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Monetary policy shocks, expectations and information rigidities

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Abstract

This paper contributes to the literature by assessing expectation effects from monetary policy for the G7 economies. We consider a sample period running from 1995M1 to 2016M6 based on a panel VAR framework, which accounts for international spillovers and time-variation. Relying on a broad set of expectation data from Consensus Economics, we start by analyzing whether monetary policy has changed the degree of information rigidity after the emergence of the subprime crisis. We proceed by estimating potential effects of interest rate changes on expectations, disagreements and forecast errors. We find strong evidence for information rigidities and identify higher forecast errors by professionals after monetary policy shocks. Our results suggest that the international transmission of monetary policy shocks introduces noisy information and partly increases disagreement among forecasters.

Keywords: Bayesian econometrics, expectations, information rigidity, monetary policy, panel VAR
JEL classification: E31, E52

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1 Introduction

Expectations play a crucial role for the transmission of policy shocks. The increasing availability of survey data over long periods of time has turned out to be useful when analyzing expectation effects in this regard. On the one hand, average (mean) forecasts across professionals are frequently found to exhibit substantial predictive power. This has for example been illustrated in the context of inflation by Ang *et al.* (2007). It is therefore straightforward to assess the effects of monetary policy shocks on expectations proxied by survey data. Although it is well-established that relying on average forecasts is superior to consulting individual expectations, the distribution of forecasts is also of potential importance. Recent evidence suggests that uncertainty among market expectations resembles an aggregate demand shock with higher unemployment and lower inflation (Leduc and Liu, 2016). After monetary policy has reached the zero lower bound, a reduction in uncertainty is of particular importance for monetary policy transmission. In such an environment, the presence of uncertainty creates a unique time-inconsistency problem for policymakers (Nakata, 2016). There is also an increasing amount of evidence for cross-border effects from monetary policy (Beckmann *et al.*, 2014) suggesting that international spillovers are also of great importance when assessing expectation or disagreement effects.

From a broader perspective, uncertainty effects arise as a result of information rigidities. It is well established that expectations often react to macroeconomic shocks with a significant delay. In this context Coibion and Gorodnichenko (2012, 2015) analyze the importance of information rigidities in the context of expectations based on sticky and noisy information models. A final piece of the jigsaw is the question whether information rigidities reflect an ex post effect of policy shocks on forecast errors of professionals.

Based on these consideration, this paper contributes to the literature by assessing expectation and information rigidity effects from monetary policy in a framework which accounts for international spillovers for the G7 countries. We start by estimating the impact of monetary policy on expectations and disagreements across forecasters regarding CPI inflation and GDP growth based on data from Consensus Economics. We then analyze the effects of monetary policy on the corresponding forecast errors of professionals. To the best of our knowledge, we are the first to account for the potential of international spillovers in this context. Recent studies such as Aastveit *et al.* (2013) focus on country-specific models and adopt alternative uncertainty measures proposed by Jurado *et al.* (2015) and Baker *et al.* (2016). Our various robustness checks also include a comparison of fixed period and fixed horizon forecasts, a crucial distinction when analyzing disagreements.

Our empirical analysis is based on the Bayesian panel VAR framework proposed by Canova and Ciccarelli (2009) and incorporates several desirable features such as cross-country lagged interdependencies and time-variation in the coefficients. It allows us to account for dynamic interaction effects across countries due to globalization as well as financial integration and potential spillovers stemming from monetary policy, which are of particular importance over the recent period (Chen *et al.*, 2016). We also allow for the fact that monetary policy effects should be analyzed in a time-varying fashion (Leeper *et al.*, 2012; Belongia and Ireland, 2016) to account for the possibility that the relationships between macroeconomic variables are subject to shifts over time. Due to the fact that official monetary policy rates are of little use since the financial crisis as a result of the the zero lower bound constraint, we (mostly) rely on shadow rates provided by Wu and Xia (2016), which are constructed based on yield curve factors as a measure of monetary policy. This enables us to assess monetary policy shocks over the recent period where official interest rates remain constant.

Our results show that monetary policy shocks entertain various transmission channels through expectations and uncertainty but hardly offer a systematic influence when compared across countries. Overall, we provide evidence that the expectation and uncertainty policy channel worked through both direct and indirect effects. We are unable to identify an overall increase in information rigidities after the onset of the global financial crisis. Our evidence also shows that rigidities frequently materialize in higher forecast errors after monetary policy shocks once international spillovers are taken into account.

The remainder of this paper is organized as follows: The next section recaptures theoretical considerations related to information rigidities and summarizes previous findings. Section 3 presents the data and our empirical approach. Section 4 discusses our findings while Section 5 concludes.

2 Literature review

2.1 Uncertainty channels and monetary policy

The changing character of monetary policy transmission has resulted in a rich literature on monetary policy in the context of expectations. This section provides a selective overview of the most relevant studies. While this subsection focuses on papers dealing with monetary policy, the following subsection discusses the importance of information rigidities in the context of the transmission of monetary policy shocks.

Expectation effects play a crucial role for monetary policy, in particular after Quantitative Easing (QE) policy has emerged and conventional Taylor rules no longer provide a guideline for the path of monetary policy.[1] The signaling channel allows policymakers to convey extra information about the future path of interest rates and affect macroeconomic expectations. In addition, QE is designed to reduce uncertainty about the future economic outlook. In this regard, a crucial question in this regard is whether people believe that QE will improve the economic outlook (Haldane *et al.*, 2016). In contrast to conventional macroeconomic aggregates, changes of mean expectations and forecasters disagreement are able to capture such dynamics.

Although some studies have provided evidence that QE influenced international bond yields, exchange rates and equity prices and also had large international spillovers (Neely, 2015), no study has directly assessed the effects of QE on expectations and uncertainty in the context of professional forecasts.[2] The existing evidence is often based on short-term effects after policy announcements (Conrad and Lamla, 2010). However, such effects are often related to short-term overshooting patterns which not necessarily reflect lasting effects.

Disagreement among forecasters has also attracted much attention recently. Uncertainty of forecasters about both inflation and GDP growth is affected by the stance of policymakers but also shows distinct dynamics, in particular in a recession (Dovern *et al.*, 2012). The data set we consider allows us to study various effects of monetary policy. First of all, we are able to analyze the impact of a monetary policy shock on both expectations and disagreement regarding future inflation and GDP growth. In addition, we assess whether changes in monetary policy affect the disagreement related to the future stance of monetary policy.[3]

Taking our topic of investigation into account, it is important to highlight that disagreement among forecasters only constitutes one dimension of uncertainty while the newspaper-based economic policy uncertainty index proposed by Baker *et al.* (2016) and the macroeconomic uncertainty index suggested by Jurado *et al.* (2015) are two frequently adopted alternatives. However, both do not reflect updates of professional forecasts.[4]

[1] The optimal design of policy rules at the zero lower bound is still subject to discussion (Piazzesi, 2014; Taylor, 2017).

[2] See Bhattarai and Neely (2016) and Haldane *et al.* (2016) for excellent surveys on the effects of Quantitative Easing.

[3] A recent study by Kunze *et al.* (2017) uses a somehow different approach based on survey data by analyzing the reliability of interest rate forecasts in times of uncertainty.

[4] See, for instance, Boumparis *et al.* (2017) for a recent analysis of policy uncertainty effects on sovereign credit ratings

2.2 Expectations and the role of information rigidities

Disagreement about macroeconomic fundamentals or the future stance of policy would not arise under perfect foresight. Coibion and Gorodnichenko (2012) study the importance of various shocks on expectations and disentangle the importance of information rigidity and asymmetric loss functions. They find that mean forecasts completely fail to account for the impact of shocks and reject the hypothesis of full information. In addition, Coibion and Gorodnichenko (2015) show that information rigidities can be derived from both sticky and noisy information models. The following section summarizes the main ideas of their framework.

Starting with the *sticky information model* in the spirit of Reis (2006), the average forecast at time t for $t+h$, $F_t(y_{t+h})$, is given by a weighted average of current and past information where $(1-\lambda)$ reflects the probability of an information update so that λ is a measure of information rigidity

$$F_t(y_{t+h}) = (1-\lambda)\sum_{j=0}^{\infty}\lambda^j E_{t-j}(y_{t+h}), \tag{1}$$

where E_t denotes the expectations operator conditional on the information up to period t. The forecast in period $t-1$ can be expressed in a similar way

$$F_{t-1}(y_{t+h}) = (1-\lambda)\sum_{j=0}^{\infty}\lambda^j E_{t-1-j}(y_{t+h}). \tag{2}$$

Hence, the current average forecast consists of a weighted average of previous periods' forecasts and the current rational expectation

$$F_t(y_{t+h}) = (1-\lambda)E_t(y_{t+h}) + \lambda F_{t-1}(y_{t+h}). \tag{3}$$

Full information rational expectations would imply that

$$E_t(y_{t+h}) = y_{t+h} - \varepsilon_{t+h,t}, \tag{4}$$

where $\varepsilon_{t+h,t}$ is the full information rational expectations error, which is uncorrelated with information from up to period t. The combination of Eqs. (3) and (4) provides the relationship between the

and the studies by Beckmann and Czudaj (2017b,c) examining the role of several forms of uncertainty on exchange rate expectations and forecast errors. Another strand of literature proposed by Husted *et al.* (2017) focuses on a direct measure of monetary policy uncertainty.

ex post forecast error across agents and the ex ante average forecast revision

$$y_{t+h} - F_t(y_{t+h}) = \frac{\lambda}{1-\lambda}[F_t(y_{t+h}) - F_{t-1}(y_{t+h})] + \varepsilon_{t+h,t}. \tag{5}$$

The information rigidity coefficient λ drives the coefficient on forecast revisions $\lambda/(1-\lambda)$. Predictability of forecast errors reflects the sow updating of information across agents ($\lambda > 0$).

The underlying idea of the *noisy information model* has been established by Lucas (1972) and Sims (2003) and states that agents continuously update their information set. The considerations of Woodford (2003) that the development of a macroeconomic variable is subject to idiosyncratic shocks offer a starting point in the present context (Coibion and Gorodnichenko, 2015). In such a case, a macroeconomic series e.g. inflation or GDP growth can be expressed as an AR(1) process

$$y_t = \rho y_{t-1} + \varepsilon_t, \quad 0 \le \rho \le 1. \tag{6}$$

Assuming that y_t is not directly observable, agents observe a signal x_t instead. Such a signal can be modeled by

$$x_{it} = y_t + \omega_{it}, \tag{7}$$

where ω_{it} represents a normally distributed error term and i is an index for the agent. Under such circumstances, forecasts are achieved via Kalman filtering by

$$F_{it}(y_t) = Gx_{it} + (1-G)F_{it-1}(y_t) \tag{8}$$

and

$$F_{it}(y_{t+h}) = \rho^h F_{it}(y_t) \tag{9}$$

where G is the Kalman gain and measures the relative weight placed on new information so that $(1-G)$ reflects the information rigidity in this model.

