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Disagreement and monetary policy

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Non-technical summary

Research Question

Time-variation in disagreement about inflation expectations is a robust fact from survey expectations data, such as the *Survey of Professional Forecasters*. Despite being closely monitored by central banks, little is known on how disagreement interacts with the efficacy of monetary policy. Against this background, this paper addresses the question: How does the transmission of monetary policy shocks change with the level of disagreement about inflation expectations?

Contribution

The aim of the paper is to examine whether monetary policy transmission changes with the level of disagreement about inflation expectations both from a theoretical and an empirical perspective. We explicitly exploit the fact that disagreement about inflation expectations varies over time to differentiate between the macroeconomic effects of monetary policy shocks in a high- and low-disagreement regime. The estimation results provide additional, novel insights for the conduct of monetary policy transmission. We then confront our theoretical predictions with our novel empirical evidence on the state-dependent effects (of disagreement) of monetary policy shocks. Therefore, our empirical results also contribute to inform the debate on different information structures used in the theoretical literature.

Results

When disagreement about inflation expectations is high, a New Keynesian dispersed information model predicts that a contractionary monetary policy shock can lead to a short-run rise in inflation, inflation expectations and a strong output decline. In contrast, in a low-disagreement environment, a contractionary monetary policy leads to a substantial decline in inflation and in inflation expectations. We test these state-dependent predictions empirically on U.S. data. In doing so this paper makes three contributions: (i) we estimate large, significant differences in the inflation and inflation expectations response between the low and high-disagreement regime, and (ii) when disagreement is high, inflation and inflation expectations increase by up to one percentage point after a contractionary monetary policy shock, and (iii) we provide empirical validation of dispersed information models where the nominal interest rate conveys additional information about the state of the economy.

Nichttechnische Zusammenfassung

Fragestellung

Zeitvariation in der Streuung individueller Inflationsprognosen ist ein etabliertes Ergebnis in Umfragedaten, wie dem *Survey of Professional Forecasters*. Obwohl Zentralbanken Inflationserwartungen und die Streuung von individuellen Inflationsprognosen genau beobachten, gibt es keine Studien, welche die Interaktion von heterogenen Inflationsprognosen und Geldpolitik analysieren. Vor diesem Hintergrund widmet sich das vorliegende Forschungspapier folgender Frage: Verändern sich die Effekte von Geldpolitik mit dem Ausmaß der Streuung in den individuellen Inflationsprognosen?

Beitrag

Die vorliegende Studie zeigt, dass die Transmission einer unerwarteten kontraktionären Geldpolitik sowohl theoretisch als auch empirisch vom Grad der Streuung in den individuellen Inflationsprognosen abhängig ist. Die Zeitvariationen in der Streuung individueller Inflationserwartungen werden hierbei ausdrücklich berücksichtigt. Die empirischen Ergebnisse dieses Forschungspapiers tragen auch zur Diskussion über unterschiedliche Informationsstrukturen in der theoretischen Literatur bei, welche zur Erklärung der Streuung individueller Inflationserwartungen herangezogen werden.

Ergebnisse

Die theoretische Analyse basiert auf einem neu-keynesianisches Modell mit einer dispersen Informationsstruktur im Firmensektor. Wenn die Streuung individueller Inflationserwartungen hoch ist, führt eine unerwartete Leitzinserhöhung zu einem kurzfristigen Anstieg der Inflation, Inflationserwartung und einem starken Rückgang der Produktionsleistung. Hingegen führt eine kontraktive Geldpolitik in einem Umfeld weitestgehend homogener Inflationserwartungen zu einem beträchtlichen Rückgang der Inflation und der Inflationserwartung. Es ergeben sich drei wesentliche Forschungsbeiträge: (i) Die empirischen Ergebnisse zeigen starke, statistisch signifikante Unterschiede in den Reaktionen der Inflation und Inflationserwartungen auf, wenn die Zustände einer hohen und geringen Streuung in den Inflationsprognosen verglichen werden, (ii) in Zeiten sehr heterogener Inflationserwartungen steigen Inflation und Inflationserwartungen in Folge eines kontraktiven geldpolitischen Schocks um bis zu einem Prozentpunkt, (iii) die Aussagen von Modellen mit dispersen Informationen, in denen der nominale Zinssatz zusätzliche Informationen zur konjunkturellen Lage liefert, werden empirisch validiert.

Bundesbank Discussion Paper No 29/2017

Disagreement and Monetary Policy*

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Abstract

Time-variation in disagreement about inflation expectations is a stylized fact in surveys, but little is known on how disagreement interacts with the efficacy of monetary policy. This paper fills this gap in providing theoretical predictions of monetary policy shocks for different levels of disagreement and testing these empirically. When disagreement is high, a dispersed information New Keynesian model predicts that a contractionary monetary policy shock leads to a short-run rise in inflation and inflation expectations, whereas both decline when disagreement is low. Estimating a smooth-transition model on U.S. data shows significantly-different responses in inflation and inflation expectations consistent with theory.

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

JEL classification: C52, D83, E31, E32, E52.

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1 Introduction

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, also be important for the transmission of monetary policy. A well-known and robust fact from survey expectations data is, indeed, 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). 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 different levels of disagreement about inflation expectations.

The conventional view of monetary policy transmission is that 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) challenges this view and argues for the existence of an additional, signaling channel of monetary policy that occurs in a model with heterogeneous information among firms. The signaling channel mutes the response of inflation and inflation expectations to a monetary policy shock. Intuitively, a rise in the nominal rate is perceived as a contractionary monetary policy shock, but also as a signal for an endogenous response of the central bank to a rise in inflation or the output gap. The second channel puts upward pressure on inflation and counteracts the conventional channel of monetary policy. The signaling channel arises due to heterogeneous information, which itself implies a certain level of disagreement about inflation expectations. However, substantial time-variation in disagreement about inflation expectations in survey data suggests that the strength of the signaling effect could vary strongly over time. In our empirical analysis, we directly use variations in disagreement over time to isolate the effects of the conventional and the signaling channel of monetary policy.

To set the stage, we derive state-dependent macroeconomic responses to monetary policy shocks for different levels of disagreement about inflation expectations building on the model of Melosi (2017). The information friction is embedded amongst firms which observe noisy idiosyncratic signals about aggregate productivity and preferences as well as a public endogenous signal: the nominal interest rate set by the central bank.[1] Through variation in the information precision of firms, we show that the model matches

[1]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).

the relative difference of high and low disagreement about one-quarter-ahead inflation expectations from the U.S. Survey of Professional Forecasters (SPF). When disagreement is high, the model predicts that a contractionary monetary policy shock increases inflation and inflation expectations for a plausible range of parameter values. 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 our empirical analysis to distinguish between regimes of low and high disagreement. Our empirical strategy allows us to test for the existence of the signaling channel of monetary policy without imposing any particular information structure.

We estimate the state-dependent effects of monetary policy shocks on the macroeconomy in regimes of high and low disagreement about inflation expectations. The estimation is based on a smooth transition local projection model on U.S. data. 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 regimes are identified with a measure for disagreement, which is calculated as the cross-sectional standard deviation of one-quarter ahead inflation expectations from the U.S. SPF. We map disagreement into a probability measure of either being in a high- or low-disagreement regime. The impulse responses to monetary policy shocks are estimated with the local projection method of Jordà (2005), which is combined with the smooth probability function to account for different disagreement regimes. The two key advantages of the empirical model are: First, we do not need to impose a specific autoregressive (VAR) structure for the data generating process and, second, we allow for a smooth transition between the regimes, since there is no clear cut-off for a fixed threshold for disagreement.

We find significant 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 and an amplified decline in output.[2] In contrast, when disagreement is low, a contractionary shock leads to a decline in inflation of close to one 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.

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

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, and to an amplified effect on output. 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, not with those in the high-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 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.

In addition, we find that disagreement itself does not respond endogenously to the monetary policy shock. This result matches the implications of noisy information models. In contrast, sticky information models imply that disagreement adjusts endogenously to the shock, as explained in Mankiw and Reis (2002). Therefore, our empirical results also allow us to distinguish between the theoretical predictions of alternative information structures widely used in the literature.

Wider literature Our paper is connected to several strands in the literature. In particular, we combine insights from three different research fields: survey data on inflation expectations, reduced-form models of dispersed information and structural dispersed information New Keynesian models.

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. In this paper, we focus on disagreement about inflation expectations and exploit the fact that disagreement varies over time in our empirical analysis. 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.[3] In addition, Coibion and Gorodnichenko (2012, 2015), and Andrade et al.

[3]Data from the Survey of Professional Forecasters (SPF) suggests 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 document that *Blue Chip Financial Forecasts*

(2016) present compelling evidence that dispersed information models provide a better fit compared to full information models. Their insights are based on reduced-form models, whereas we derive predictions from a structural New Keynesian model commonly used for monetary policy analysis, since our interest lies in the transmission of monetary policy shocks on the macroeconomy.

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 (2013) is the first paper that combines 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 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.

The paper is closely related to 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. Melosi (2017) estimates a richer version of the stylized model outlined here with Bayesian methods on U.S. data, where the signal precision and hence disagreement about inflation expectations is constant over time. We follow a different, complementary approach based on an empirical estimation strategy. We explicitly exploit the fact that disagreement about inflation expectations varies over time to differentiate between the macroeconomic effects of monetary policy shocks in a high- and low-disagreement regime.

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.

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indicate very low disagreement about the next quarter's Federal Funds Rate.

2 Disagreement in a New Keynesian model

This section presents a New Keynesian model with dispersed information on the firm side. 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). The main difference to Melosi (2017) is that we assume that the central bank has full information, which does not change the existence of the signaling channel. The main objective is to 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

We outline a theoretical framework with the necessary ingredients to examine the interaction of disagreement and the transmission of monetary policy shocks. First, we briefly present the widely-used full information New Keynesian model, which serves as a useful benchmark to assess the transmission of monetary policy. In a second step, we describe the dispersed information model in detail which otherwise builds on the full information New Keynesian model. In this model we can control the level of disagreement about inflation expectations.

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 $\epsilon_t^i, i = a, d, m$. We assume that household utility is additively-separable in consumption and labor, where γ denotes the coefficient of constant relative risk aversion and φ measures the inverse Frisch elasticity. A fraction, $1 - \theta$, 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:

$$
\begin{aligned}
\gamma\widehat{y}_t &= \hat{d}_t - \mathbb{E}_t\hat{d}_{t+1} + \mathbb{E}_t\gamma\widehat{y}_{t+1} + \mathbb{E}_t\widehat{\pi}_{t+1} - \hat{r}_t & (1)\\
\widehat{\pi}_t &= \frac{(1-\theta)(1-\theta\beta)}{\theta}((\gamma+\varphi)\widehat{y}_t - (1+\varphi)\widehat{a}_t) + \beta\mathbb{E}_t\widehat{\pi}_{t+1} & (2)\\
\hat{r}_t &= \phi_\pi\widehat{\pi}_t + \phi_y\left(\hat{y}_t - \frac{1+\varphi}{\gamma+\varphi}\hat{a}_t\right) + \widehat{m}_t\ , & (3)
\end{aligned}
$$

where $\hat{x} = \log(x_t) - \log(\bar{x})$ denotes log-deviations from steady state. The three exogenous stochastic processes are:

$$a_t = \rho_a a_{t-1} + \epsilon_t^a, \qquad \epsilon_t^a \sim N(0, \sigma_a^2) \tag{4}$$
$$d_t = \rho_d d_{t-1} + \epsilon_t^d, \qquad \epsilon_t^d \sim N(0, \sigma_d^2) \tag{5}$$
$$m_t = \rho_m m_{t-1} + \epsilon_t^m, \qquad \epsilon_t^m \sim N(0, \sigma_m^2) \; . \tag{6}$$

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 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.[4] 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:

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

[4] Coibion and Gorodnichenko (2012) estimate regressions of forecast errors on structural shocks. They find strong evidence for autocorrelation in the average forecast errors, which can be explained by dispersed information models.

Hence, the 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:

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

Firms also observe the policy instrument R_t, i.e. the nominal interest rate, as a public endogenous signal of the central bank as well as their own price history. Each firm j has its individual information set in period t:

$$\mathbb{I}_{j,t} = \{\log A_\tau(j), \log D_\tau(j), R_\tau : \tau \leq t\} \,, \tag{9}$$

which results in cross-sectional heterogeneity in beliefs across firms. The unobserved aggregate processes, a_t and d_t, follow the specification in equations (4) and (5). 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 at all.

As mentioned before we assume that all firms observe the central bank's policy instrument, r_t. The nominal interest rate follows the same policy rule as in the full information model, specified in equations (3) and (6). 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. As mentioned before, the signaling channel of monetary policy (Melosi, 2017) is also referred to as 'Delphic effect' (Campbell, Evans, Fisher, and Justiniano, 2012), since the interest rate signals the central bank's judgment about its current macroeconomic outlook to market participants.

