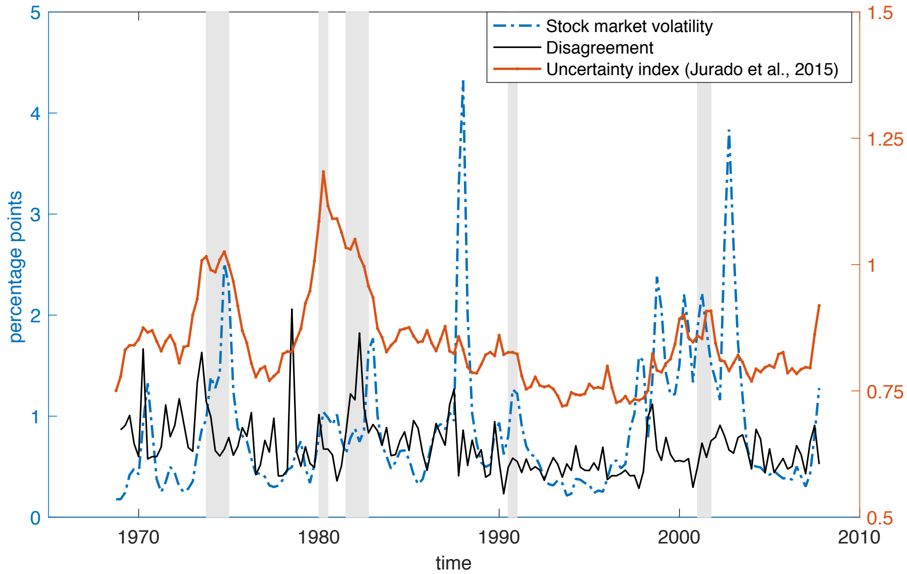
As mentioned before, the probability of being in the high-disagreement regime shows no clear pattern during NBER recessions (see Figure 4). While Dovern et al. (2012) document that disagreement about GDP expectations is correlated with recessions in G7 countries since the early 1990s, disagreement about inflation expectations is less correlated with recessions. In contrast, uncertainty and stock market volatility are positively correlated with the state of the economy and are significantly heightened in downturns (see Figure 27).

The probability of being in a high-disagreement regime is only weakly correlated with an equivalent measure for the probability to be in a recession. Following Tenreyro and Thwaites (2016), the probability to be in a recession is constructed by using a backward moving average of GDP growth as z_t variable in equation (11). The correlation between the probability to be in a recession and the probability to be in a high-disagreement regime amounts to 0.11 only. This observation is strengthened by a comparison of their and our empirical findings. In particular, as for

[39]We include lags of the variables because uncertainty very likely responds endogenously to the monetary policy shock.

uncertainty and stock market volatility, Tenreyro and Thwaites (2016) find state-dependent effects for real GDP, which increases on impact in recessions, but decreases in booms. Interestingly, the response of PCE-inflation is nearly identical in booms and contractions, with an only slightly faster decrease in expansions. We conclude that disagreement about short-term inflation expectations is not well proxied by various measures of uncertainty or the business cycle, and its interaction with monetary policy needs to be studied separately.

Figure 27: Disagreement and aggregate uncertainty



Notes: The figure shows the series of the uncertainty measure from Jurado et al. (2015) *(right axis)*, for stock market volatility measured by the quarterly sum of squared (daily) realizations of the S&P 500 index, as well as our regime-indicating variable z_t, which measures disagreement *(both left axis)*. The latter reflects the standard deviation over individual forecasts for next quarters price level (GDP deflator, SPF), scaled by the lagged expected inflation rate over the next quarter (SPF). The shaded areas reflect NBER recession dates.