Based on these considerations, the relationship between the ex post mean forecast error and the ex ante mean forecast revision can be expressed as

$$y_{t+h} - F_t(y_{t+h}) = \frac{1-G}{G}[F_t(y_{t+h}) - F_{t-1}(y_{t+h})] + \varepsilon_{t+h,t}, \tag{10}$$

where $\varepsilon_{t+h,t} = \sum_{j=1}^{h} \rho^{h-j} \varepsilon_{t+j}$. Coibion and Gorodnichenko (2015) show that both the sticky and the noisy information model lead to the same general testable equation, which measures the degree of information rigidity. This results in a regression of the ex post mean forecast error on the ex ante mean forecast revision

$$y_{t+h} - F_t(y_{t+h}) = \beta_0 + \beta_1 [F_t(y_{t+h}) - F_{t-1}(y_{t+h})] + \varepsilon_t, \tag{11}$$

where β_1 measures the amount of information rigidity. Coibion and Gorodnichenko (2015) argue that such a relationship does solely hold at the aggregated but not at the individual level.

2.3 Disagreement and time-varying information rigidity

The theoretical underpinnings based on the study by Coibion and Gorodnichenko (2015) have demonstrated that both the sticky and the noisy information model result in the same empirical equation in the context of information rigidities. Both kinds of model also exhibit information related to the dispersion across forecasters, which results in disagreement (Coibion and Gorodnichenko, 2012). Taking into account that we also consider disagreement among forecasts in our empirical analysis, the following section briefly reconsiders the main implications of both models. A full derivation of the underlying models is provided by Coibion and Gorodnichenko (2012).

Starting with the sticky information model, $\overline{\text{Var}}(y_{t+h|t}(i))$ provides the variance of h-period-ahead forecasts at time t, where $\overline{\text{Var}}(.)$ denotes the variance taken across agents. It can be expressed as follows

$$\overline{\text{Var}}(y_{t+h|t}(i)) = (1 - \lambda) \sum_{k=0}^{\infty} \lambda^k [F_{t-h}(y_{t+h}) - y_{t+h|h}]^2. \tag{12}$$

Coibion and Gorodnichenko (2012) show that the impulse response of the cross-sectional variance of h-period-ahead forecasts at time $t + j$ to a shock δ at time t is given by

$$\rho^{2(j+h)} \lambda^{j+1} (1 - \lambda^{j+1}) \delta^2 = \left(\frac{dy_{t+j+h}}{d\delta} \right)^2 \lambda^{j+1} (1 - \lambda^{j+1}) \delta^2. \tag{13}$$

In case of a rigidity factor larger than zero ($\lambda > 0$), disagreement across agents will increase as a response to both positive and negative shocks. In contrast, the dispersion of forecasts in the noisy information model is potentially invariant to shocks on fundamentals. We refer to Coibion and Gorodnichenko (2012) for a formal derivation of this finding.

Comparing both frameworks in the context of monetary policy suggests that sticky information models provide more room for disagreement effects stemming from monetary policy. Rigidity is a necessary condition for disagreement. Noisy information models additionally require that policy shocks result in idiosyncratic signals distinguishing between different forms of information rigidities. Overall, we conclude that information rigidities potentially materialize in a relationship between forecast updates and forecasts errors. A response of disagreement to policy shocks also signals informational frictions according to the sticky information model. Finally, a response of forecast errors can point to information rigidities. We will reconsider this distinction in Section 4.

3 Data and empirical modeling

3.1 Data

The panel of economies under observation includes the G7 (i.e. Canada, France, Germany, Italy, Japan, UK, and US) and this choice is motivated by data availability and the idea to include the major central banks. Our sample period consists of data from 1995:01 until 2016:06 on a monthly basis. Expectation data on annual CPI inflation and GDP growth is obtained from Consensus Economics. Our novel data set also includes expectations regarding the future stance of monetary policy based on expectations about three month and 12 month interest rates at the end of the following year. The number of forecasters varies between 15 and 40 depending on the variable under investigation. The fact that the name of contributing professional forecaster is published increases the credibility of forecasts due to reputation effects.[5] We consider both the mean and the standard deviation of expectations across forecasters for CPI inflation, GDP growth and interest rates. While the mean reflects average market expectations, the standard deviation is a useful measure of disagreement or uncertainty among forecasters.

The forecasts provided by Consensus Economics are fixed event forecasts, that is expectations are provided for the current and the next year at each point in time. $g_{i,j}$ denotes the expected growth rate in period j for period i. This implies that disagreement about the current year naturally decreases over time, that is the uncertainty about this year's inflation or GDP growth is e.g. much lower in November than in January. We therefore adopt the approach suggested by Patton and Timmermann (2011), which has also been applied by Dovern *et al.* (2012) to transform fixed event

[5] See `http://www.consensuseconomics.com/` for further details.

into fixed horizon forecasts via weighted averaging.[6] The intuitive idea is to use the weighted average of fixed event forecasts for the current and the next year with the weight of the former (latter) linearly decreasing (increasing) as time evolves based on the following formula

$$\hat{g}_{t,t-12} = w\hat{g}_{1,0} + (1-w)\hat{g}_{2,1}, \tag{14}$$

where $\hat{g}_{t,t-12}$ denotes the approximated fixed horizon growth rate forecast while $\hat{g}_{1,0}$ and $\hat{g}_{2,1}$ give the fixed event forecasts for the current and the next year and w denotes the ad hoc weight $(24 - t)/12$. As a robustness test, we have also conducted estimations where we have directly adopted the fixed event forecast of the next year since this measure should be less affected by this year's macroeconomic development. Moreover, to account for the special character of monetary policy after the emergence of unconventional monetary policy, we mostly rely on shadow policy rates to calibrate monetary policy at the zero lower bound (Wu and Xia, 2016). This is crucial given the fact that our empirical assessment includes interest rate shocks.

3.2 Empirical methodology

To examine expectation effects from monetary policy we apply a panel vector autoregression (VAR) in the tradition of Canova and Ciccarelli (2009) and Beckmann and Czudaj (2017a), which builds on the formulation of the VAR model

$$y_{it} = \sum_{j=1}^{p_1} D_{it,j} Y_{t-j} + \sum_{j=1}^{p_2} C_{it,j} W_{t-j} + e_{it}, \tag{15}$$

where $i = 1, \ldots, N$ and $t = 1, \ldots, T$ are the indices for the cross-section and the time dimension, respectively. For our VAR model the vector y_{it} of dimension $G \times 1$ is defined as

$$y_{it} = [pr_{it}, F_{i,t-12}(\pi_{i,t}), F_{i,t-12}(\text{GDP}_{i,t}), \pi_{it}, \text{GDP}_{it}]' \quad \forall \quad i, \tag{16}$$

where pr_{it} denotes the monetary policy rate for country i, π_{it} gives its inflation rate and GDP_{it} represents its GDP growth rate. $F_{i,t-12}(.)$ denotes a forecast made in period $t-12$ for period t.[7]

[6] See Knüppel and Vladu (2016) for an alternative way of transforming fixed event into fixed horizon forecasts by choosing a different weighting w.

[7] To analyze monetary policy effects on forecast disagreements, the mean forecasts for inflation and GDP growth denoted by $F_{i,t-12}(.)$ are replaced by the corresponding standard deviations across individual forecasters. To examine the corresponding effects on forecast errors of professionals, we have substituted actual and expected inflation and GDP growth by their differences (i.e. $\pi_{it} - F_{i,t-12}(\pi_{i,t})$ and $\text{GDP}_{it} - F_{i,t-12}(\text{GDP}_{i,t})$).

y_{it} can be compressed to an $NG \times 1$ vector $Y_t = (y'_{1t}, \ldots, y'_{Nt})'$. In addition, W_t represents an $q \times 1$ vector of exogenous variables that also includes a constant term and e_{it} denotes an $G \times 1$ vector of random errors. $D_{it,j}$ and $C_{it,j}$ are time-varying coefficient matrices of order $G \times GN$ and $G \times q$ for each lag j, where p_1 is the lag length of the endogenous and p_2 of the exogenous variables.

The main advantage of this approach is that it allows for cross-country lagged interdependencies and time-variation in the coefficients. However, the flexibility of this framework has a major drawback: Eq. (15) is highly overparameterized. Without imposing restrictions there are more coefficients to estimate than observations available ($k = NGp_1 + qp_2$ per equation and per t). To solve this problem we impose a factor structure on the model given in Eq. (15). In doing so, we stack the G rows of the matrices $D_{it,j}$ and $C_{it,j}$ in the $k \times 1$ vector δ^g_{it}. Then $\delta_{it} = (\delta^{1\prime}_{it}, \ldots, \delta^{G\prime}_{it})'$ is an $Gk \times 1$ vector and $\delta_t = (\delta'_{1t}, \ldots, \delta'_{Nt})'$ is an $NGk \times 1$ vector, which is factored as follows

$$\delta_t = \sum_{f=1}^{F} \Xi_f \theta_{ft} + u_t \quad \text{with} \quad u_t \sim \mathcal{N}(0, \Omega \otimes V). \tag{17}$$

θ_{ft} is a low-dimensional vector describing factor f and Ξ_f is its corresponding matrix. u_t is an $NGk \times 1$ vector of unmodeled and idiosyncratic error terms. The variance-covariance matrix of u_t can be decomposed into the $NG \times NG$ matrix Ω and the $k \times k$ matrix $V = \sigma^2 I_k$. Our empirical model has a factorization with $F = 2$ factors as follows

$$\delta_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} + u_t, \tag{18}$$

where θ_{1t} is an $N \times 1$ vector of country-specific factors and θ_{2t} is an $G \times 1$ vector of variable-specific factors. Therefore, the corresponding indices are constructed as: $\chi_{1it} = \sum_g \sum_j y_{ig,t-j}$, $i = 1, \ldots, N$, and $\chi_{2gt} = \sum_i \sum_j y_{ig,t-j}$, $g = 1, \ldots, G$. The resulting vector $\theta_t = (\theta'_{1t}, \theta'_{2t})'$ is of order $(N + G) \times 1$.