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*:

$$\widehat{\pi}_t = (1-\theta)\,(1-\theta\beta)\sum_{k=1}^{\infty}(1-\theta)^{k-1}\,\widehat{mc}_{t|t}^{(k)} + \theta\beta\sum_{k=1}^{\infty}(1-\theta)^{k-1}\,\widehat{\pi}_{t+1|t}^{(k)}\,, \tag{10}$$

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 (2)). 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.[5]

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 any future macroeconomic variables. 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. $\bar{X}_{t|t}(i)$. 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 Lyaponov equation, as shown in Nimark (2011):

$$V_t = \Sigma_j = (I-KD)M\Sigma_j M'(I-KD)' + K\Sigma_{EE}K'\,. \tag{11}$$

[5]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 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. 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

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 to build up economic intuition on how these beliefs drive the aggregate effects. The Online 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, L'Huillier, and Lorenzoni (2013). Among these papers there is

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 TFP	0.9
ρ_d	Autocorrelation preference	0.9
$100\sigma_m$	Std. dev. of monetary policy shock	0.2
$100\sigma_a$	Std. dev. TFP shock	1.0
$100\sigma_d$	Std. dev. preferences shock	1.0
$100\tilde{\sigma_a}$	Std. dev. idiosyncratic TFP noise	1.0
$100\tilde{\sigma_d}$	Std. dev. idiosyncratic preference noise	1.0

some disparity regarding the calibration of the signal-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.[6] 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.[7] We show that the model can 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-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, as indicated by the bottom part of Table 1.

2.2.1 Prior predictive analysis

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. In particular, 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.[8] Since we are interested in the monetary 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.[9]

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

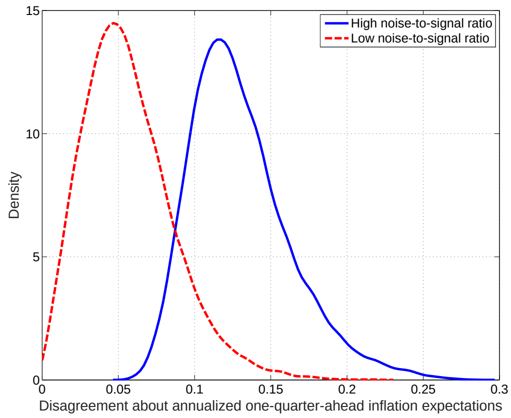
[6]The first-order expectation corresponds to the expectation reported in survey data, such as the U.S. Survey of Professional Forecasters.

[7]Figure 18 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.

[8]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.

[9]Our results are robust to keeping the Taylor rule coefficients fixed.

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.

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.[10] 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.

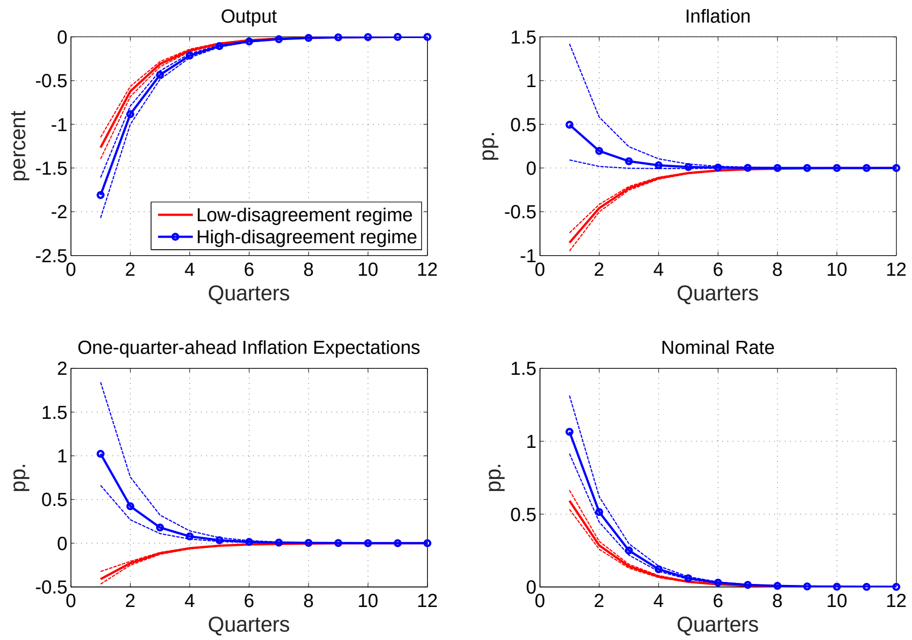
Overall, we use relatively wide prior distributions for the noise variances such that disagreement about one-quarter-ahead inflation expectations has some overlap in both regimes in line with our empirical estimation results shown later (see Figure 18). Using tighter priors implies that the distributions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

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 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 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 significantly different and strongly changes with the level of disagreement about inflation expectations.

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

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

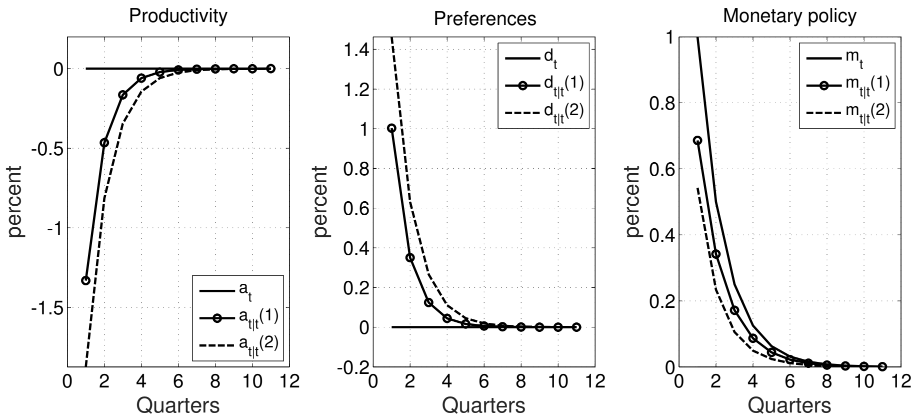


Notes: Impulse responses to a 100 basis points contractionary monetary policy shock in the low- and the high-disagreement regime. Inflation expectations are the firms' average first-order expectations. Confidence bands represent the 90^{th} and 10^{th} percentile based on prior predictive analysis.

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).

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. Note that the evolution of the higher-order beliefs determines the current inflation rate as shown by the dispersed information NKPC (see equation (10)). 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

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.

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, while the output response is amplified. To trace out the relative importance of the information and interest rate channel in driving the aggregate macroeconomic dynamics, the next section decomposes the overall effect of a monetary policy shock into the two channels.

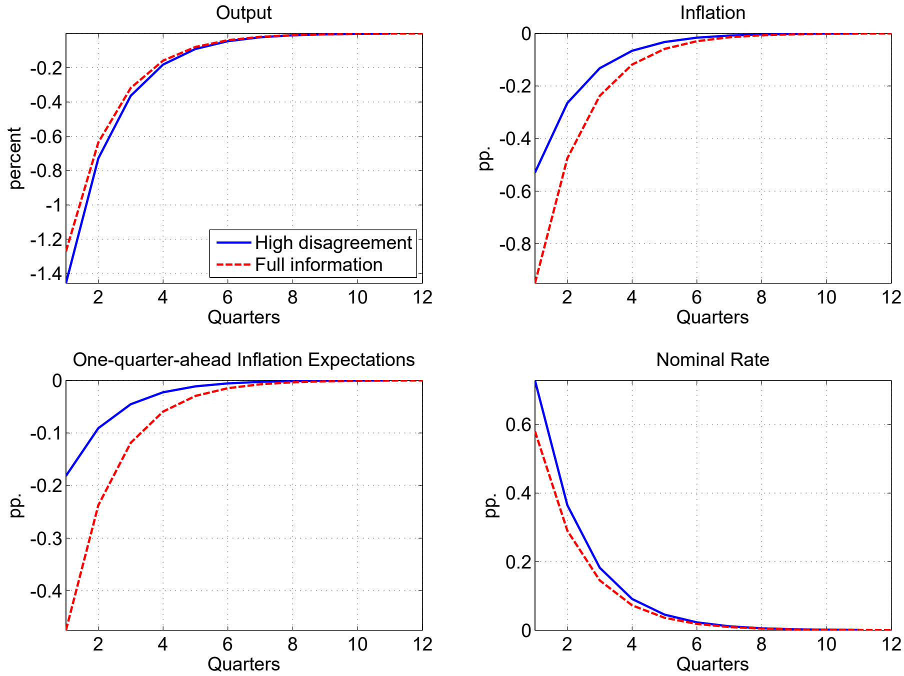
2.2.3 Dissecting the signaling and the interest rate channel

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 4 illustrates the effects of the pure interest rate channel in the high-disagreement case and compares them to 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. Thefore, 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 5 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 drives the strong increase in inflation and in inflation ex-

Figure 4: The interest rate channel



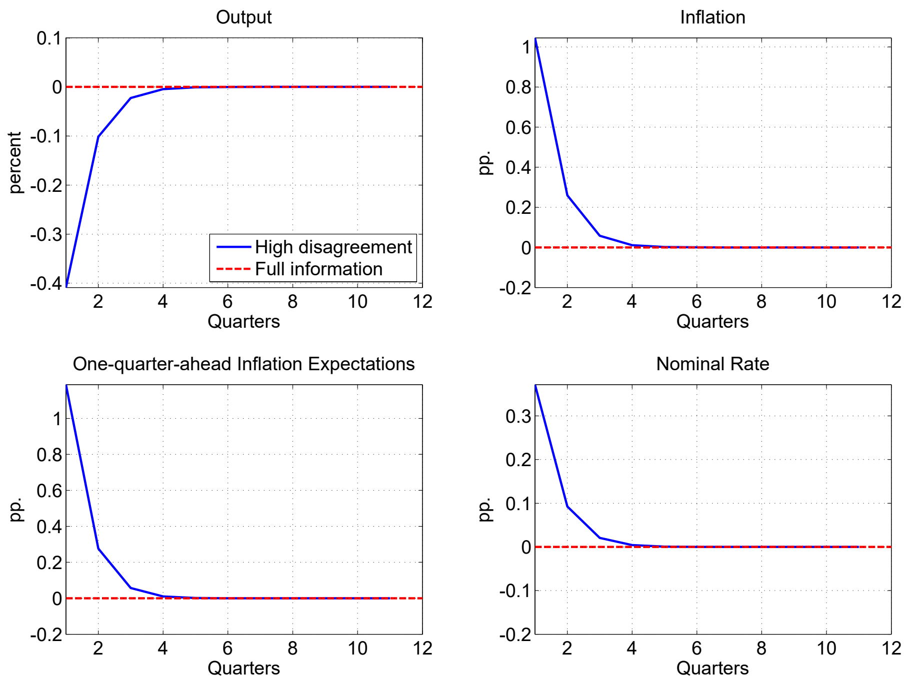
Notes: Impulse responses to a 100 basis points contractionary monetary policy shock in the dispersed information (high-disagreement) New Keynesian model only attributed to the response of beliefs stemming from an actual monetary policy shock. The dashed line is the response to the monetary policy shock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

pectations. The intution 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 5.

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.

One goal of our empirical estimation strategy is to test the theoretical predictions to provide external validation of the signaling channel and potential state-dependent effects

Figure 5: 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.

of monetary policy shocks. In addition, our empirical evidence also provides quantitative results on the transmission of monetary policy in states of low and high disagreement and whether these differ significantly. The next section carefully outlines our empirical methodology.

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:

$$y_{t+i} = \tau_i t + (\alpha_i^H + \beta_i^H \varepsilon_t + \gamma_i^H x_t)F(z_t) + (\alpha_i^L + \beta_i^L \varepsilon_t + \gamma_i^L x_t)(1 - F(z_t)) + u_{t+i}, \quad (12)$$

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.[11] The smooth shape of the function, therefore, takes into account that some periods cannot be clearly allocated to one of the regimes. We model the continuous function $F(z_t)$ with a logistic shape:

$$F(z_t) = \frac{exp(\theta \frac{z_t - c}{\sigma_z})}{1 + exp(\theta \frac{z_t - c}{\sigma_z})}, \quad (13)$$

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.[12] Previous studies parameterize rather than estimate the degree of regime-switching (Auerbach and Gorodnichenko, 2013; Tenreyro and Thwaites, 2016; Santoro, Petrella, Pfajfar, and Gaffeo, 2014).[13] We use a value of $\theta = 5$, but our results are robust to a wide range of values. It is noteworthy that equation (12) 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

[11] 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.

[12] For $\theta \to \infty$, the model converges to a discrete threshold model with a clear cutoff (as in Ramey and Zubairy (ming)), 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.

[13] 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.

(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 12 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 autoregressive model would require the modeling of the exact transmission process for z_t.[14]

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.[15]

3.2 Data

Our sample is based on quarterly U.S. data and covers the period from 1968: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 expecta-

[14]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.

