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Fundamental disagreement ☆

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ABSTRACT

We document a novel set of facts about disagreement among professional forecasters: (1) forecasters disagree at all horizons, including the long run; (2) the term structure of disagreement is downward sloping for real output growth, relatively flat for inflation, and upward sloping for the federal funds rate; (3) disagreement is time varying at all horizons. We propose a generalized model of imperfect information that can jointly explain these facts. We further use the term structure of disagreement to show that the monetary policy rule perceived by professional forecasters features a high degree of interest-rate smoothing and time variation in the intercept.

1. Introduction

People, even informed specialists, disagree about the future. Surveys of expectations taken from consumers, firms, professional forecasters, financial analysts or FOMC members show that individuals have different forecasts about the same economic variable. Differences of opinion matter for economic outcomes such as monetary policy decisions or the price of assets. Theories incorporating heterogenous beliefs have gone a long way toward explaining empirical regularities that are challenging for representative agent frameworks. In particular, sources of disagreement can lead to inertia in price dynamics (Mankiw and Reis, 2002; Woodford et al., 2003; Maćkowiak and Wiederholt, 2009), non-fundamental driven business cycle fluctuations (Lorenzoni, 2009; Angeletos and La'O, 2013; Rondina and Walker, 2012; Ilut and Schneider, 2014), as well as speculative dynamics and booms and busts in asset prices (Scheinkman and Xiong, 2003; Nimark, 2012; Burnside et al., 2013).[1] As a growing theoretical literature relies on agents with heterogenous beliefs, it is crucial to confront these models with the empirical properties of disagreement.

Our paper makes three contributions. First, we use the term structure of disagreement of professional forecasters to document a novel set of facts about forecasts for real output growth, CPI inflation and the federal funds rate. Second, we propose a model of imperfect information in which forecasters disentangle low-frequency shifts in fundamentals from short-term fluctuations and identify key model features needed to match these new facts. Third, we illustrate that the term structure of disagreement is informative about how professional forecasters perceive the reaction function of the central bank.

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[1] See, for example, Hansen (2007), Sargent (2008), and Mankiw and Reis (2010) for general discussions.

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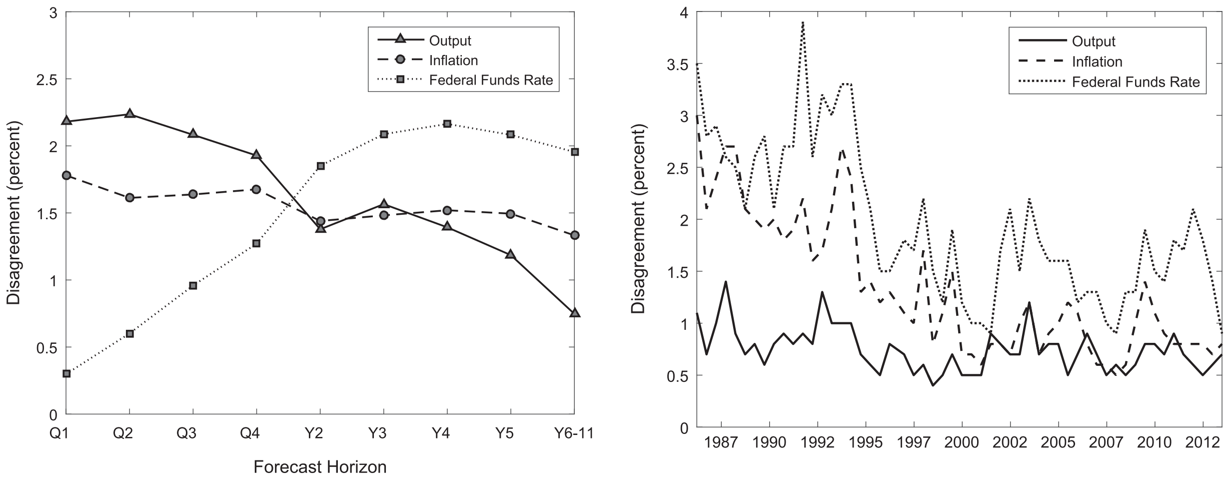


Fig. 1. This figure shows selected statistics for forecast disagreement from the Blue Chip Financial Forecasts survey. Disagreement is defined as the average forecast of the highest 10 responses minus that of the lowest 10 responses of survey participants (in percent). The left panel shows the term structure of disagreement averaged across time for real output growth, CPI inflation, and the federal funds rate for various forecast horizons. Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. The right panel displays the time series of the 6-to-11 years ahead forecast disagreement for the three variables.