Then, Eq. (15) can be rewritten as

$$Y_t = X_t \delta_t + E_t = X_t(\Xi \theta_t + u_t) + E_t \equiv \chi_t \theta_t + \zeta_t, \tag{19}$$

where $\mathbf{X_t} = (Y'_{t-1}, \ldots, Y'_{t-p_1}, W'_{t-1}, \ldots, W'_{t-p_2})'$, $X_t = I_{NG} \otimes \mathbf{X'_t}$, and $\Xi = (\Xi_1, \Xi_2)$. E_t is an $NG \times 1$ vector of normally distributed error terms with zero mean and variance-covariance matrix Ω, $\chi_t \equiv X_t \Xi$ is a matrix of constructed regressors (i.e. indices) that are also observable, and $\zeta_t \equiv X_t u_t + E_t$ is a vector of the reparameterized error terms. In this reparameterized version the panel VAR model includes a substantially smaller number of regressors and the factors θ_{it} load on these.

In order to allow for time-variation in the factors, we apply the law of motion given by

$$\theta_t = \theta_{t-1} + \eta_t, \quad \text{with} \quad \eta_t \sim \mathcal{N}(0, B_t), \tag{20}$$

where η_t is independent of E_t and u_t, and $B_t = \text{diag}(B_1, \ldots, B_F) = \gamma_1 B_{t-1} + \gamma_2 B_0$. The Markov Chain Monte Carlo (MCMC) approach to estimate Eq. (19) is presented in Appendix A.1 and Appendix A.2 gives the corresponding algorithm to calculate the impulse responses based on the estimated model. Section 4.2 draws on the results from our impulse responses analysis.

4 Empirical results

4.1 Information rigidities and monetary policy

As discussed in Section 2, information rigidities are a requirement for monetary policy effects related to uncertainty or disagreement. It is therefore straightforward to start analyzing whether the degree of information rigidity varies over time and whether it is affected by the recent crisis. Table 1 provides estimates for Eq. (11) over the full sample period for both CPI inflation and GDP growth in the G7 economies. Estimations for the information rigidity coefficient β_1 display a great variation and are often insignificant. For all 14 regressions, the R^2 is very low, suggesting a weak link between the ex post forecast error and the ex ante forecast revision. Figures 1 and 2 provide rolling window regression estimates for β_1 with a window size of 30 months and illustrate the time-varying nature of information rigidities. In case of inflation, estimates for the UK and Japan provide a positive coefficient around 2008 while the estimated coefficients are negative and significant for Germany and the US prior to 2010. The GDP growth coefficient estimates display a unambiguous picture with positive information rigidities increasing after the great recession except for the US. Taking the substantial degree of policy changes into account, it is quite surprising that rigidities are mostly not observed after the financial crisis. However, this finding is in line with recent results by Dovern and Jannsen (2017) that GDP forecasts for expansions do not exhibit systematic errors.

When interpreting our findings, it should be highlighted that significance and magnitude obviously depend on the choice of the window size so the only robust conclusion is that the degree of information rigidities changes over time and sample period. At the same time, the overall evidence of information rigidities in terms of a relationship between ex post forecast errors and ex ante forecast updates is rather weak. As a final step of our preliminary analysis, we assess the effect of inflation and GDP growth disagreement on disagreement regarding the monetary policy interest rate. The findings provided in Table 2 also account for lagged interest rate disagreement and show that inflation uncertainty has a direct positive effect on interest rate uncertainty in many cases while the effect of GDP growth uncertainty is ambiguous.

*** Insert Tables 1 and 2 about here ***

*** Insert Figures 1 and 2 about here ***

Having showed that information rigidities in terms of a link between forecast errors and forecast updates did not uniquely increased after the financial crisis, the next two subsections shed further light on the direct effects stemming from monetary policy. We will assess in the following whether expectations and disagreement react to monetary policy changes.

4.2 Effects of monetary policy shocks on expectations and disagreements

Having traced back the degree of information rigidities, the next step is to analyze the impact of monetary policy shocks on expectations and disagreement related to CPI inflation and GDP growth in terms of an impulse response analysis based on the VAR model given by Eqs. (16) and (19). To make inference about the corresponding reactions, we refer to both 68% and 95% confidence bands.[8]

We start by analyzing the link between expected and actual inflation and GDP growth based on Figures 3 and 4. The underlying idea is to test whether the reaction of forecasts is in line with theory in the sense that new information is reflected in a changing stance of expectations. A positive shock to the inflation rate over the previous month indeed increases inflation expectations for most countries. Such an effect is significant for the US, UK, Italy and Japan. The effects of actual GDP growth on its expectations are clearly significant for all countries at least at the 68% level. The overall results mostly show an expected pattern and also provide evidence that forecasts react to

[8]It is worth noting that 68% confidence intervals are quite common, especially in the VAR literature. See, for instance, Uhlig (2005), Inoue and Kilian (2013) and Lütkepohl *et al.* (2015) as three prominent examples.

new information on the variable being forecasted. They also suggest that expectations proxied by survey data can be considered as an important tool when it comes to the transmission of monetary policy shocks.

*** Insert Figures 3 and 4 about here ***

Against this background, we examine the effects of monetary policy in three steps. We start by assessing effects on expectations before we move to an analysis of effects on disagreement and forecast errors by professionals. Based on our theoretical considerations in Section 2, information rigidities potentially materialize in one of these effects.

Figures 5 and 6 display impulse response functions for the effect of monetary policy rates on expected inflation and GDP growth. An increase in interest rates lowers CPI inflation for Germany and UK while this effect is on the margin of significance for the US and France. The reaction for Italy and Canada shows an opposite pattern with inflation expectations increasing in case of higher interest rates. For Italy this might be explained by the fact that monetary policy is conducted by the ECB since 1999. We also observe a negative response of GDP growth expectations to interest rate shocks for Germany, UK and the US. While this is in line with theory, we find a positive response for the remaining countries, which is slightly surprising. A possible explanation is that monetary policy was characterized by the Taylor rule prior to the financial crisis so that higher interest rates potentially coincided with an increase in GDP as a result of a monetary policy reaction. The positive effect on expectations potentially reflects the belief that GDP growth does not directly respond to monetary policy shocks due to time lags in the transmission of monetary policy. This might in particular be the case if participants expect a stronger interest rate change so that an increase (decrease) in interest rates transmits in an expected increase (decrease) in GDP growth.

*** Insert Figures 5 and 6 about here ***

Taking into account that point forecasts do not consider the full distribution of forecasts, we also focus on disagreements among forecasters by substituting the average forecasts on inflation and GDP growth by their standard deviations in Eq. (16). As previously discussed, such an exercise is also interesting since the theoretical effects are ambiguous. While updates in expectations are expected, disagreement among forecasters might increase or decrease depending on the nature of the policy signal and its credibility. More importantly, disagreement shocks have attracted much attention recently due to the fact that they reflect negative demand shocks (Leduc and Liu, 2016). Similar to our assessment of point forecasts, we analyze the response of CPI inflation and GDP growth disagreement to a shock on (shadow) policy rates as reported in Figures 7 and 8. The impulse response functions are direct measures of the effectiveness of monetary policy. As outlined in Section 2, disagreement among forecasters will increase in case of the sticky information model in case of information rigidities. Policy signals also potentially increase disagreement due to heterogeneity or idiosyncratic differences in information or different signal to noise ratios (Coibion and Gorodnichenko, 2012). In contrast, disagreement is potentially reduced through the coordination channel if participants believe that a policy shock is both credible and informative, implying a negative response of disagreement to positive changes in the policy rate. The findings presented in Figure 7 show that all responses are insignificant based on the 95% confidence interval for inflation disagreement while disagreement significantly increases for Italy and the UK relying on the 68% confidence interval. The latter provides evidence for information rigidities in the spirit of the noisy information model. The findings for disagreement about future GDP growth presented in Figure 8 provide a significant impact for Canada and the US while the findings are again insignificant based on the 95% confidence interval for the remaining countries. The observed significance can be interpreted as evidence for coordination or uncertainty effects in the sense that disagreement is affected by monetary policy.

*** Insert Figures 7 and 8 about here ***

On the one hand, the overall findings show that policy shocks reduce disagreement in some cases, where the uncertainty channel seems to be effective. On the other hand, we also find disagreement to be increasing after a positive monetary policy shocks. Taking into account that the theoretical predictions only refer to significant or insignificant responses, our results provide evidence that the sticky information model characterizes parts of the international transmission of monetary policy shocks. However, some of our insignificant impulse responses are also in line with the findings of Coibion and Gorodnichenko (2012), which suggest that, in line with the noisy information model, there is no systematic effect of fundamental shocks on forecasters disagreement.[9]

[9]It is worth noting that Coibion and Gorodnichenko (2012) rely on a different setting, which considers technology

As a final step of our analysis, we also assess the impact of monetary policy shocks on expectation errors by professionals provided in Figures 9 and 10. In this case we have replaced actual and expected inflation and GDP growth by their differences (i.e. forecast errors) in Eq. (16). This part is directly connected to our previous analysis since an effect on disagreement does not reflect the actual impact of shocks on forecasts errors by professionals. The findings display a significantly positive effect on inflation forecast errors for the US. Similar evidence is provided for France, Italy, Japan and the UK at the 68% confidence interval. Interestingly, the findings for Germany and Canada suggest a reduction in forecast errors based on the 68% confidence interval. Similarly, forecast errors regarding future GDP growth increase after a monetary policy shock for all countries except for Germany and the UK where forecast errors are reduced.

*** Insert Figures 9 and 10 about here ***

4.3 Robustness checks

We have performed several robustness tests to check for the validity of our findings. Most importantly, we have re-estimated all models based on fixed event forecasts, that is by analyzing expectations and disagreements for the next year. The results which are available upon request did not change the overall conclusions and confirm the potential importance of information rigidities after monetary policy shocks. The pattern that information rigidities in terms of a relationship between forecast errors and forecast updates are less frequently observed after the financial crisis also continues to hold. Related to this result, we have also analyzed the path of the information rigidity measure in recessions as introduced by Coibion and Gorodnichenko (2015). In line with our previous time-varying estimates, we do not find a significant increase of information rigidities in terms of a relationship between forecast errors and forecast revisions in recession periods. This pattern might of course be due to the length of our sample period, which does not include recessions before 1995. We have also included disagreement related to the future interest rate into our model. The latter findings are presented in Appendix A.3 and confirm the result that disagreement significantly reacts to monetary policy shocks.

shocks, oil shocks and news shocks and a different survey data set.