[15]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.

tions 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). In particular, we use the updated and extended shock series by Wieland and Yang (2016) to account for the longer sample.[16]

We measure inflation expectations and disagreement about inflation expectations across forecasters from the U.S. Survey of Professional Forecasters (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

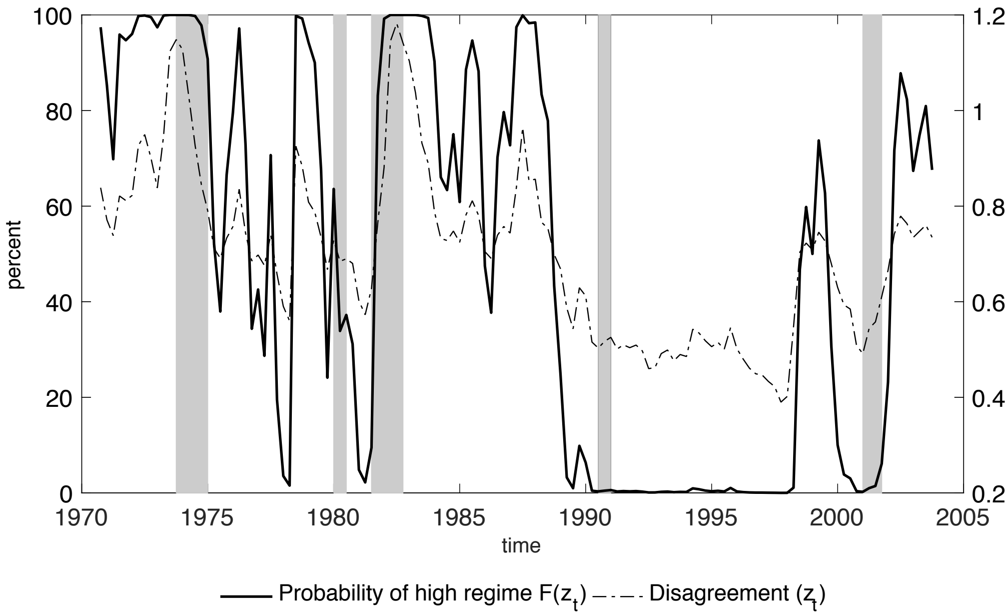
Disagreement about inflation expectations shows considerable variation over time and at all horizons (Andrade et al., 2016; Mankiw et al., 2004). In accordance with the theoretical model, we focus primarily on forecasts for the next quarter. However, our results remain unchanged if we instead use the forecast for the next year.[17] Our sample includes the 1970s where inflation and disagreement prevailed at historically high levels (see Figure 16). We address this issue along four different dimensions: (i) we scale disagreement by the expected inflation rate in the previous quarter in order to control for periods of relatively high inflation rates, and we provide robustness results: (ii) excluding the first part of the sample, (iii) employing alternative measures of disagreement, and (iv) adding further control variables.[18] Figure 19 in the Appendix shows the evolution of disagreement which is scaled by the lagged value of expected inflation and its unscaled version. The figure

[16] 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 find no significant predictability of the shock series.

[17] In our sample, the correlation between disagreement (measured as the standard deviation across forecasters) over inflation for the next quarter and next year is above 0.9.

[18] 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). The scaled disagreement reduces the correlation below a level of 0.2.

Figure 6: 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 (U.S. SPF). $F(z_t)$ covers the years 1970:IV to 2003:IV. The grey areas indicate NBER recessions.

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.

As suggested in the literature, we use a seven-period backward looking moving average to smooth our regime-indicating variable z_t.[19] 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.

Figure 6 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 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

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

the *Great Moderation*. 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 6 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. From a theoretical perspective, disagreement is the result of information dispersion, with heterogeneous but certain expectations about the future stance of the economy. A fact which distinguishes it from other variables, such as uncertainty and aggregate volatility. We will address this issue in detail in our robustness section.

4 The state-dependent effects of monetary policy

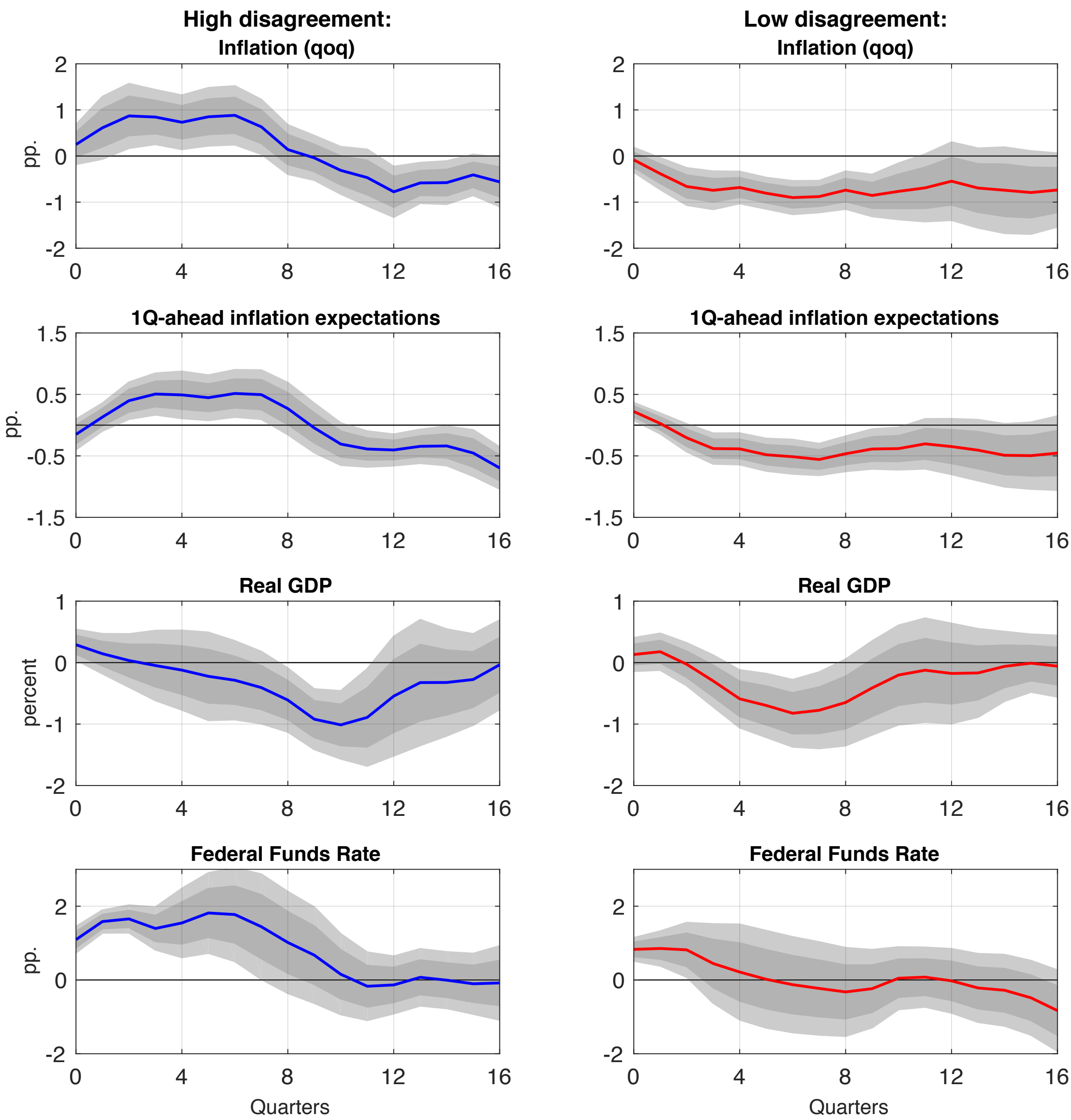
This section presents the main results of our empirical analysis. It particular, we show that the transmission of monetary policy differs strongly between the low- and high-disagreement regime. In addition, we assess the empirical results against the backdrop of the theoretical predictions derived in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

4.1 Baseline results

Figure 7 shows the impulse responses of 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 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 in order to smooth the impulse response functions (the first and last coefficient is not smoothed). In the Appendix we also show the non-smoothed version.

The first and second row of Figure 7 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

Figure 7: The state-dependent effects of a 100 basis points monetary policy innovation



Notes: Estimation results of equation (12) with (annualized) inflation (qoq) and (annualized) expected inflation (qoq), 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 endpoints, the coefficients are smoothed over three consecutive periods. The grey areas display 68% and 90% confidence intervals.

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 hit 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 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 7. On impact, the monetary policy shock leads to a small but insignificant output puzzle in the both regimes.[20] 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 7. 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 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 (expectations) under high and low disagreement. More precisely, to counteract the rise 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.

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 8 shows the corresponding values of the t-statistic and critical values also for longer horizons. The coefficients of inflation and inflation ex-

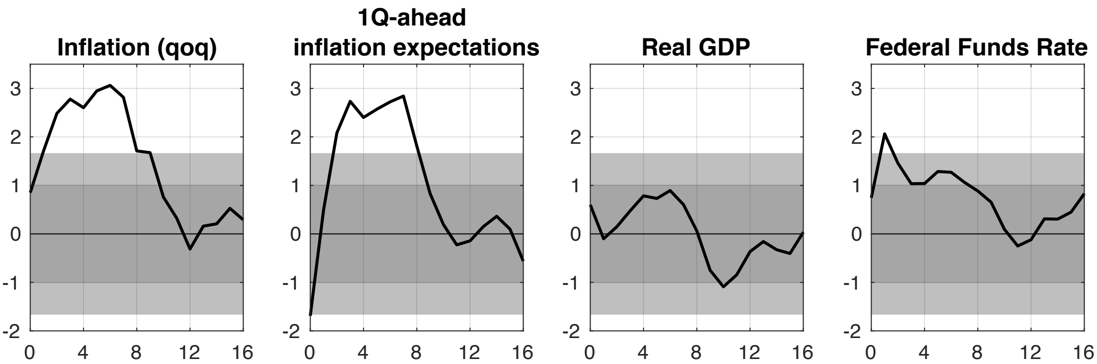
[20]The output puzzle is also found for state-dependent effects of monetary policy shocks in booms and recessions by Tenreyro and Thwaites (2016). We address the similarities and differences to their results in the robustness section.

Table 2: Difference of coefficients between the regimes

Horizon	Inflation (qoq)	Exp. Inflation (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.

Figure 8: t-Tests of state-dependent effects



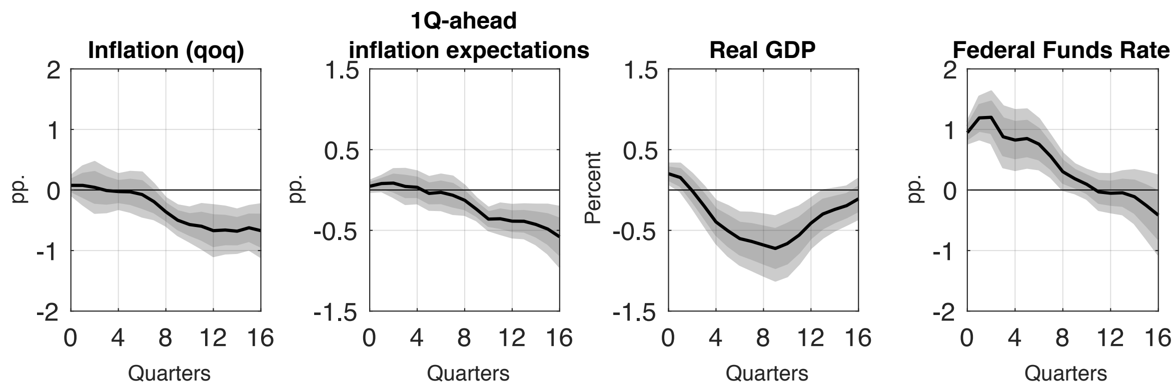
Notes: The figure shows the value of the t-statistic that tests whether the coefficients in the two regimes are significantly different from each other at horizon i: $H_0 = \beta_i^H - \beta_i^L = 0$. The estimation covers the sample 1970:IV-2007:IV. The grey areas show critical values at the 68% and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

pectations 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 (12) for an extended sample which includes the Great Recession: 1970:IV until 2015:IV.[21] 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 (forthcoming). These additional results can be found in Figure 25 in the Appendix.[22] In particular, the responses of inflation and one-quarter-ahead inflation expectations are significantly state-dependent on the disagreement regime. We prefer our 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 9 shows the results for the linear model that is estimated without accounting for state-dependent effects. This corresponds to equation (12) with $F(z_t)$ being zero (or one) in each period. Output declines by up to 0.8 percent and inflation 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, Eichenbaum, and Evans, 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.

Figure 9: Estimation of linear model without regimes



Notes: Results from the linear estimation of equation (12), 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 grey areas show 68% and 90% confidence intervals.

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

[22] 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.