The new stylized facts about disagreement can be illustrated by the two graphs in Fig. 1. The figures display forecast disagreement for our three variables from the Blue Chip Financial Forecasts (BCFF) survey. This dataset has three important and distinct features: it contains forecasts for short-, medium- and long-term horizons for the same survey participants; these data begin in the mid-1980s and represent the longest running comprehensive source of survey forecasts and disagreement available; it includes forecasts for the three key macroeconomic variables: output growth, inflation and the policy rate. To our knowledge, we are the first paper to use the BCFF data to study disagreement. The left panel of Fig. 1 shows our measure of average disagreement across time for a set of different forecast horizons ranging from one quarter to 6-to-11 years ahead. Throughout the paper, we define disagreement as the average forecast of the highest 10 responses minus that of the lowest 10 responses of survey participants for a given variable and forecast horizon. A first regularity that stands out from this figure is that, for each of the three variables we consider, the disagreement is non-zero even for long horizons. We refer to this as *fundamental disagreement*, since it likely captures different views about low-frequency changes in the fundamentals of the economy such as changes in potential output growth or the (implicit) inflation target. A second striking fact is that fundamental disagreement can be lower, comparable to, or higher than disagreement about short-term economic fluctuations. In short, the shape of the average term structure of disagreement varies across variables. It is downward sloping for real output growth, almost flat for CPI inflation, and upward sloping for the federal funds rate. Finally, a third fact is shown in the right panel of Fig. 1 which reports the time series of the long-run forecast disagreement for the three variables from 1986 through 2013. It underlines that in addition to being non-zero, fundamental disagreement is not constant over time and covaries between variables.

In order to rationalize these facts we introduce a generalized model of imperfect information which captures three important challenges that economic agents face. The first one is that they are not fully informed at all times about the true state of the economy. The second challenge is that when facing fluctuations in economic conditions, agents need to distinguish in real time between temporary and permanent factors. The latter capture low-frequency shifts in the structure of the economy. The third challenge is that the nature of economic fluctuations is inherently multidimensional and consequently agents must take into account the dynamic interactions across variables when forming expectations.

We address the first challenge by modeling agents' expectation formation process subject to information frictions. In our model, this friction arises because agents only infrequently update their information set as in the sticky information framework of Mankiw and Reis (2002). However, the model improves on the existing literature along two important dimensions, which are crucial in addressing the two remaining challenges faced by forecasters. Specifically, the second challenge is addressed by adding the assumption that the imperfectly observed state is the sum of two unobserved components: a transitory one which captures short-lived economic fluctuations and a permanent one which captures structural changes to the economy. Finally, the third challenge is tackled by extending the Mankiw and Reis (2002) model to a multivariate setup where agents' separately update information on individual variables. We also show that our findings are similar when agents observe a noisy signal of the current state of the economy (Sims, 2003; Woodford et al., 2003).

We show that agents' need to disentangle short- and long-term factors and to accommodate the dynamic interaction between variables, as captured in a multivariate framework, are critical to matching the term structure of disagreement. The unobserved slow-moving drift component in the model is vital to capturing forecast disagreement at all horizons except the very short term. The multivariate setup of the model is required to generate the different shapes of the term structures of disagreement that we observe in the data. In particular, it is essential to produce an upward sloping term structure of disagreement for a variable that is perfectly observed, such as the federal funds rate. The multivariate setup is also necessary to capture the fact that forecasts and forecast disagreement display strong correlation across variables. More generally, the class of models that can generate fundamental disagreement helps to better understand the formation of expectations at all horizons. It offers a rationale for why agents can disagree about the future evolution of variables that they perfectly observe, or why they can disagree more about slow-moving fundamentals than about short term fluctuations.