5 Conclusion

This paper has analyzed various expectation effects stemming from monetary policy with a focus on information rigidities. As a first step, we have illustrated the time-varying nature of information rigidities. The degree of rigidities is country-specific and subject to changes over time. Interestingly, information rigidities are partly less frequently observed after the emergence of the global financial crisis.

As a next step, we have estimated a panel VAR model, which allows for cross-country lagged interdependencies, time-variation in the coefficients and country-specific factors. Our results point to the importance of distinguishing between different forms of information rigidities. The overall evidence of information rigidities in terms of a relationship between forecast errors and forecast revisions is rather weak. In addition, such a relationship is unaffected by the recent stance in unconventional monetary policy. In contrast, assessing effects on both expectations and disagreements shows that monetary policy actions are not solely successful in triggering expectation changes and a reduction of disagreements among forecasters. Forecasters often revise expectations about future inflation and GDP growth while the former is more frequently affected. At the same point in time policy changes often trigger higher disagreement among forecasters, a result in line with the implications of the sticky information approach. Considering that disagreement resembles demand shocks, such a transmission is of particular importance. Overall, our results suggest that international spillovers of monetary policy potentially increase information rigidity since they increase the complexity of the monetary policy transmission. From the theoretical perspective according to Coibion and Gorodnichenko (2015), features of the international monetary policy transmission channel can be characterized by noisy information models.

While our results have demonstrated the importance of international spillovers, identifying the exact magnitude of spillover effects between the G7 and the implications for emerging and industrial countries is an important avenue for further research. An obvious restriction of our analysis is that a final identification of causal effects stemming from monetary policy in terms of structural shocks is difficult to achieve. It is also important to mention that disagreement among forecasters might increase or decrease depending on the nature of the policy signal and its credibility. This feature has yet to be analyzed in a comprehensive way. Another remaining research question is the effect of monetary policy announcements on expectations on a higher frequency. However, such an analysis is restricted by availability of survey data. Finally, the response of individual forecasters to monetary policy shocks also provides an interesting avenue for future research. Such an analysis potentially provides additional insights on monetary policy effects at a disaggregated level.

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A. Technical appendix

A.1 MCMC approach

Markov Chain Monte Carlo (MCMC) methods can be applied to obtain the posterior distributions of the time-varying factors θ_{it} (see Canova and Ciccarelli (2009) and Beckmann and Czudaj (2017a) for details). To illustrate the MCMC routine followed in our study, consider the likelihood of the reparameterized model given in Eq. (19)

$$L(\theta, \Upsilon|Y) \propto \prod_t |\Upsilon_t|^{-1/2} \exp\left[-\frac{1}{2}\sum_t (Y_t - \chi_t\theta_t)'\Upsilon_t^{-1}(Y_t - \chi_t\theta_t)\right], \tag{21}$$

with

$$\Upsilon_t = (1 + \sigma^2 \mathbf{X_t'X_t})\Omega \equiv \sigma_t\Omega \tag{22}$$

and the prior distribution for $(\Omega^{-1}, \sigma^{-2}, B^{-1})$ is as follows

$$p(\Omega^{-1}, \sigma^{-2}, B^{-1}) = p(\Omega^{-1})p(\sigma^{-2})\prod_f p(B_f^{-1}), \quad f = 1, \ldots, F, \tag{23}$$

with

$$p(\Omega^{-1}) = \mathcal{W}(z_1, Q_1), \quad p(\sigma^{-2}) = \mathcal{G}(a_1/2, a_2/2), \quad p(B_f^{-1}) = \mathcal{W}(z_{2f}, Q_{2f}). \tag{24}$$

We apply a Gibbs sampler to approximate the posterior distribution since an analytical computation is infeasible. In order to illustrate this, the notation is simplified as follows. $Y^T = (Y_1, \ldots, Y_T)$ denotes the data and $\psi = (\Omega^{-1}, \sigma^{-2}, B^{-1}, \{\theta_t\})$ the parameters, where $\psi_{-\alpha}$ is ψ excluding the parameter α.

The conditional posteriors are given by

$$\Omega^{-1}|Y^T, \psi_{-\Omega} \sim \mathcal{W}(z_1 + T, \hat{Q}_1), \quad B_f^{-1}|Y^T, \psi_{-B_f} \sim \mathcal{W}(T \cdot \dim(\theta_t^f) + z_{2f}, \hat{Q}_{2f}), \tag{25}$$

$$\sigma^{-2}|Y^T, \psi_{-\sigma^2} \propto (\sigma^{-2})^{a_1/2-1} \exp\left[-\frac{a_2\sigma^{-2}}{2}\right] \cdot L(\theta, \Upsilon|Y^T), \tag{26}$$

with

$$\hat{Q}_1 = \left[Q_1^{-1} + \sum_t (Y_t - \chi_t\theta_t)\sigma_t^{-1}(Y_t - \chi_t\theta_t)'\right]^{-1}, \tag{27}$$

and

$$\hat{Q}_{2f} = \left[Q_{2f}^{-1} + \sum_t (\theta_t^f - \theta_{t-1}^f)(\theta_t^f - \theta_{t-1}^f)'\right]^{-1}. \tag{28}$$

The conditional posterior for σ^{-2} is non-standard. Therefore, we run a Metropolis-Hastings step within the Gibbs to achieve draws for this parameter. This is done using a random walk kernel $(\sigma^2)^n = (\sigma^2)^c + v$ with $v \sim \mathcal{N}(0, d^2)$. The candidate's acceptance probability is equal to the ratio of the kernel of the density of $(\sigma^2)^n$ to the one of $(\sigma^2)^c$.

Finally, the conditional posterior of $(\theta_1, \ldots, \theta_T | Y^T, \psi_{-\theta})$ is computed by the following Kalman filter recursions

$$\theta_{t|t} = \theta_{t-1|t-1} + (R_{t|t-1}\chi_t F_{t|t-1}^{-1})(Y_t - \chi_t \theta_{t-1|t-1}), \tag{29}$$

$$R_{t|t} = [I - (R_{t|t-1}\chi_t F_{t|t-1}^{-1})\chi_t](R_{t-1|t-1} + B), \tag{30}$$

$$F_{t|t-1} = \chi_t R_{t|t-1}\chi_t' + \Upsilon_t. \tag{31}$$

The output of the Kalman filter is used to obtain the sample $\{\theta_t\}$ as follows. θ_T is simulated from $\mathcal{N}(\theta_{T|T}, R_{T|T})$, θ_{T-1} from $\mathcal{N}(\theta_{T-1}, R_{T-1})$, ..., θ_1 from $\mathcal{N}(\theta_1, R_1)$ with

$$\theta_t = \theta_{t|t} + R_{t|t}R_{t+1|t}^{-1}(\theta_{t+1} - \theta_{t|t}), \quad \text{and} \quad R_t = R_{t|t} - R_{t|t}R_{t+1|t}^{-1}R_{t|t}. \tag{32}$$

The starting values $\theta_{0|0}$ and $R_{0|0}$ can be obtained from a training sample or by choosing small values.

We have run the MCMC 30 times with 2,100 draws and a burn-in of 100. Furthermore, we set $a_1 = 10$ and $a_2 = 1$. $p(\Omega^{-1}) = \mathcal{W}(z_1, (z_1\Omega_{OLS})^{-1})$ with $z_1 = NG + 217$ and Ω_{OLS} as the covariance matrix of the residuals derived from univariate autoregressions. The degrees of freedom z_1 haven been chosen to approximately match the sample size T.

A.2 Impulse response analysis

The impulse responses are computed as the difference between two conditional expectations of $y_{t+\tau}$ conditional on the data (Y^t), the factors (θ_t), the parameters that determine the law of motion of the coefficients as well as all future shocks (Koop *et al.*, 1996; Canova and Ciccarelli, 2009). The only distinction between this two conditional expectations is that one is also conditional on a random draw for the current shocks, whereas the other conditioned on the unconditional value of the current shocks.

To formalize this, $\mathcal{U}_t = (\zeta_t', \eta_t')'$ denotes the vector of reduced-form shocks while $\mathcal{Z}_t = (H_t^{-1}\zeta_t', H_t^{-1}\eta_t')'$ is the vector of structural shocks with $E_t = H_t v_t$, $H_t H_t' = \Omega$ so that $\text{var}(v_t) = I$. $H_t = J \cdot K_t$ with $K_t K_t' = I$, J is a lower triangular matrix that orthogonalizes the shocks, and $\mathcal{V}_t = (\Omega, \sigma^2, B_t)$. $\bar{\mathcal{Z}}_{j,t}$ denotes a particular realization of $\mathcal{Z}_{j,t}$ and $\mathcal{Z}_{-j,t}$ represents structural shocks excluding the one to the jth component of $\mathcal{Z}_t$. Finally, we define $\mathcal{F}_t^1 = (Y^{t-1}, \theta^t, \mathcal{V}_t, H_t, \mathcal{Z}_{j,t} = \bar{\mathcal{Z}}_{j,t}, \mathcal{Z}_{-j,t}, \mathcal{U}_{t+1}^{t+\tau})$ and $\mathcal{F}_t^2 = (Y^{t-1}, \theta^t, \mathcal{V}_t, H_t, \mathcal{Z}_{j,t} = E(\mathcal{Z}_{j,t}), \mathcal{Z}_{-j,t}, \mathcal{U}_{t+1}^{t+\tau})$. Then responses to an impulse in the jth component of $\mathcal{Z}_t$ at period t are given as

$$IR(t, t+\tau) = E(Y_{t+\tau}|\mathcal{F}_t^1) - E(Y_{t+\tau}|\mathcal{F}_t^2), \quad \tau = 1, 2, \ldots. \tag{33}$$

Given that, the responses can be obtained as follows:

(1) Choose t, τ, and J and draw $\Omega^l = H_t^l(H_t^l)'$ as well as $(\sigma^2)^l$ from their posterior distributions and u_t^l from $\mathcal{N}(0, (\sigma^2)^l I \otimes H_t^l(H_t^l)')$. Then, calculate $y_t^l = \chi_t\theta_t + H_t v_t + X_t u_t^l$.