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, with the results from the estimation without regimes (see Figure 9). 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

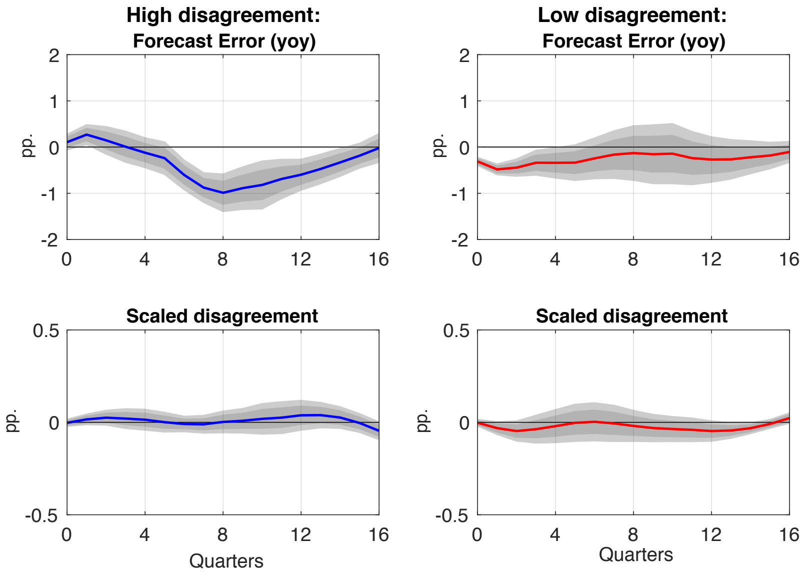
	Full info	Exogenous dispersed info	Exo. dispersed info + endogenous signal
Monetary policy shock observed	yes	yes	no
Misperception of MP shock	no	no	yes
Disagreement about exogenous var.	no	yes	yes
Disagreement about infl. expect.	no	yes	yes
Autocorr. of forecast errors	no	yes	yes
Inflation response	negative	negative	positive
Inflation expectations response	negative	negative	positive
Output response	negative	negative	amplified

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 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 do not differ markedly.[23]

[23] As described in Section 2, the differences in the impulse responses are driven by the fact that agents

Figure 10: The indicator variable z_t and inflation forecast error



Notes: Empirical results from estimating equation (12) with the forecast error for next years inflation rate and the regime-indicating variable z_t (scaled 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 grey areas display 68% and 90% confidence. intervals

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 analysis we can further distinguish between the different information assumptions that we summarized in Table 3. In Figure 10, 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. The observation of autocorrelated average forecast errors is in fact a general property of a larger class of imperfect information models (Coibion and Gorodnichenko, 2012, 2015). The finding that the forecast errors are also mildly autocorrelated in the low-disagreement regime highlights that this regime is also characteerized 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 re-

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.

sults 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 their settings, 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 add 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.[24] These models also predict correlated forecast errors. When price-setting firms have the same imprecise information about the true supply 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 information model predicts zero disagreement about macroeconomic expecations. Hence the empirical results for the high disagreement regime cannot be reconciled with incomplete information models.

Other papers, among these Giordani and Söderlind (2003), suggest that disagreement and uncertainty can be good proxies for each other. However, the effects of uncertainty are typically studied in full-information models. As a result, agents in the model do not make any systematic forecast errors. Therefore, a pure uncertainty model is not suited to explain the empirical results. Later, in our robustness section we explore the differences between disagreement and uncertainty as regime-indicating variable.

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.

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

We test the endogeneity of disagreement by using it as dependent variable in equation (12). Our results confirm that disagreement does not respond significantly to the monetary policy surprise (Figure 10).[25] 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. Furthermore, we compare our findings to estimates when replacing disagreement by measures for uncertainty.

5.1 Measures and scaling of disagreement

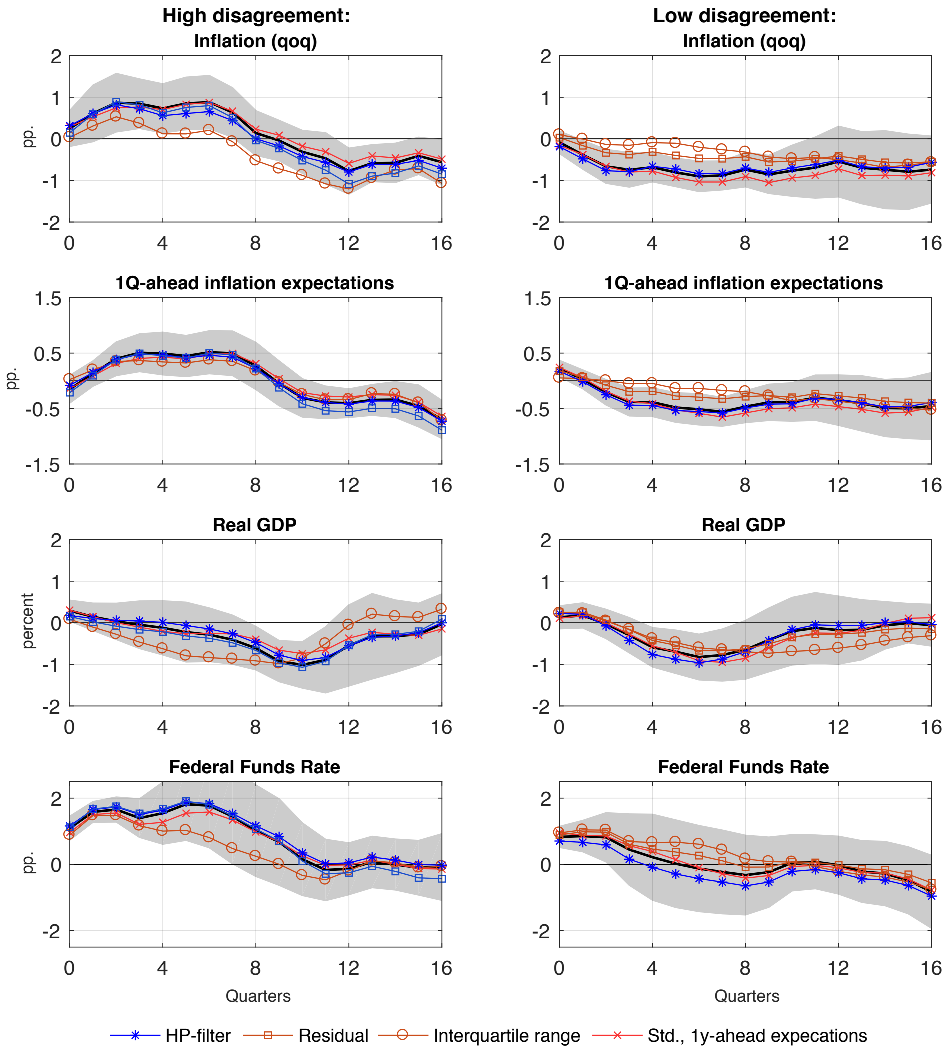
So far we have measured disagreement by the standard deviation of the individual point forecasts for the price index in the next quarter. In this section, we test the robustness of our results when we use alternative measures for our regime-indicating variable disagreement. Our baseline results remain unchanged when we use disagreement about one-year ahead price expectations instead. This results are reflected by the crossed red lines in Figure 11.

We measure the disagreement about one-year ahead price expectations by the standard deviation over the individual point forecasts (SPF) for the price index one year ahead. Furthermore, it is sometimes argued that calculating disagreement by the interquartile range (IQR) makes it a more robust measure against possible outliers. The circled red lines in Figure 11 illustrate that our baseline results do not change qualitatively when

[25] 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 (12).

employing the IQR instead of the standard deviation of the individual point forecasts for the price index.

Figure 11: Results for various measures for disagreement



Notes: Responses to a 100 bps contractionary monetary policy shock using alternative regime-indicating variables in our baseline estimation in equation (12). The figures show 90% confidence intervals of the baseline specification. The *HP-filter* estimation uses a HP-trend of expected inflation ($\lambda = 100$) to scale disagreement, whereas the specification *Residual* uses the residual from a regression of disagreement on one lag of expected inflation. 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 Section 3.3 we have discussed the scaling of our disagreement measure to control for possible effects of the actual level and volatility of inflation on disagreement. We also confirm that our results are robust to alternative scaling methods. In particular we provide results for two alternative methods: (i) we either use a HP-trend of expected inflation ($\lambda = 100$) to scale disagreement, and (ii) the alternative specification *Residual* uses the residual from a regression of disagreement on one lag of expected inflation as regime-indicating variable. The respective blue lines with stars or squares in Figure 11 mirror that also for those measures our baseline results remain unchanged.

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 z_t. Previous literature has not reached a consensus on a specific parameter value. Therefore, we explore whether our results change for alternative values of θ. Figure 20 in the Appendix illustrates how the curvature of the indicator function $F(z_t)$ changes with θ. For a very high value of θ, the model converges to a fixed threshold model in which each period is assigned to one regime only. To investigate the robustness of our results to different parameter values, we re-estimate equation 12 for alternative values for θ. Figure 26 shows the impulse responses for $\theta = 2$ and $\theta = 10$, together with our baseline results. The results for the alternative values are nearly identical to our baseline results, indicating that our findings are robust to variations in θ over a plausible range.

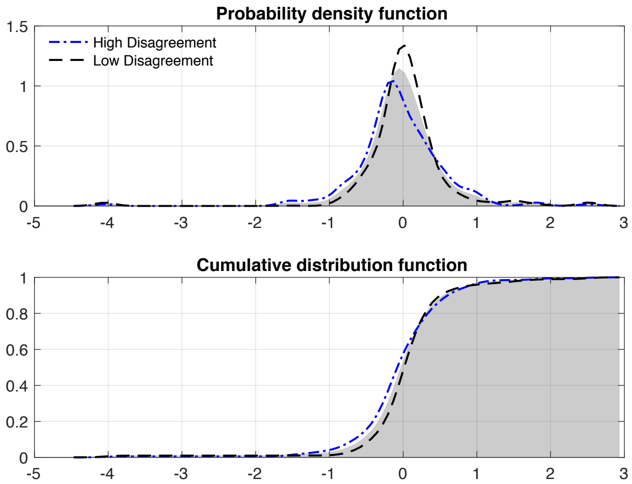
5.3 Distribution of shocks

A potential concern is that monetary policy shocks are larger (or different) in periods of high disagreement about inflation expectations. In principle, differences in the monetary policy shock series could account for the state-dependent effects of monetary policy shocks in the regimes. To address this concern, Figure 12 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.

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

Figure 12: 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). For the figure, the monetary policy shock series of Wieland and Yang (2016) 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 in for 2007:IV.

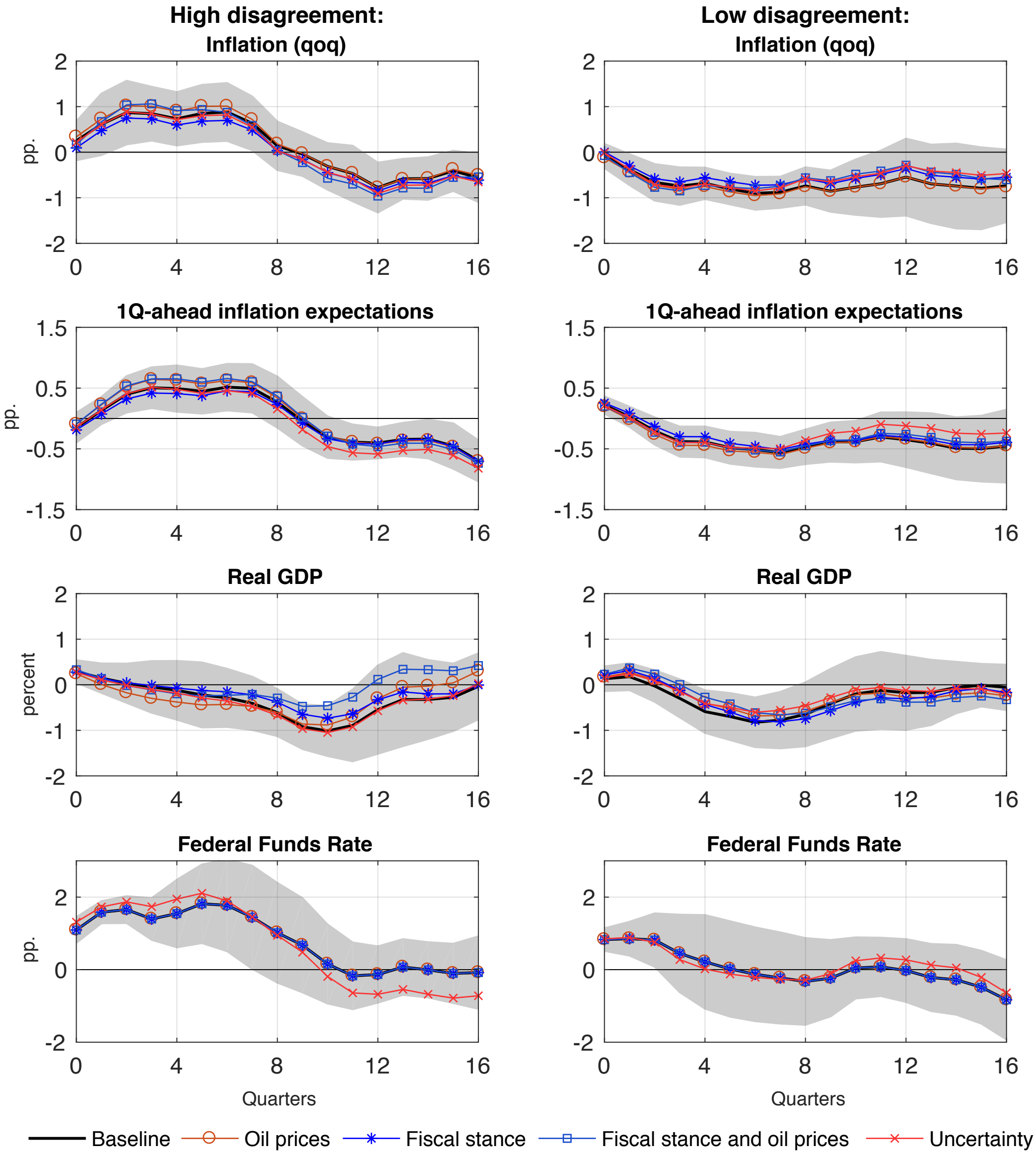
baseline specification in equation (12), we include one lag of the Federal Funds Rate and one lag of the dependent variable as control variables. As mentioned earlier, we do not need to model the dynamics of the dependent variable due to the horizon-specific estimation of the impulse response functions. As expected, robustness checks confirm that our findings are robust to alternative specifications with more lags of the dependent variable (see Figure 27). 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 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.