Perhaps surprisingly, our model's modest departure from the homogeneous full information setup goes a long way toward explaining short- and long-term disagreement. Our model is able to replicate the shapes of the term structure of disagreement that we observe in the data. However, it fails to replicate the magnitude of time variation of medium- and long-term disagreement. This last result is particularly notable as the previous literature has highlighted the ability of the sticky information model to generate time-varying disagreement (Mankiw and Reis, 2010), and thus emphasizes the importance of using the entire term structure of disagreement for model evaluation.

While these results are obtained without assuming any structural model behind agents' forecasts, we also go one step further by giving a structural interpretation to their reduced-form model. We focus on the monetary policy reaction function and show that our reduced-form model parameters are consistent with a policy rule with coefficients similar to those found in the empirical literature (e.g., Clarida et al., 2000). A counterfactual analysis of the role of the different components in the monetary policy rule further highlights that the monetary policy rule perceived by professional forecasters features both a high degree of interest-rate smoothing and time variation in the intercept. Moreover, fundamental disagreement about the federal funds rate is largely driven by disagreement about the inflation target and the long-run growth rate of output.

In our model no agent is systematically endowed with "better" information than any other agent and all know the true data-generating process (DGP). This stands in contrast to models where agents observe more informative signals either because they have more precise priors or higher signal-to-noise ratios. It also contrasts with models which feature persistent disagreement about the true DGP, either because agents can never fully learn about the true DGP or have immutable priors. These latter models featuring asymmetric agents have the implication that certain forecasters should produce more precise forecasts than others. However, it is a well-documented fact that the consensus forecast is difficult to beat, i.e., that no individual forecaster has systematically better forecast performance (e.g., Bauer et al., 2003; Stock and Watson, 2004). Our approach is consistent with this latter result. Finally, it is important to point out that in our modeling setup, agents forecast an exogenous data generating process. That is, we abstract from any feedback from forecasts to outcomes in general equilibrium as well as from strategic interactions or other forms of endogenous information acquisition. While we believe that these effects may also be important, our focus is to keep the model environment as simple as possible.

Our paper is related to the growing literature that uses survey data to evaluate models of expectation formation.[2] Mankiw et al. (2003) emphasize that disagreement about short-term inflation forecasts in different surveys of the US economy is time varying and somewhat correlated with changes in macroeconomic variables such as inflation and output growth. In addition, they relate the properties of a sticky information model to the observed forecast disagreement about future inflation. Carroll (2003) uses consensus forecasts from households and professional forecasters to validate an epidemiological model of expectations. Lahiri and Sheng (2008) and Patton and Timmermann (2010) study disagreement up to two years ahead and propose models of expectation formation based on heterogeneous priors. Branch (2004, 2007), Coibion and Gorodnichenko (2015, 2012) and Andrade and Le Bihan (2013) use survey data to discriminate among various models of expectation formation including sticky and noisy information models. All of these papers have in common that they investigate the properties of forecast disagreement only up to horizons of at most two years (i.e., short-term forecasts). Moreover, the existing literature has almost exclusively relied on univariate models (see, for example, the comprehensive study by Coibion and Gorodnichenko, 2012). Andrade and Le Bihan (2013) is an exception.

The decomposition between unobserved long-run fundamentals and short-run fluctuations follows a long tradition in macroeconomics that goes back at least to Kydland and Prescott (1982) and is also used in more recent references such as Blanchard et al. (2013). Several studies argue that unobserved slow moving fundamentals are helpful to account for the dynamics of real GDP growth (Stock and Watson, 1989; Cogley and Sargent, 2005; Laubach and Williams, 2003), the inflation rate (Stock and Watson, 2007; Cogley and Sbordone, 2008; Cogley et al., 2010), and the federal funds rate (Kozicki and Tinsley, 2001; Gürkaynak et al., 2005). Decompositions into persistent and transitory components also play an important role in finance, in particular the literature on long-run risk models (e.g., Bansal and Yaron, 2004).

Our paper is organized as follows. Section 2 provides a detailed description of the BCFF data and our new set of facts. In Section 3 we introduce our model, discuss its properties and describe how we calibrate it to the data. Our main results are presented in Section 4. In Section 5, we use the observed and model-implied disagreement to discriminate between different monetary policy rules perceived by forecasters. Section 6 concludes.