(2) Draw $\Omega^l = H^l_{t+1}(H^l_{t+1})'$, $(\sigma^2)^l$, B^l_{t+1}, and η^l_{t+1} from their posterior distributions. Then, use this to compute the factors θ^l_{t+1} and the indices χ_{t+1}. Draw u^l_{t+1} from $\mathcal{N}(0, (\sigma^2)^l I \otimes H^l_{t+1}(H^l_{t+1})')$ and calculate $y^l_{t+1} = \chi_{t+1}\theta^l_{t+1} + H_{t+1}v_{t+1} + X_{t+1}u^l_{t+1}$, $l = 1, \ldots, L$.

(3) Repeat step 2 and compute $\theta^l_{t+k}, y^l_{t+k}$, $k = 2, \ldots, \tau$.

(4) Repeat steps 1-3 setting $v_{t+k} = E(v_{t+k})$, $k = 0, \ldots, m$ using the draws for the shocks obtained in steps 1-3.

A.3 Additional findings

Figure A.3.1 **Response of 12 month interest rate disagreements to a shock on the US policy rate**

The plots show the reaction of disagreement regarding 12 month interest rates to a shock on the US (shadow) policy rate in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

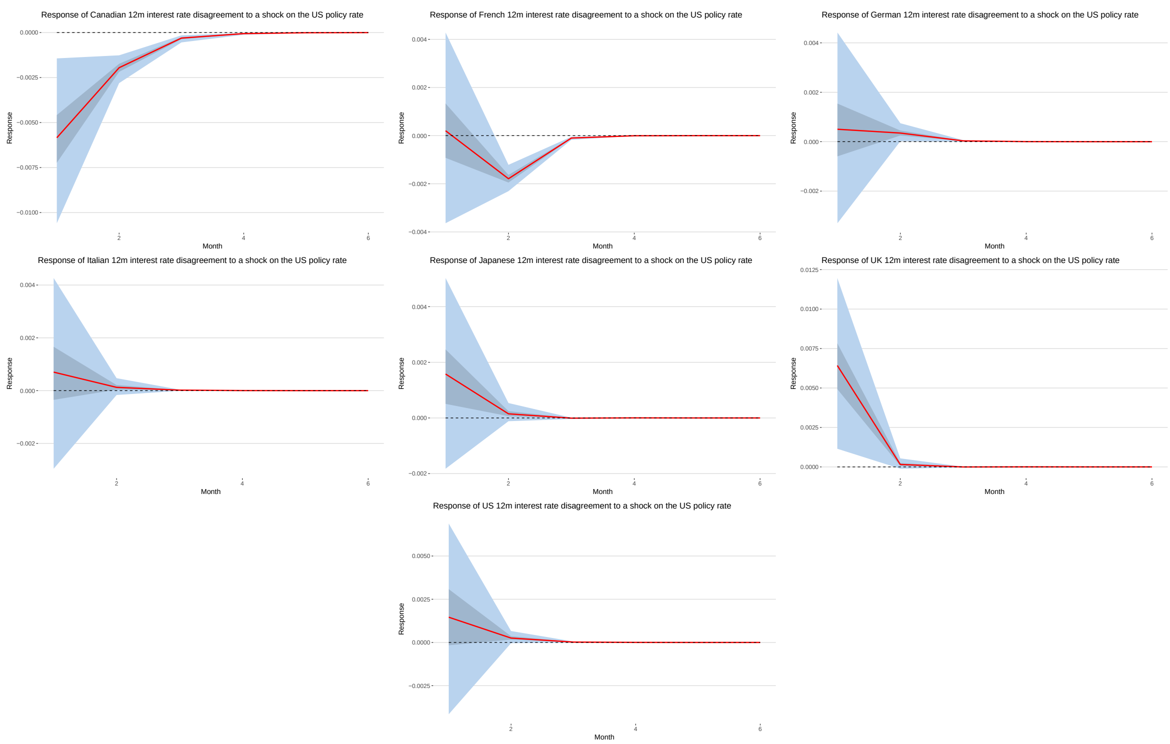
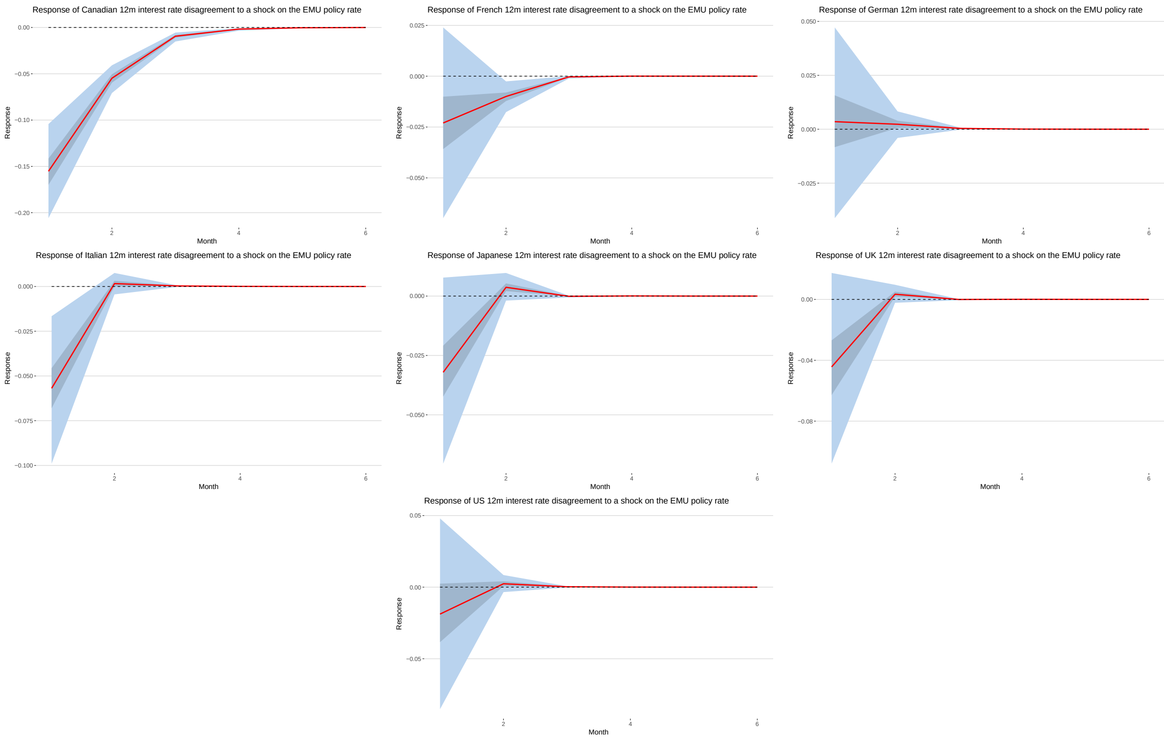


Figure A.3.2 **Response of 12 month interest rate disagreements to a shock on the EMU policy rate**

The plots show the reaction of disagreement regarding 12 month interest rates to a shock on the European Monetary Union (EMU) (shadow) policy rate in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.



Tables

Table 1 **Tests for the nature of the expectations formation process**

	CPI inflation								GDP growth							
	CA	**FR**	**GER**	**IT**	**JP**	**UK**	**US**	**Pooled**	**CA**	**FR**	**GER**	**IT**	**JP**	**UK**	**US**	**Pooled**
β_0	-0.0775	-0.0848	-0.0157	0.1194	-0.0371	-2.3166	0.0197	-0.3462	-0.2900	-0.2844	0.2759	-0.5528	-0.5073	0.0157	-0.1334	-0.2112
s.e.	0.0502	0.0306	0.0379	0.0259	0.0390	0.4342	0.0515	0.0856	0.0908	0.1082	0.2170	0.1656	0.1766	0.1452	0.1353	0.0723
p-value	0.1233	0.0059	0.6787	0.0000	0.3422	0.0000	0.7031	0.0001	0.0016	0.0090	0.2046	0.0009	0.0044	0.9142	0.3249	0.0035
β_1	-0.0555	0.1369	-0.0397	0.0376	0.0193	-0.5296	-0.1587	-0.4829	-0.0098	0.0461	-0.0566	0.0823	-0.0879	-0.1794	-0.1591	-0.0661
s.e.	0.1069	0.1213	0.1102	0.1000	0.0948	0.0883	0.0793	0.0692	0.1133	0.1428	0.1480	0.1510	0.1339	0.1154	0.1206	0.0514
p-value	0.6040	0.2598	0.7188	0.7071	0.8392	0.0000	0.0463	0.0000	0.9311	0.7472	0.7021	0.5864	0.5120	0.1212	0.1879	0.1989
R^2	0.0016	0.0056	0.0004	0.0006	0.0002	0.0795	0.0151	0.0559	0.0000	0.0003	0.0003	0.0008	0.0015	0.0068	0.0047	0.0006
Observations	314	314	314	314	314	314	314	2198	314	314	314	314	314	314	314	2198

Note: The table reports coefficient estimates, HAC standard errors (s.e.), p-values, the R^2 and the number of observations for the OLS regression $y_{t+h} - F_t(y_{t+h}) = \beta_0 + \beta_1[F_t(y_{t+h}) - F_{t-1}(y_{t+h})] + \varepsilon_t$, where y_{t+h} is CPI inflation or GDP growth, respectively, for period $t+h$ in percent and $F_t(y_{t+h})$ is its forecast at time t. The model has been estimated for the G7 economies: Canada (CA), France (FR), Germany (GER), Italy (IT), Japan (JP), United Kingdom (UK) and United States (US).

Table 2 **Tests for the effect of CPI inflation and GDP growth disagreements on monetary policy disagreements**

	CA	**FR**	**GER**	**IT**	**JP**	**UK**	**US**
β_2	0.1654	-0.0981	-0.0118	0.0609	0.0750	0.0079	-0.0841
s.e.	0.0561	0.0776	0.0430	0.0759	0.0303	0.0044	0.0433
p-value	0.0034	0.2071	0.7848	0.4228	0.0139	0.0773	0.0529
β_3	0.0737	0.1014	0.0591	-0.1152	-0.0159	-0.0249	0.0653
s.e.	0.0498	0.0548	0.0339	0.0588	0.0141	0.0355	0.0356
p-value	0.1398	0.0650	0.0820	0.0510	0.2587	0.4838	0.0676
R^2	0.7942	0.7198	0.8093	0.6293	0.8396	0.8818	0.7968
Observations	324	324	324	324	324	324	324

Note: The table reports coefficient estimates, HAC standard errors (s.e.), p-values, the R^2 and the number of observations for the OLS regressions $SD(\text{MP})_t = \beta_0 + \beta_1 SD(\text{MP})_{t-1} + \beta_2 SD(\text{CPI})_t + \beta_3 SD(\text{GDP})_t + \varepsilon_t$, where $SD(.)$ denotes the standard deviation of monetary policy (MP), CPI inflation (CPI) or GDP growth (GDP) forecasts, respectively. The model has been estimated for the G7 economies: Canada (CA), France (FR), Germany (GER), Italy (IT), Japan (JP), United Kingdom (UK) and United States (US).