To control for the possibility that other factors drive the observed rise in inflation, 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).

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 13).

There is an ongoing debate about the interaction between fiscal and monetary policy.

Figure 13: 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 (12). The *uncertainty* specification controls for one lag of stock market volatility and the uncertainty measure of Jurado, Ludvigson, and Ng (2015). 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.

For example, Davig and Leeper (2011) identify the late 1960s and 1970s as a regime of passive monetary policy and a more active fiscal policy stance. 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. Woodford (1995) shows that this positive wealth effect occurs under fiscal dominance, because households believe that higher government debt does not cause any higher future taxes. Households therefore increase their consumption. Then, for a given aggregate supply, the government's budget constraint requires the price level to increase enough to reduce real debt. The rise in the price level ensures then also an equilibrium in the goods market. To account for the stance of fiscal policy, we control both for the change in the debt-to-GDP ratio as 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 13).

5.5 Disagreement and uncertainty

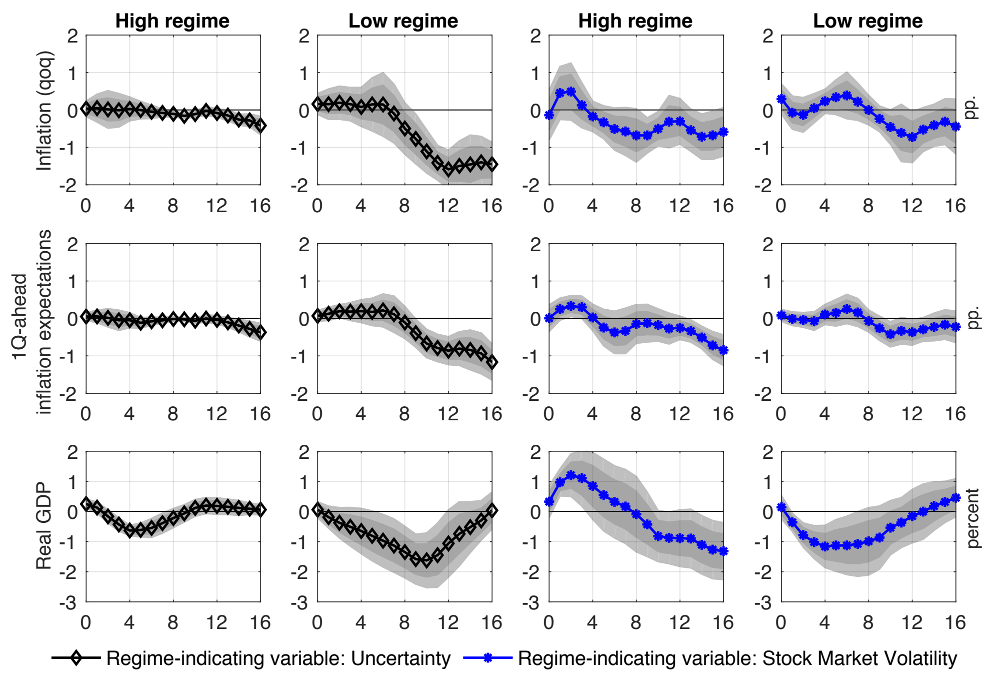
There is some discussion to what extend disagreement constitutes a good proxy for uncertainty, among these Giordani and Söderlind (2003). However, recent work by Boero, Smith and Wallis (2008), Rich and Tracy (2010); Abel, Rich, Song, and Tracy (2016); Rich and Tracy (2017) argues that disagreement is a poor proxy for uncertainty for both the U.S. SPF and the ECB SPF. In our sample, disagreement about inflation expectations and measures of uncertainty do not co-move strongly.[26] Therefore, we expect that the state-dependent results for times of high an low uncertainty differ from our baseline findings for disagreement. 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 Born and Pfeifer, 2014; Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2015). For example, periods with large aggregate shocks but no noise in the idiosyncratic signals are characterized by high uncertainty and no disagreement. To assess this conjecture, 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.[27] Figure 28 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 as shown in Figure 14. Interestingly, we find a significant initial increase in output in the high-

[26]Our measure of disagreement and the uncertainty measure of Jurado et al. (2015) are mildly positively correlated (0.32).

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

Figure 14: 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 (12) for different levels of stock market volatility and the uncertainty measure of Jurado et al. (2015). The shock market volatility is measured by the variance of the S&P 500 Index. The figure shows the smoothed IRFs and the estimation covers the period from 1970:IV to 2007:IV.

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 pattern 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, Natvik, and Sola (2013); Pellegrino (2017); Caggiano, Castelnuovo, and Nodari (2017); Eickmeier et al. (2016). Therefore, using uncertainty measures instead of disagreement in the regime-switching estimation do not 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 (12) leaves the results unchanged (see Figure 13).[28]

As mentioned before, the probability of being in the high-disagreement regime shows no clear pattern during NBER recessions (see Figure 6). While Dovern et al. (2012)

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

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 28).

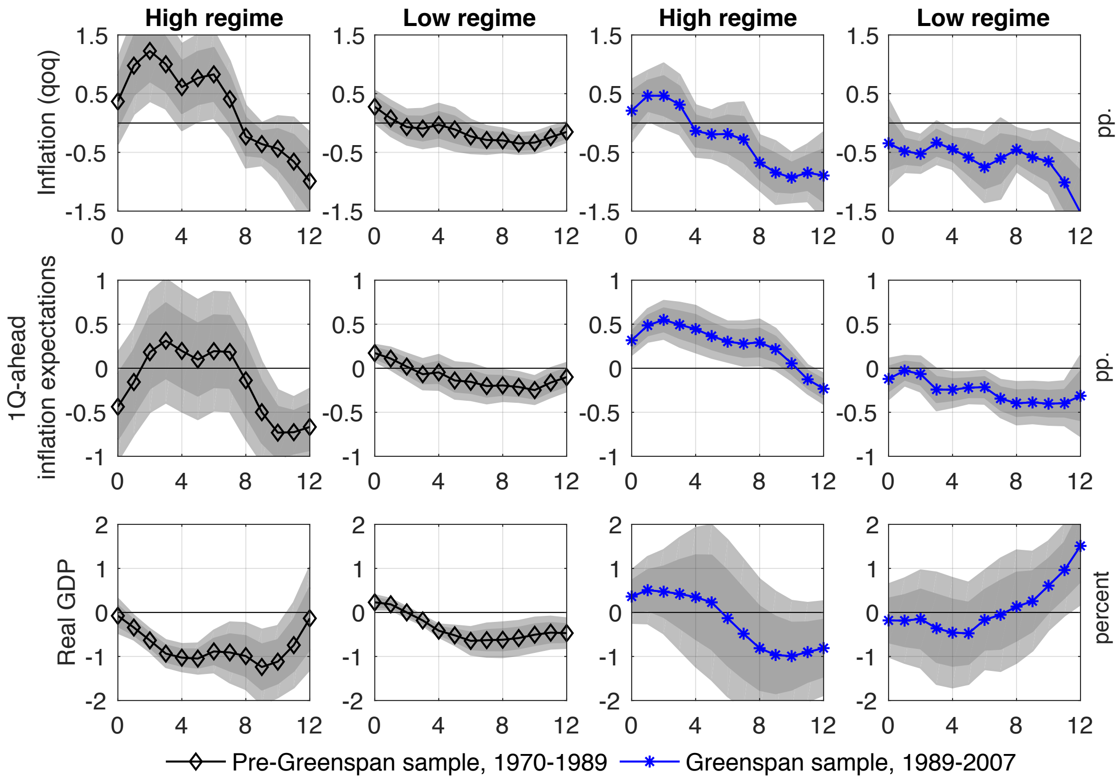
The probability of being in a high-disagreement regime is only weakly correlated with an equivalent measure for the probability to be in a recession. Following Tenreyro and Thwaites (2016), the probability to be in a recession is constructed by using a backward moving average of GDP growth as z_t variable in equation (12). 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 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.

5.6 Sub-sample stability

Previous literature argues that monetary policy transmission has changed over time. Among these, Barakchian and Crowe (2013) find quite different results of monetary policy shocks for the sub-samples pre- and post-1988 across various identification methods. Also Ramey and Zubairy (ming) re-estimate the regression of Romer and Romer for the period 1983-2007 and find that the monetary policy shock has an expansionary effect on output. While monetary policy has become more forward-looking in the more recent sample, our results might also depend on the fact that disagreement was rather low after 1990 and rather high before. We address this concern and re-estimate our baseline results for the periods pre- and post-1988. Our precise sample split corresponds to the start of the Greenspan-era, which aligns 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.

Reassuringly, Figure 15 shows that our baseline results are qualitatively unchanged for the two samples. The response of inflation in the two regimes remains statistically significant from each other at the 90% confidence level at small horizons in both sub-samples. For expected inflation the responses are significantly different from each other at the 90% level in the Greenspan sample. However, the difference is not statistically significant in

Figure 15: Sub-sample stability



Notes: Responses to a 100 bps contractionary monetary policy shock in the two sub-samples. The coefficients are smoothed over three consecutive periods. The x-axes indicates quarters after the shock hits the economy.

the pre-Greenspan sample due to larger error bands in the high regime. In line with Ramey and Zubairy (ming), we also find for the post-1988 sample a more positive output response in the high-disagreement regime, which however, is not statistically significant.

6 Conclusion

Survey expectations data displays a considerable 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 (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.

We use our empirical results to gain further insights on possible theoretical explanations for our findings. Our estimates for the high-disagreement regime are, in fact, 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 (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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Appendix

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). Finally, this section presents additional results from measuring information flows conveyed by the central bank's nominal interest rate.

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 technology, (ii) idiosyncratic demand 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

$$U_t = \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s D_{t+s} \left[\frac{C_{t+s}^{1-\gamma}}{1-\gamma} - \frac{N_{t+s}^{1+\varphi}}{1+\varphi} \right] , \tag{14}$$

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

$$P_t C_t + B_t = W_t N_t + R_{t-1} B_{t-1} + \Pi_t - T_t , \tag{15}$$

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

$$\max_{\widetilde{P}_t} E_t(j)\left[\sum_{s=0}^{\infty}(\theta\beta)^s\lambda_{t,t+s}\left(\overline{\pi}\widetilde{P}_t(j)-MC^n(j)_{t+s}\right)\left(\frac{\widetilde{P}_t(j)}{P_{t+s}}\right)^{-\nu}C_{t+s}\right]. \tag{16}$$

From the Calvo (1983) price setting we have that

$$p_t=\theta\left(p_{t-1}+\log\overline{\pi}\right)+(1-\theta)\int_0^1\widetilde{p}_t(j)\,dj. \tag{17}$$

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

$$\int_0^1 \widehat{\widetilde{p}}_t(j)\,dj = \frac{\theta}{1-\theta}\widehat{\pi}_t. \tag{18}$$

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

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

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:

$$\begin{aligned} \widehat{mc}_{t|t}^{(1)} &= \varphi\widehat{n}_{t|t}^{(1)} + \gamma\widehat{y}_{t|t}^{(1)} - \widehat{a}_t \\ \widehat{mc}_{t|t}^{(1)} &= (\varphi+\gamma)\widehat{y}_{t|t}^{(1)} + \varphi\hat{a}_t^{(1)} - \hat{a}_t \end{aligned} \tag{19}$$

Solving the price setting problem (16) 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:

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

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

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

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

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

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

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

Rewriting equation (20) yields

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

Substituting in (21), 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

$$\begin{aligned}
\widetilde{p}_t(j) &= (1-\theta\beta)\left(E_t(j)\left(\widehat{mc}_t(j)\right)+\frac{1}{1-\theta\beta}E_t(j)(p_t)\right) \qquad (22)\\
&+\theta\beta\left[E_t(j)\left(\widetilde{p}_{t+1}(j)\right)-E_t(j)(p_{t+1})\right]-(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s+1}\sum_{\tau=1}^{s}E_t(j)\left(\widehat{\pi}_{t+\tau+1}\right)\\
&+(1-\theta\beta)\sum_{s=1}^{\infty}(\theta\beta)^{s}E_t(j)\sum_{\tau=1}^{s}\widehat{\pi}_{t+\tau}.
\end{aligned}$$

Rewrite the last term:

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

and

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

Plug this into (22), we have

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

which becomes

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

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

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

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

Then integrating (23) across firms, we obtain the average reset price:

$$\widetilde{p}_t = (1-\theta\beta)\,\widehat{mc}^{(1)}_{t|t} + (1-\theta\beta)\,p^{(1)}_{t|t} + \theta\beta\widetilde{p}^{(1)}_{t+1|t} - (\theta\beta)\log \overline{\pi}. \tag{24}$$

Combine equation (17) with the following relationship:

$$\widetilde{p}_t = \int_0^1 \widetilde{p}_t\,(j)\,dj, \tag{25}$$

yields:

$$p_t = \theta\,(p_{t-1} + \log \overline{\pi}) + (1-\theta)\,\widetilde{p}_t. \tag{26}$$

Next, we substitute the following equation into equation (26)

$$p_t = \widehat{\pi}_t + p_{t-1} + \log \overline{\pi}, \tag{27}$$

and we obtain

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

$$\widetilde{p}_{t+1} \quad = \quad \frac{\widehat{\pi}_{t+1}}{(1-\theta)} + p_t + \log \overline{\pi}. \tag{28}$$

Plug (24) into equation (26) gives

$$p_t = \theta\,(p_{t-1} + \log \overline{\pi}) + (1-\theta)\,\widetilde{p}_t \tag{29}$$

$$\begin{aligned}
p_t &= \theta\,(p_{t-1}) + (\theta - (1-\theta)\,(\theta\beta))\log \overline{\pi} \\
&\quad + (1-\theta)\left((1-\theta\beta)\,\widehat{mc}^{(1)}_{t|t} + (1-\theta\beta)\,p^{(1)}_{t|t} + \theta\beta\widetilde{p}^{(1)}_{t+1|t}\right)
\end{aligned} \tag{30}$$

Next, we substitute (27) and (28) into equation (30)

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

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

$$\widehat{\pi}_t = (1-\theta)(1-\theta\beta)\,\widehat{mc}_{t|t}^{(1)} + (1-\theta)\,\widehat{\pi}_{t|t}^{(1)} + \theta\beta\widehat{\pi}_{t+1|t}^{(1)}. \tag{31}$$

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 (31) 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 (31) 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 $\widehat{\pi}_{t+1|t}^{(k)} = \underbrace{\int E_t^j \ldots \int E_t^j \ldots \int E_t^j}_{k} \widehat{\pi}_{t+1} dj \ldots dj.$

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:

$$
\Gamma_0 s_t = \Gamma_1 E_t s_{t+1} + \Gamma_2 X_{t|t}^{(0:k)} \tag{32}
$$

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

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

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:

$$
\begin{aligned}
\Gamma_0 s_t &= \Gamma_1 E_t s_{t+1} + \Gamma_2 X_{t|t}^{(0:k)} \qquad (33) \\
X_{t|t}^{(0:k)} &= M X_{t-1|t-1}^{(0:k)} + N\epsilon_t \qquad (34)
\end{aligned}
$$

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 (33) and (34) 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

$$X_{t|t}^{(0:k)} = MX_{t-1|t-1}^{(0:k)} + N\epsilon_t \;, \tag{35}$$

where $\begin{bmatrix} \epsilon_t^a & \epsilon_t^m & \epsilon_t^d \end{bmatrix}'$. 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:

$$X_t = MX_{t-1} + N\epsilon_t \tag{36}$$

$$Z_t(j) = DX_t + Q\eta_{j,t} \;, \tag{37}$$

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

$d_1{}' = \begin{bmatrix} 1 & 0_{1x3(k+1)-1} \end{bmatrix}, d_2{}' = \begin{bmatrix} 0 & = & 1 & 0_{1x3(k)} \end{bmatrix}, 1_3^T = \begin{bmatrix} 0 & 0 & 1 & 0_{1x5} \end{bmatrix}, \eta_{j,t} = \begin{bmatrix} \eta_{j,t}^a & \eta_{j,t}^d \end{bmatrix}'$
and

$$\mathrm{Q} = \begin{bmatrix} \tilde{\sigma}_a & 0 \\ 0 & \tilde{\sigma}_d \\ 0 & 0 \end{bmatrix}.$$

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 $P_{t|t}$:

$$X_{t|t}(j) = X_{t|t-1}(j) + P_{t|t-1}D'F_{t|t-1}^{-1}\left(Z_t(j) - Z_{t|t-1}(j)\right) \tag{38}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}D'F_{t|t-1}^{-1}DP_{t|t-1}' \;, \tag{39}$$

where

$$P_{t|t-1} = MP_{t-1|t-1}M' + NN' \;, \tag{40}$$

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

$$F_{t|t-1} = DP_{t|t-1}D' + QQ' \; . \tag{41}$$

Thus, from combining these equations we obtain:

$$P_{t+1|t} = M\left[P_{t|t-1} - P_{t|t-1}D'F_{t|t-1}^{-1}DP_{t|t-1}'\right]M' + NN' \; . \tag{42}$$

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

$$\begin{aligned} X_{t|t}(j) &= X_{t|t-1}(j) + K_t\left[DX_t + Q\eta_{j,t} - DX_{t|t-1}(j)\right] && (43)\\ K_t &= P_{t|t-1}D'F_{t|t-1}^{-1} \; , && (44) \end{aligned}$$

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:

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

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

$$X_{t|t}^{(1)} = (M - KDM)X_{t-1|t-1}^{(1)} + K_t\left[DMX_{t-1} + DN\epsilon_t\right] \; . \tag{46}$$

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:

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

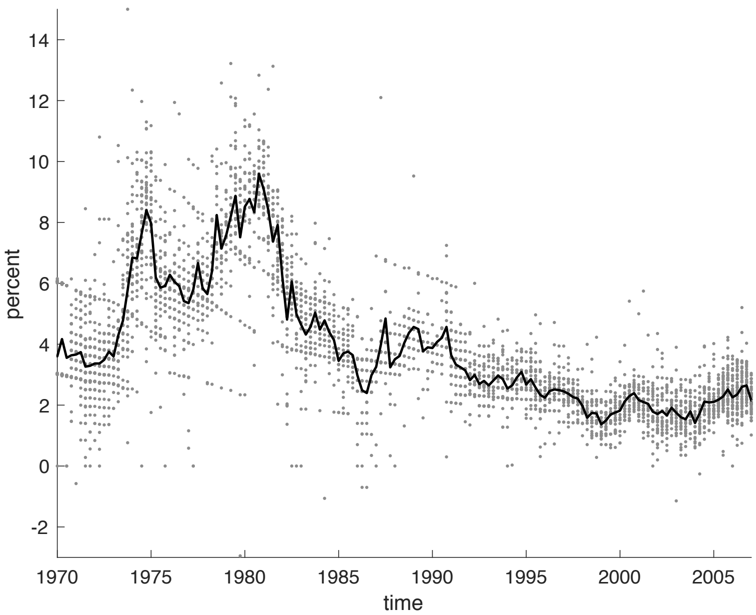
Assuming common knowledge in rationality, i.e. agents form model consistent rational expectations (see Nimark (2008)), we construct matrices M and N:

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

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.

B Further empirical results

Figure 16: Individual inflation forecasts



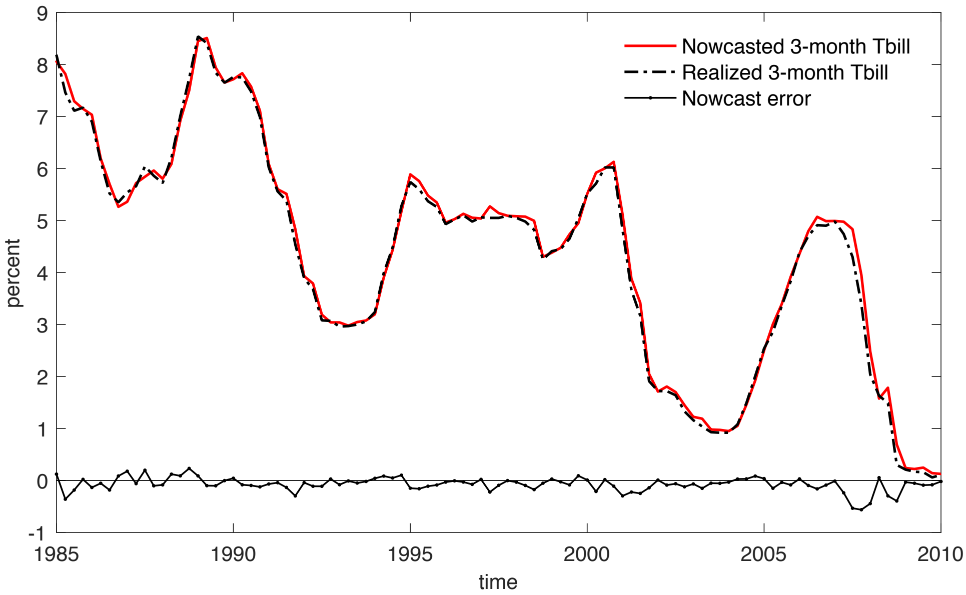
Notes: The figure shows the evolution of the (annualized) expected inflation rate, measured as the difference of the (log) mean forecast of the price index in the next quarter across agents minus the log of the mean nowcast of the price index. The dots reflect the individual forecasts of the inflation rate. The data stems from the U.S. Survey of professional forecasts. 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 (qoq)	0.20	0.90
Expected inflation (qoq)	0.03	0.99
Real GDP	0.34	0.80
Disagreement	1.33	0.27
Uncertainty (Jurado et al.)	0.54	0.65

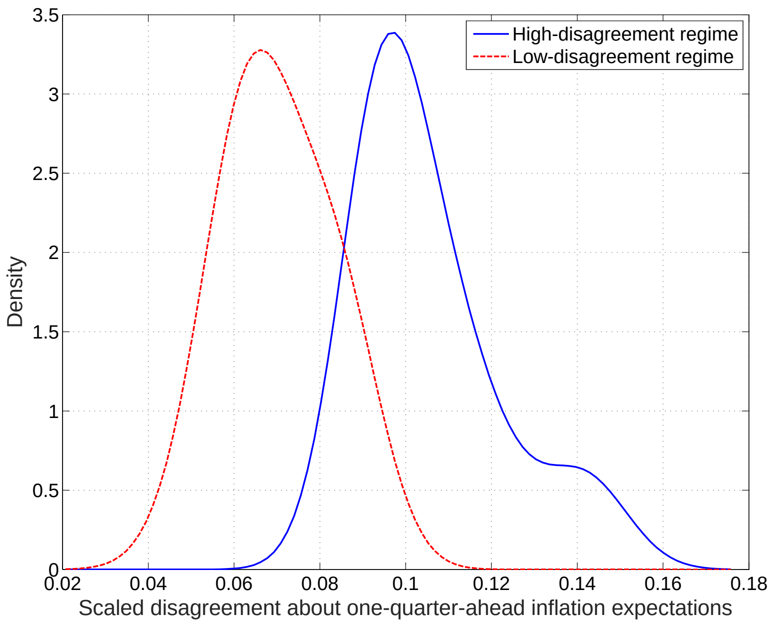
Notes: We run the following regression for each variables: $\epsilon_t = c + \sum_{l=0}^{I} \beta_l y_{t-1} + u_t$. The table reports F-statistics and P-values for the null hypothesis that all coefficients β_l are equal to zero. The estimation covers the baseline sample from 1970:IV to 2007:IV. The standard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