Figures

FIGURE 1 **Time-varying information rigidity (β_1) coefficients for CPI inflation for G7 economies**

The plots show rolling window OLS estimates for the following regression model $y_{t+h} - F_t(y_{t+h}) = \beta_0 + \beta_1[F_t(y_{t+h}) - F_{t-1}(y_{t+h})] + \varepsilon_t$, where y_{t+h} is CPI inflation for period $t+h$ in percent and $F_t(y_{t+h})$ is its forecast at time t. The coefficient β_1 provides the amount of information rigidity. See Section 2.2 for details. We use a window size of 30 observations. The red line highlights time periods, in which the corresponding coefficient estimate is statistically significant at least at the 10% level. The shaded areas correspond to US recession periods according to the definition of the National Bureau of Economic Research (NBER).

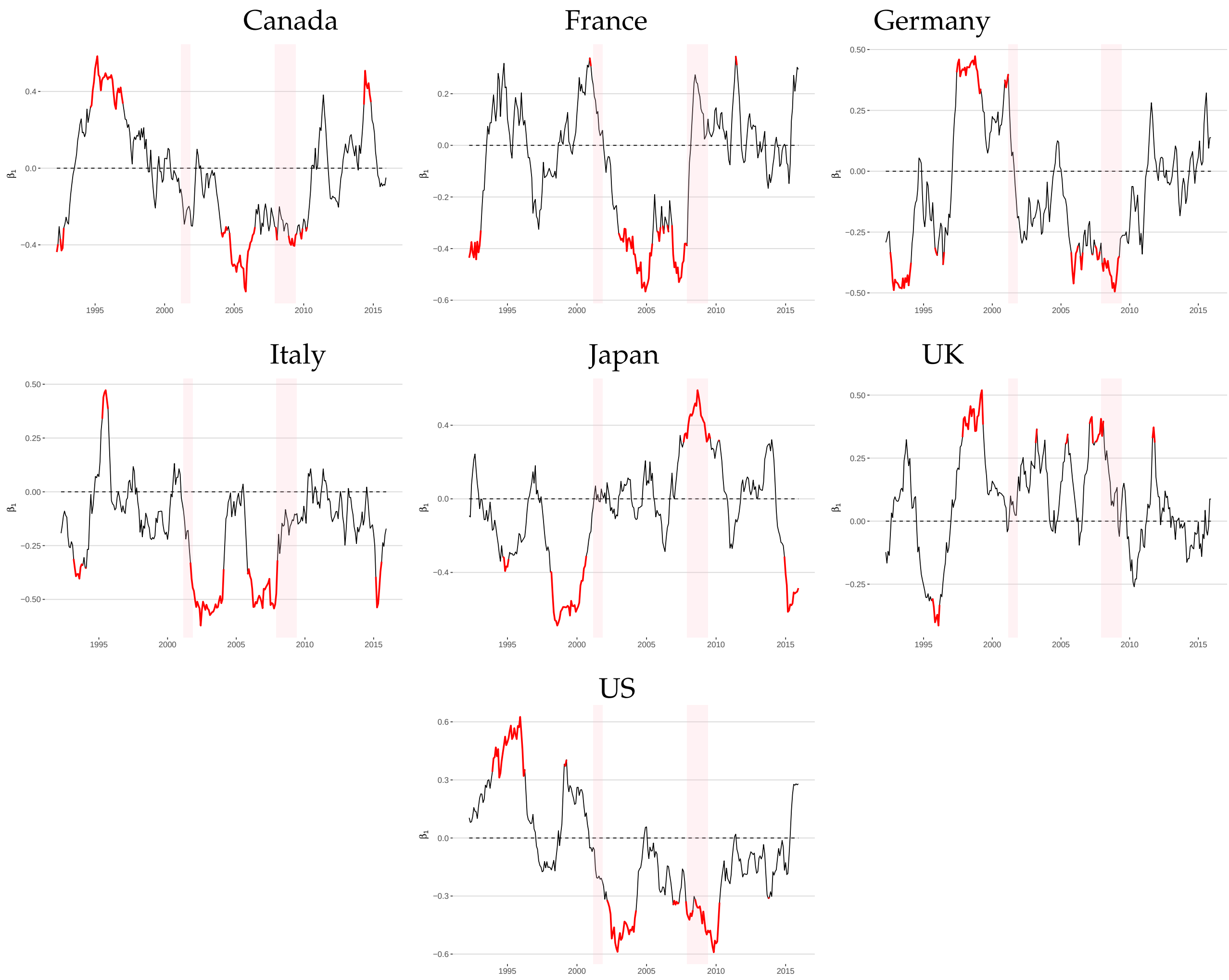


FIGURE 2 **Time-varying information rigidity (β_1) coefficients for GDP growth for G7 economies**

The plots show rolling window OLS estimates for the following regression model $y_{t+h} - F_t(y_{t+h}) = \beta_0 + \beta_1[F_t(y_{t+h}) - F_{t-1}(y_{t+h})] + \varepsilon_t$, where y_{t+h} is GDP growth for period $t+h$ in percent and $F_t(y_{t+h})$ is its forecast at time t. The coefficient β_1 provides the amount of information rigidity. See Section 2.2 for details. We use a window size of 30 observations. The red line highlights time periods, in which the corresponding coefficient estimate is statistically significant at least at the 10% level. The shaded areas correspond to US recession periods according to the definition of the National Bureau of Economic Research (NBER).

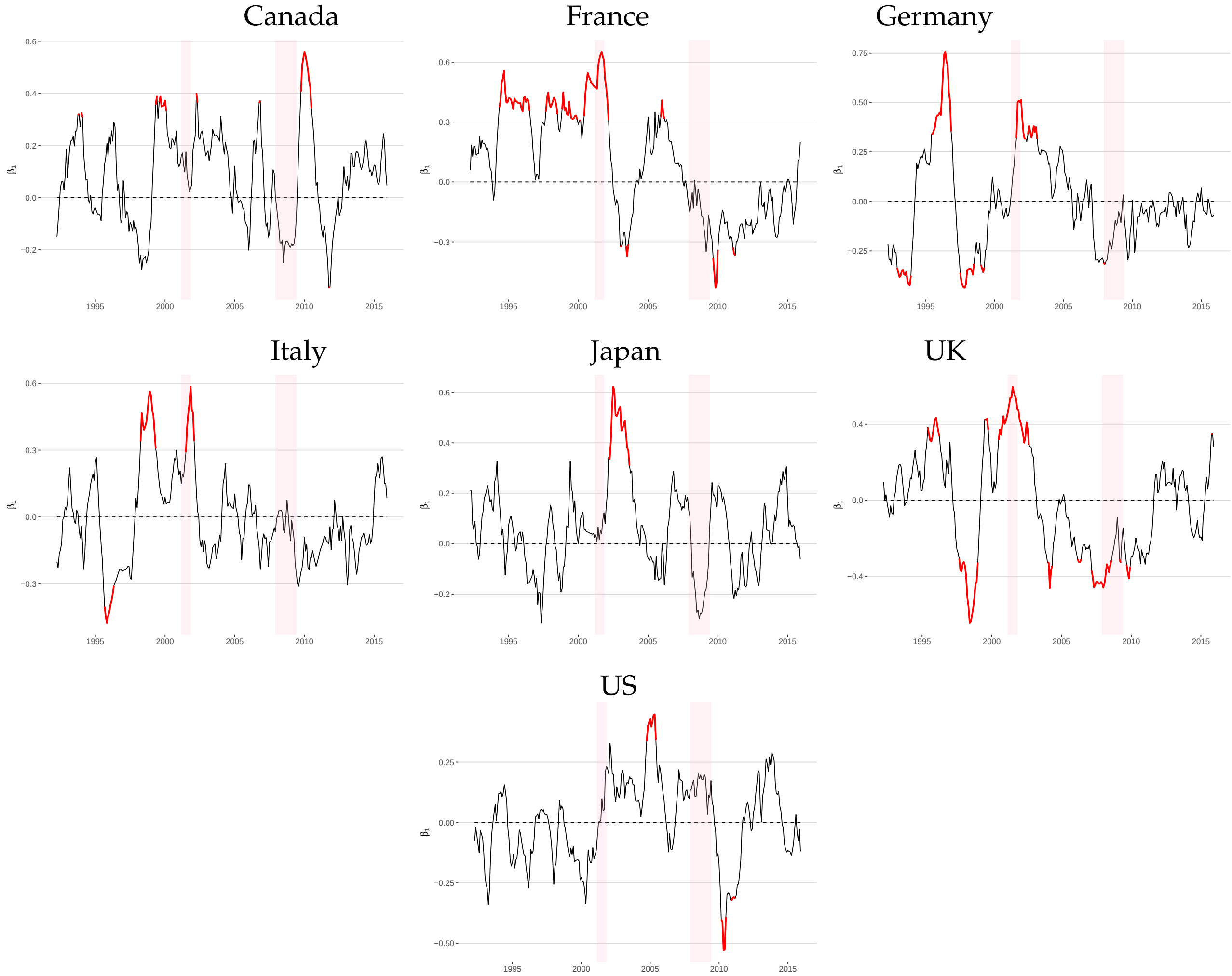


FIGURE 3 **Response of expected CPI inflation to a shock on actual CPI inflation**

The plots show the reaction of expected CPI inflation to a shock on actual CPI inflation in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