Figure 17: The nowcasted nominal interest rate



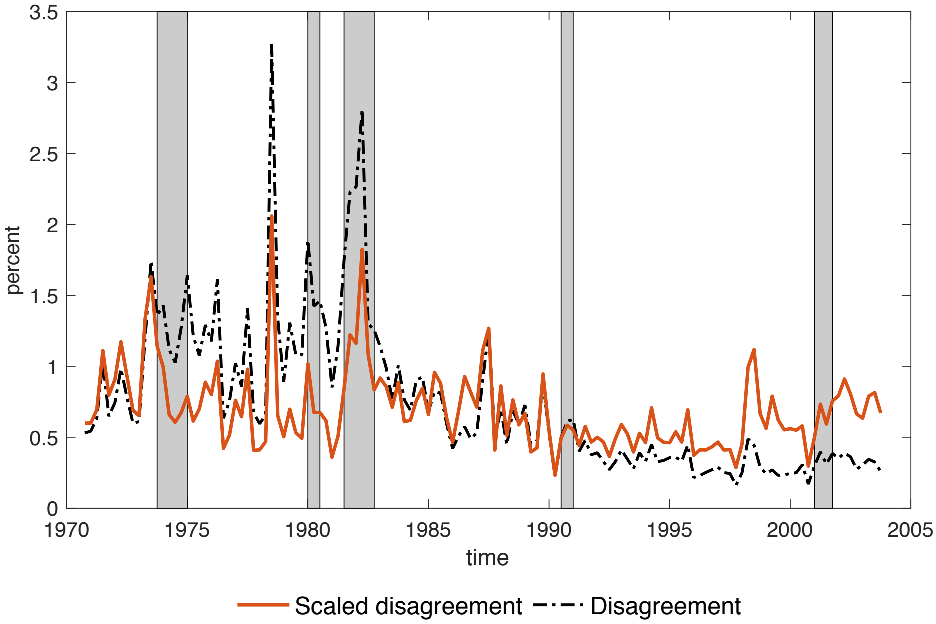
Notes: The figure shows the mean point forecasts for the current value of the three-month Tbill from the survey of professional forecasters (SPF) and the actual level of the current period three-month Tbill (from St.Louis FRED database). Both series are on quarterly basis. The solid black line corresponds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

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



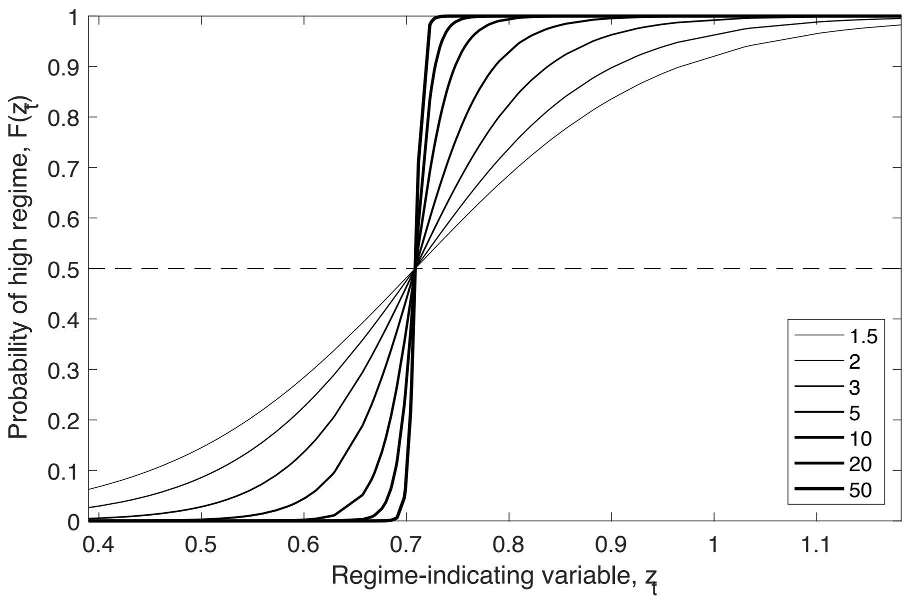
Notes: Kernel density estimate of disagreement about one-quarter-ahead inflation expectations in the high- (solid line) and low-disagreement regime (dashed line) based on the U.S. SPF data. Disagreement in each regime is scaled by a factor of eight to normalize with the theoretical distributions in Figure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

Figure 19: Scaled disagreement



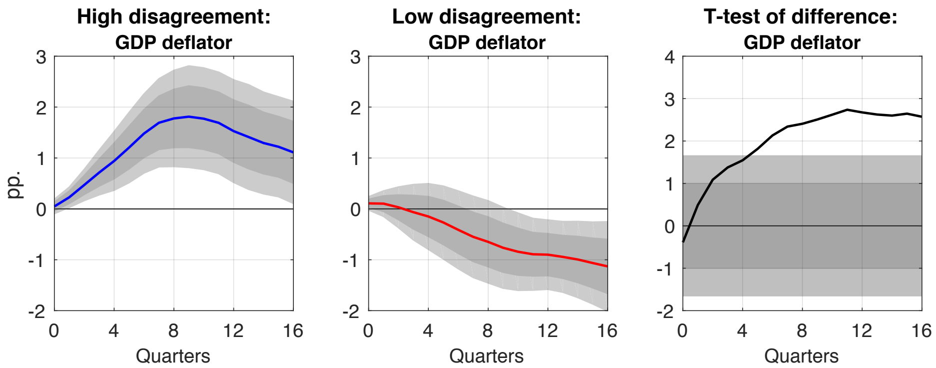
Notes: The dashed line shows *disagreement* measured as the standard deviation of the point forecasts about the price level (GDP deflator) in the next quarter, based on U.S. SPF data. The solid line shows the previous variable scaled by the expected inflation rate in the previous quarter. The latter 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



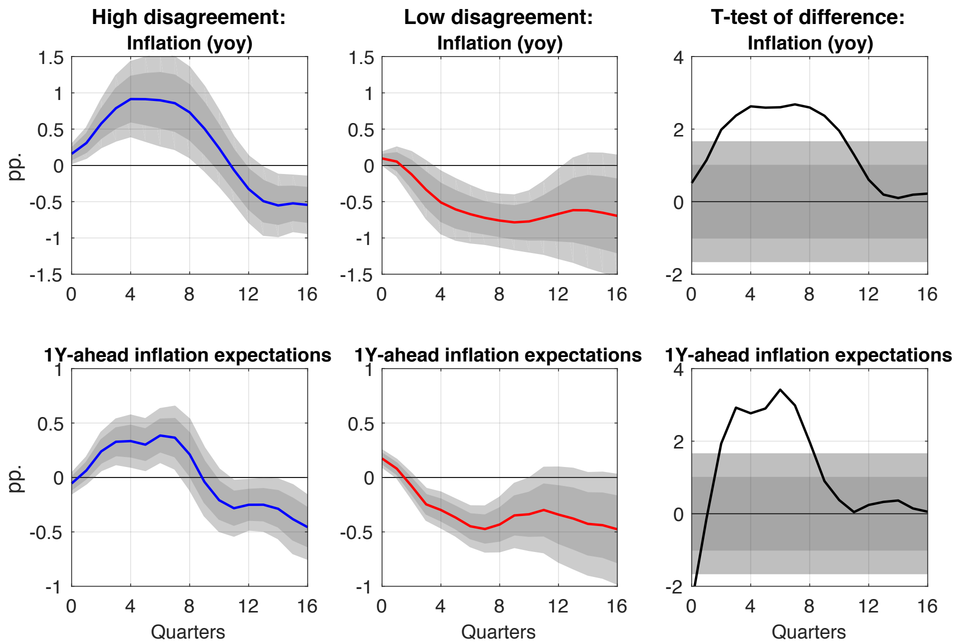
Notes: The figure shows the value of the probability function $F(z_t)$ for different values of the regime-switching intensity θ over the whole range of values of the regime-indicating variable z_t, i.e. the scaled disagreement. The intersection point of the dashed line and the functions indicates the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

Figure 21: Impulse response of GDP deflator



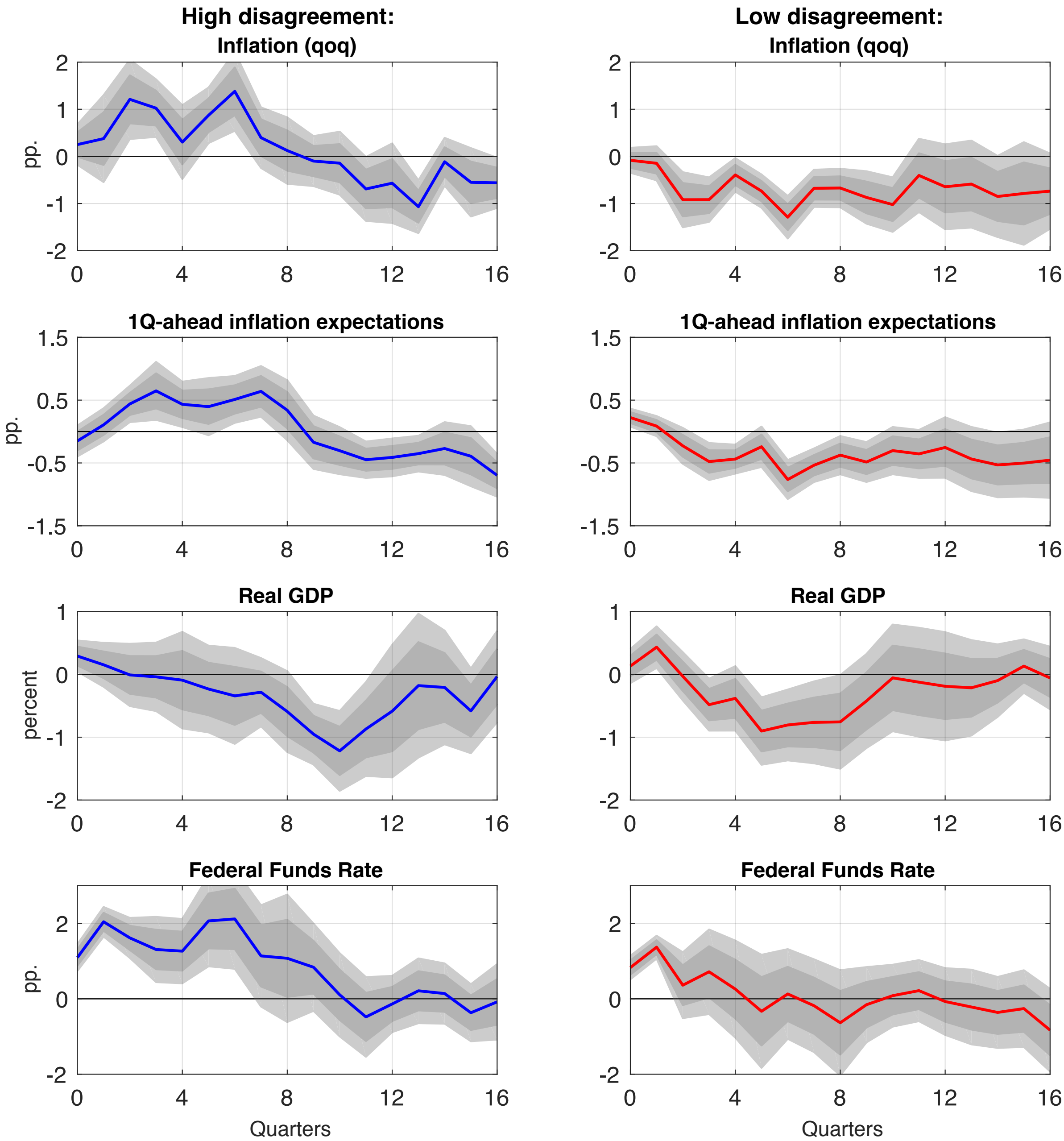
Notes: Results for the estimation with the level of the (log) GDP deflator (minus the level in period $t-1$) as dependent variable. We estimate the following equation: $y_{t+i} - y_{t-1} = \tau_i t + (\alpha_i^H + \beta_i^H \varepsilon_t + \gamma_i^H x_t)F(z_t) + (\alpha_i^L + \beta_i^L \varepsilon_t + \gamma_i^L x_{t-2})(1 - F(z_t)) + u_{t+i}$. 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 expected inflation over the next year



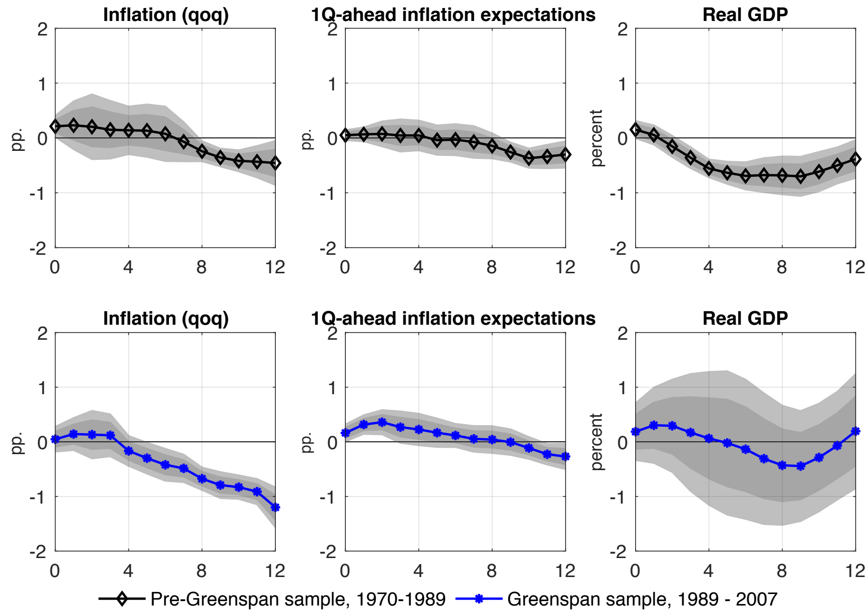
Notes: Results from the estimation of equation (12) with the actual yoy-inflation and inflation expectations over the next year as dependent variables. The estimation covers the sample 1970:IV-2007:IV. The solid lines in the left (middle) column show the point estimates β_i^H (β_i^L) for horizon i (x-axes). 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