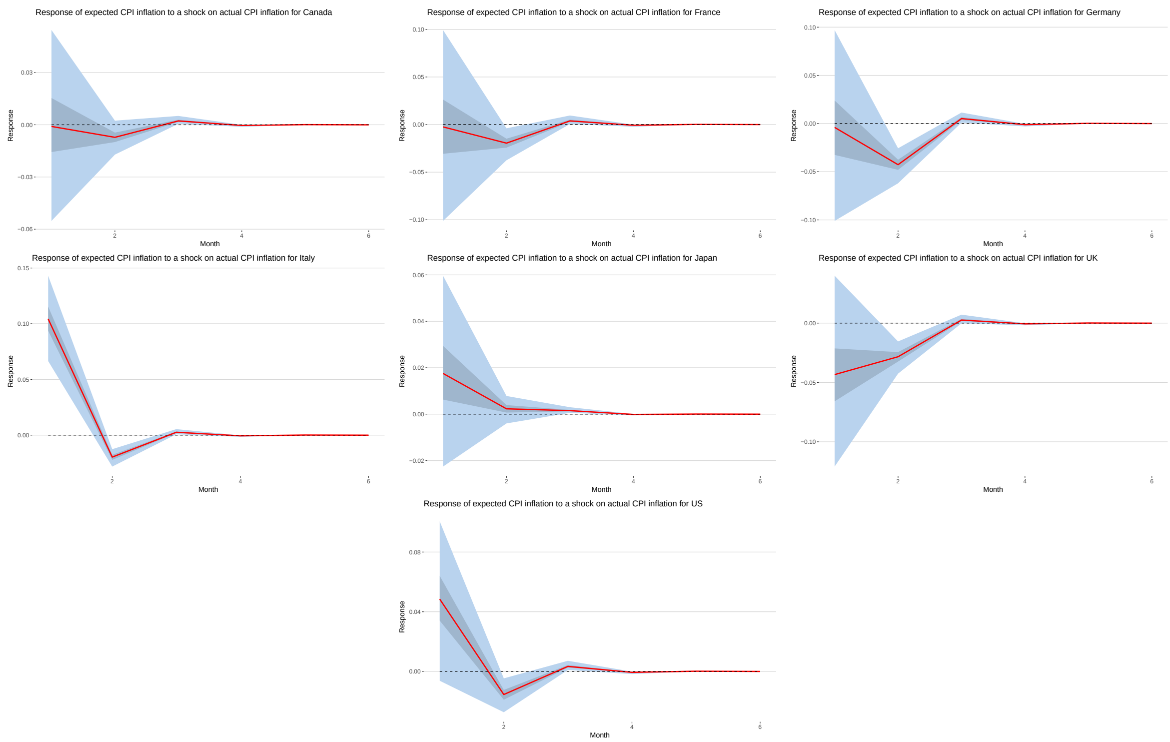


Figure 4 **Response of expected GDP growth to a shock on actual GDP growth**

The plots show the reaction of expected GDP growth to a shock on actual GDP growth in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

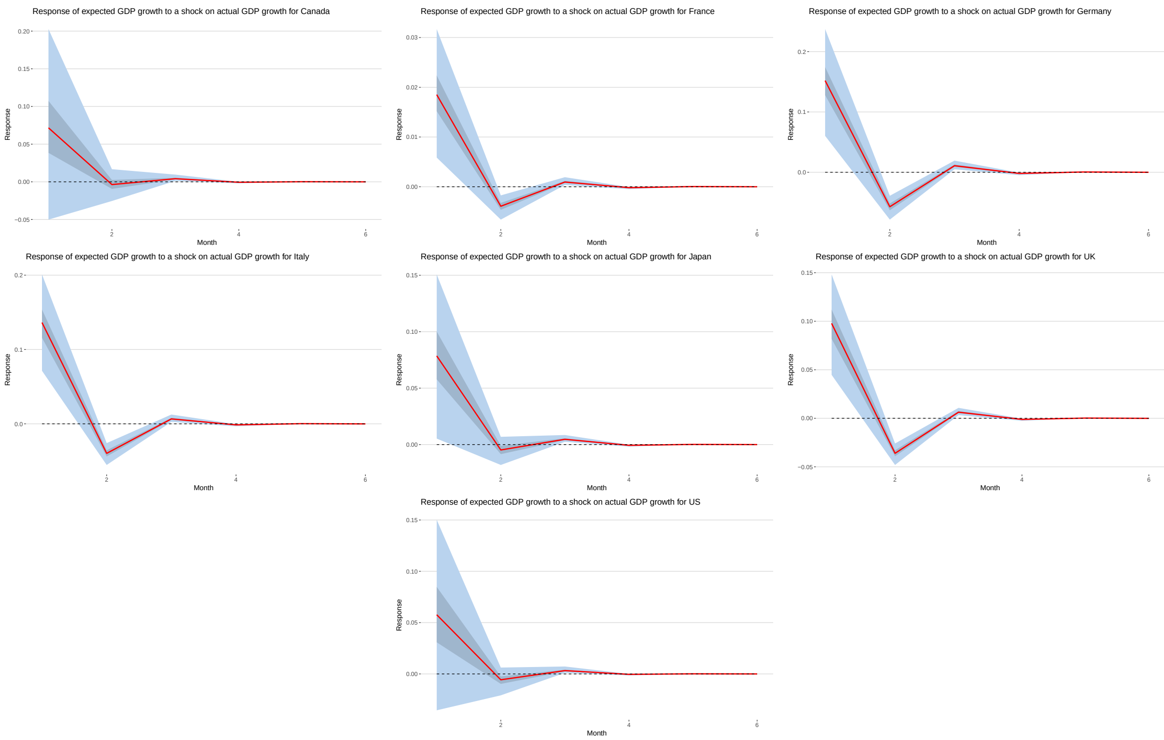


Figure 5 **Response of expected CPI inflation to a shock on (shadow) policy rates**

The plots show the reaction of expected CPI inflation to a shock on (shadow) policy rates in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

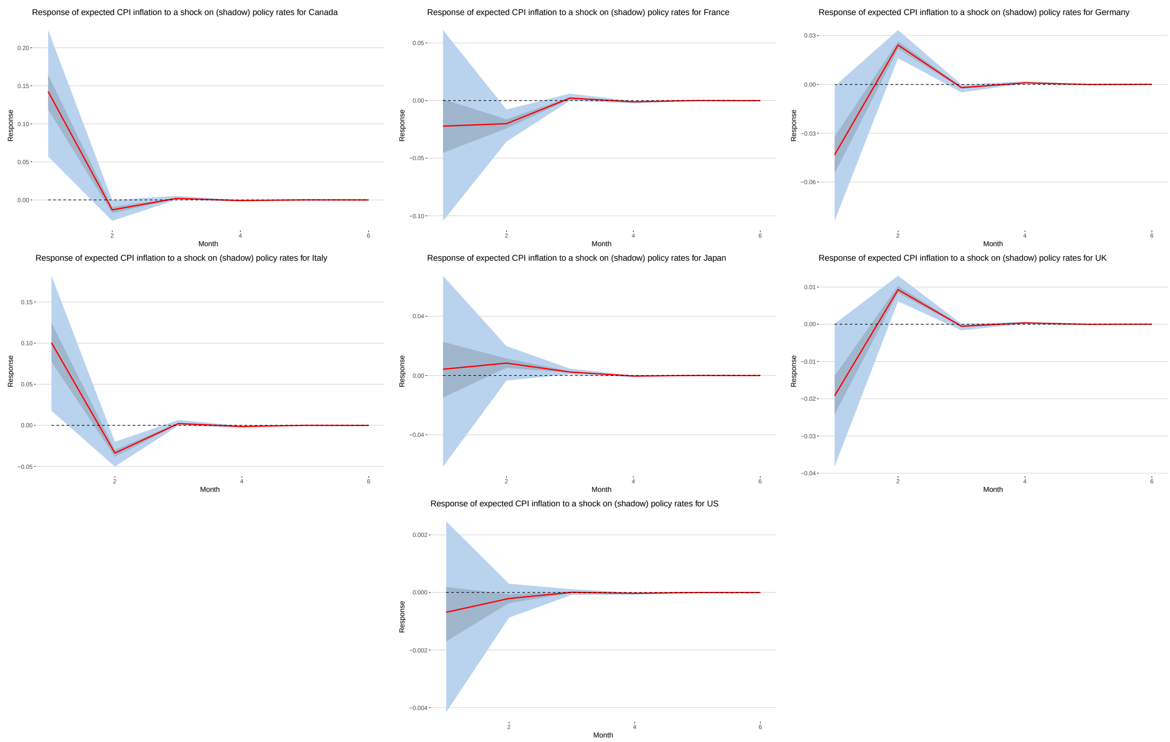


FIGURE 6 **Response of expected GDP growth to a shock on (shadow) policy rates**

The plots show the reaction of expected GDP growth to a shock on (shadow) policy rates in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

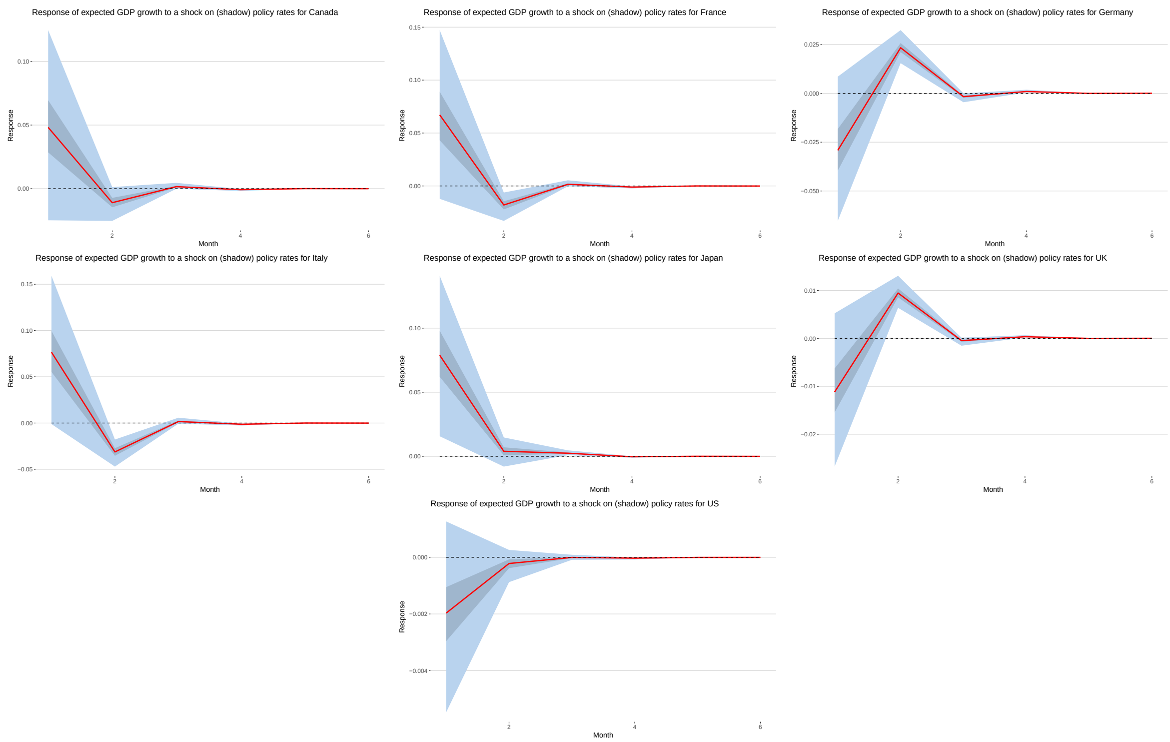


FIGURE 7 **Response of CPI inflation disagreement to a shock on (shadow) policy rates**