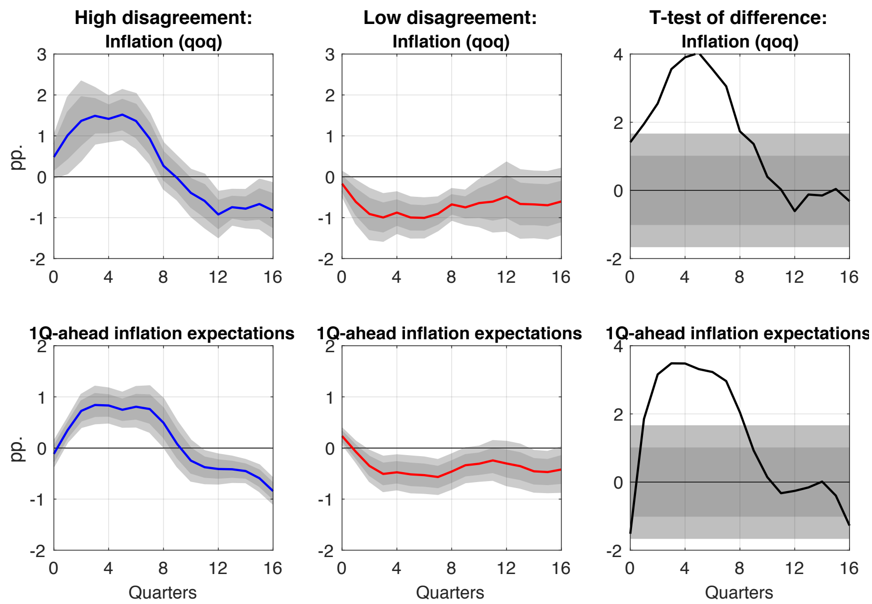
Notes: Non-smoothed results from the estimation of equation (12) with the Federal Funds Rate (FFR), real GDP (log), (annualized) inflation (qoq) and expected inflation (qoq) as dependent variables. The estimation covers the sample 1970:IV-2007:IV. The solid lines in the left (right) column show the point 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: Linear Results



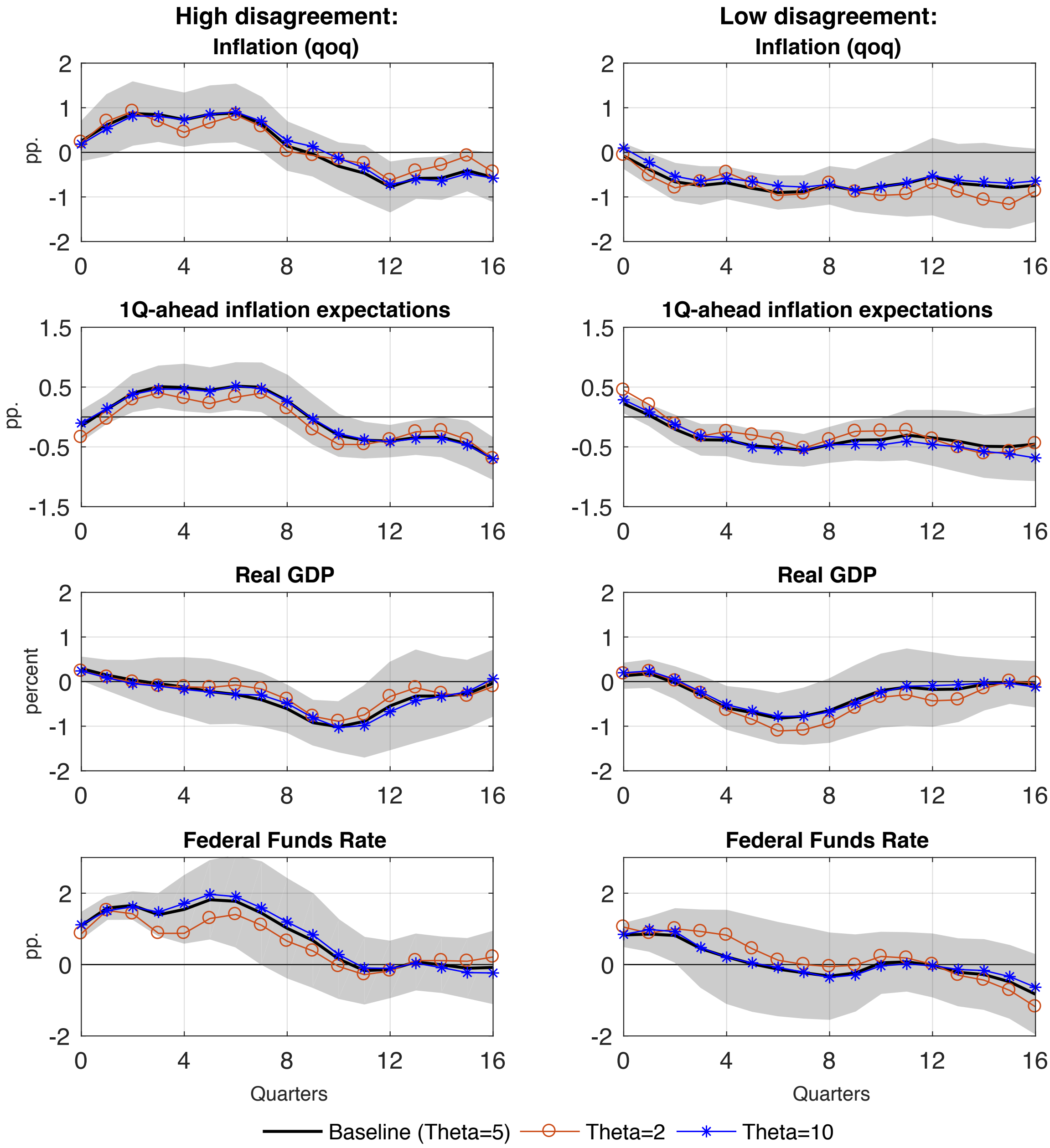
Notes: Results from the linear estimation of equation (12), i.e. $F(z_t) = 0$ or 1, for the sample split. The estimation covers the sample 1970:IV-2007:IV. The coefficients are smoothed over three consecutive periods. The grey areas display 68% and 90% confidence intervals.

Figure 25: Results for sample including the Great Recession



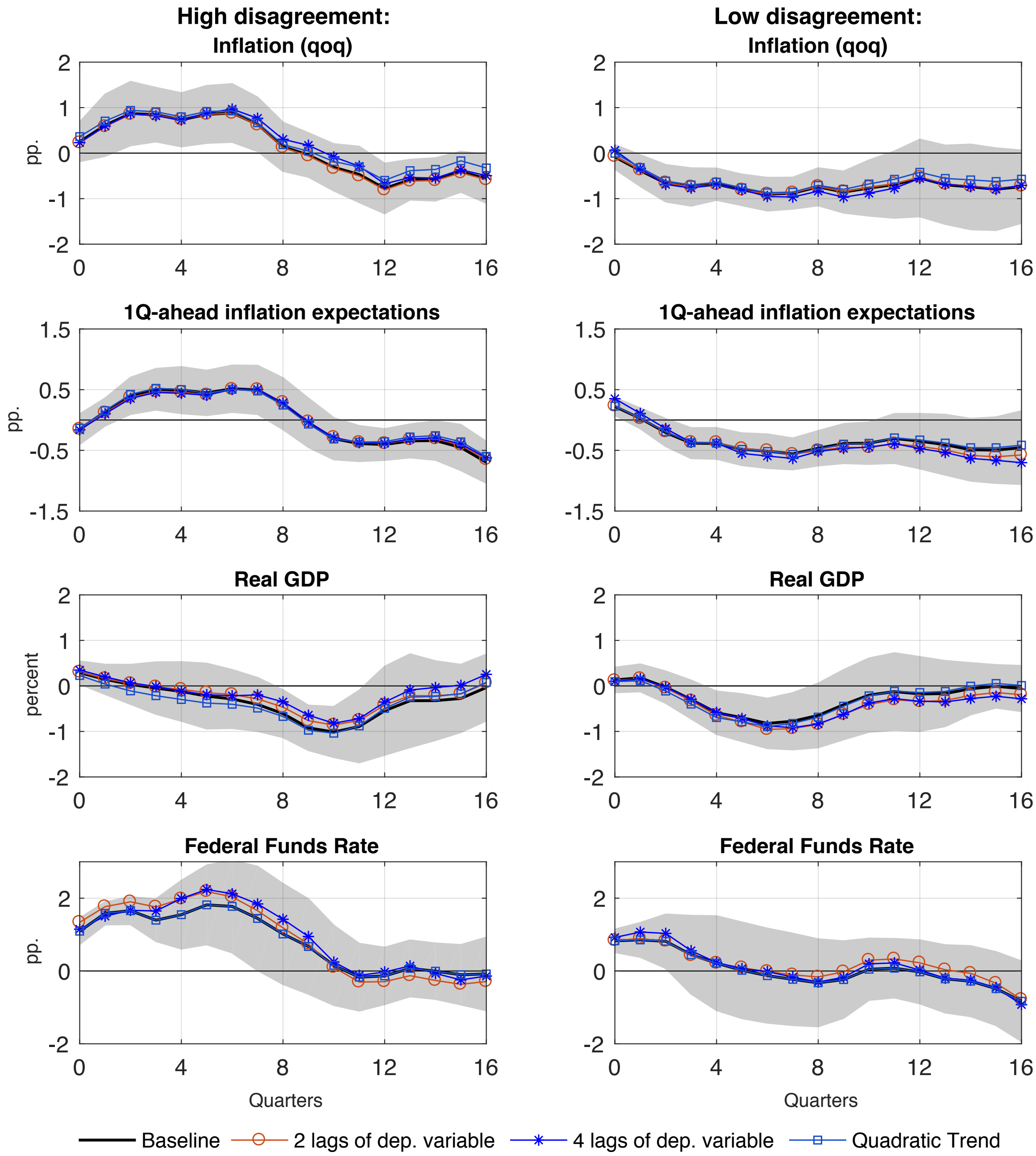
Notes: Results from estimation of equation (12) for the extended sample, 1970:IV-2015:IV, for (annualized) inflation (qoq) and expected inflation (qoq) as dependent variables. We include two lags of the Federal funds Rate and the dependent variable as controls. The solid line in the left (middle) column 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 26: Results for different regime-switching parameters



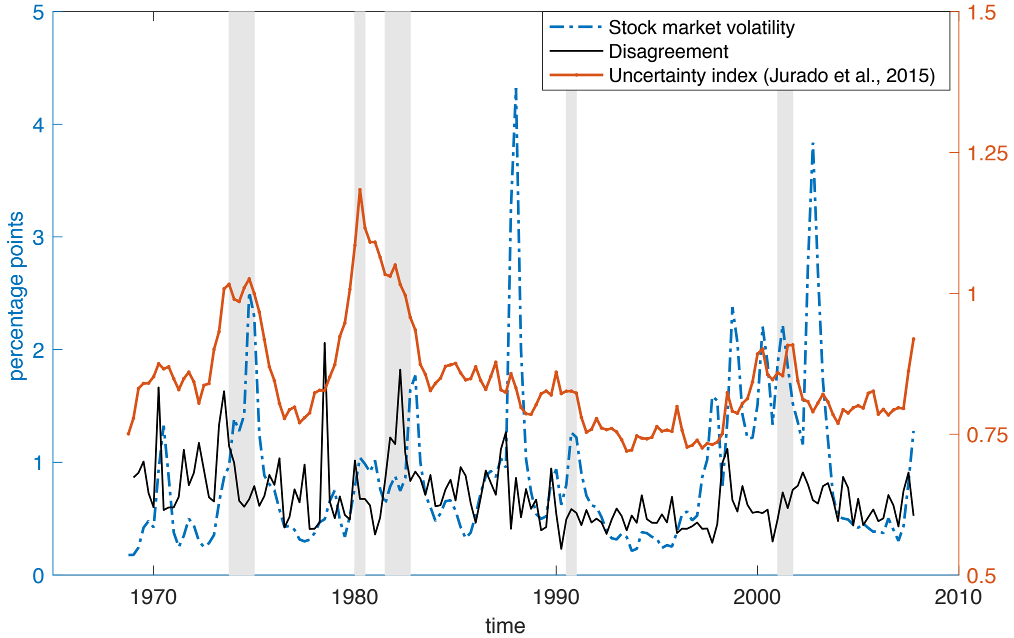
Notes: Responses to a 100 bps contractionary monetary policy shock using alternative values for θ in our baseline estimation in equation (12). The figures show 90% confidence intervals of the baseline specification. The black solid line reflects the baseline results from Section 4. The estimation covers the period: 1970:IV-2007:IV.

Figure 27: 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 (12). The figures show 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.

Figure 28: Diagreement and 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.