The plots show the reaction of disagreement regarding CPI inflation to a shock on (shadow) policy rates in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

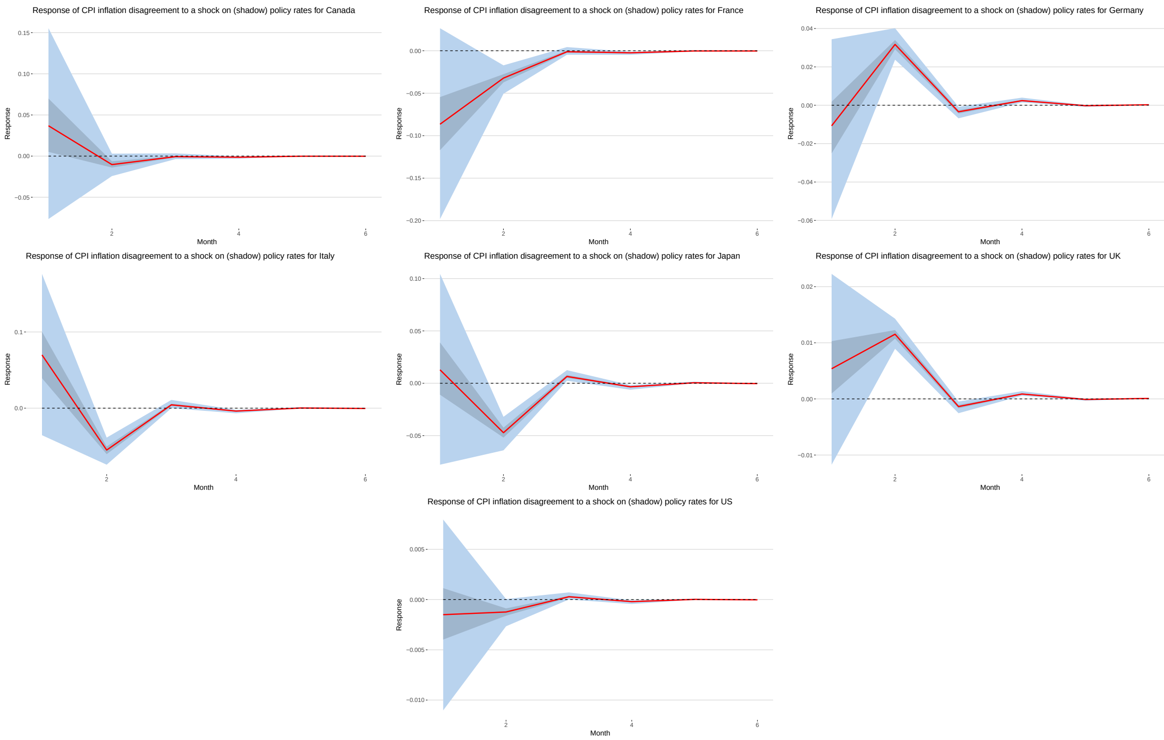


FIGURE 8 **Response of GDP growth disagreement to a shock on (shadow) policy rates**

The plots show the reaction of disagreement regarding GDP growth to a shock on (shadow) policy rates in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

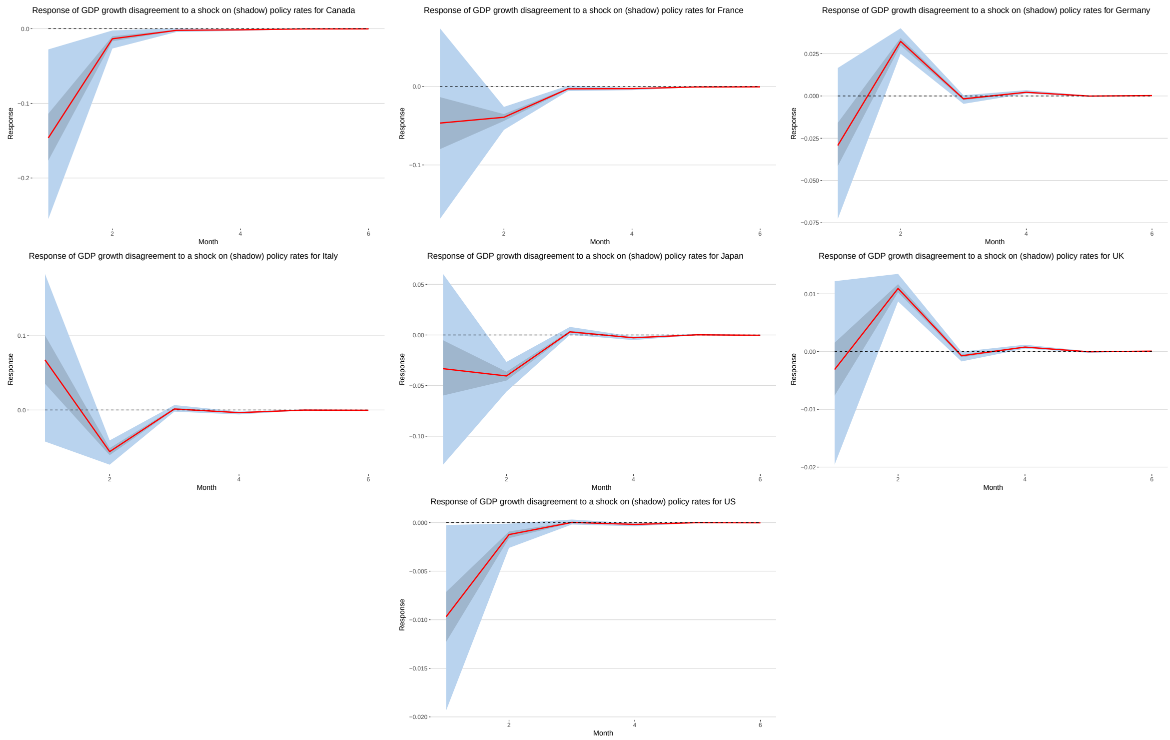


FIGURE 9 **Response of CPI inflation forecast error to a shock on (shadow) policy rates**

The plots show the reaction of CPI inflation forecast error (i.e. deviation of actual and expected CPI inflation) to a shock on (shadow) policy rates in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.

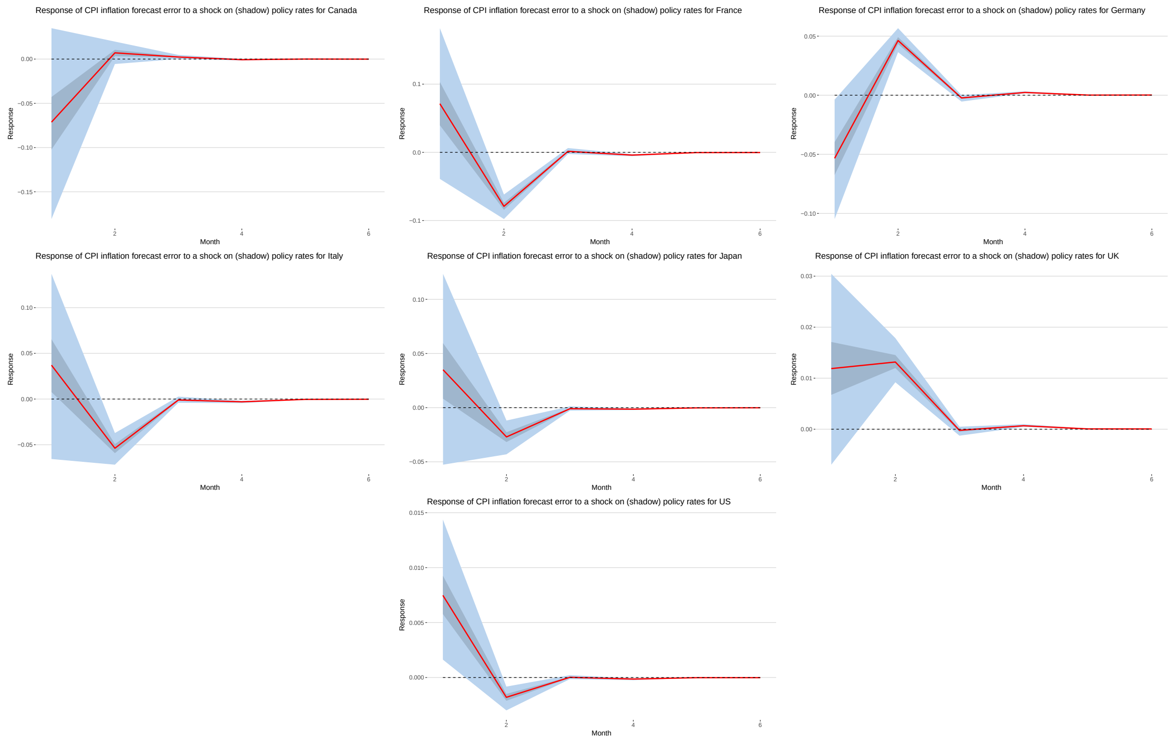


FIGURE 10 **Response of GDP growth forecast error to a shock on (shadow) policy rates**

The plots show the reaction of GDP growth forecast error (i.e. deviation of actual and expected GDP growth) to a shock on (shadow) policy rates in the corresponding economies. The reaction is represented by the solid red line and the corresponding 95% (68%) confidence bands by blue (dark blue) shadings. The dashed black line displays the zero line.