[2] The properties of consensus or median survey forecasts have been widely documented. In particular, numerous papers have discussed the bias and the efficiency of consensus forecasts (see, for example, Pesaran et al., 2006 for a survey) or have used consensus forecasts in model evaluation and estimation (e.g., Roberts, 1995; Adam and Padula, 2011; Del Negro and Eusepi, 2011).

2. Stylized facts about disagreement

In this section, we document a novel set of stylized facts about disagreement among professional forecasters. We first present the survey data that our analysis is based on in Section 2.1 and then summarize the facts in Section 2.2, also relating them to the features of disagreement that have previously been documented in the literature.

2.1. Data

We study a collection of individual forecasts of real output growth, CPI inflation, and the federal funds rate from the Blue Chip Financial Forecasts (BCFF) survey. This survey, conducted monthly since 1982, asks participants ranging from broker-dealers to economic consulting firms to provide forecasts of the quarterly average of a variety of economic and financial variables for specific calendar quarters as far as six quarters in the future. Importantly, since 1986, this survey has also been collecting information on professional forecasts as far as 6-to-11 years ahead. On average, there are about 50 institutions answering the survey, with small variations around this average.

The survey is typically released on the first day of the month, and is based on participants' responses that have been collected during the last week of the previous month. Interest rate forecasts are reported as the average over the target period at an annual rate. Real output and CPI targets are period-over-period percent changes at an annual rate. Real output forecasts are measured with respect to forecasts for real GNP prior to April 1992 and with respect to real GDP thereafter. Since its inception in November 1982, each monthly survey compiles individual forecasts for horizons of one quarter ahead to at least five quarters ahead. We collect the one- through four-quarters ahead forecasts as the four-quarters ahead forecast is the longest horizon forecast available in every month. Beginning in 1986, twice a year, participants were also surveyed on their longer-term forecasts for a selected set of financial and macroeconomic variables for upcoming calendar years between two and five years ahead along with an average value for a 6-to-10-years ahead horizon. Because the longer-term forecasts refer to specific calendar years and are collected biannually, the forecast horizons vary somewhat across surveys. For example, the horizon we refer to as two-years ahead (Y2) is either six or eight quarters ahead depending on whether we are using the survey taken later in the year or earlier in the year, respectively. Between March 1986 and March 1996 long-run forecasts are provided in the March and October surveys. From December 1996 onward, long-run forecasts are provided in the June and December releases.[3] The longest horizon 5-year-average forecasts sometimes shifts between horizons of 6-to-10 years ahead to 7-to-11 years ahead. We combine these time series for our analysis to approximately double the number of observations and label the series as the "6–11 years ahead" (Y6–11) forecast for simplicity. Importantly, when calibrating the model in Section 3.3, we mimic this sampling scheme to ensure consistency with the survey.

Unfortunately, individual long-run forecasts are not available. Instead the BCFF survey reports the top-10 average long-run forecast and the bottom-10 average long-run forecast. Consequently, at all horizons, we use the difference between the average forecast of the highest 10 responses and the average forecast of the lowest 10 responses as our measure of disagreement. For the shorter term forecasts up to five quarters ahead for which individual forecasts are observed, this measure of disagreement is almost perfectly correlated with the cross-sectional standard deviation of forecasts and highly correlated with the interquartile range of individual forecasts which have both been used as measures of disagreement in the literature. As discussed in Section 3.3, this data limitation also guides our choice of calibration technique.

Although the survey begins in late 1982, our data sample starts with the March 1986 survey and ends with the July 2013 survey. This guarantees that there are no missing observations for consensus forecasts or disagreement at all horizons. All data are quarterly where we choose the January, April, July, and October surveys for the short-horizon forecasts matched with the nearest monthly survey which includes long-run forecasts.[4] This results in 110 observations for nine reported forecast horizons (Q1, Q2, Q3, Q4, Y2, Y3, Y4, Y5, Y6–11).

2.2. Three novel facts about forecaster disagreement

We use the dataset to establish a novel set of stylized facts about forecasters' disagreement. Fig. 2 shows the time series of forecaster disagreement for real output growth (upper panel), CPI inflation (middle panel), and the federal funds rate (lower panel) for two forecast horizons: the very short term (one quarter ahead) and the very long term (6-to-11 years ahead). The time series of long term forecast disagreement was already shown in the right panel of Fig. 1, and is contrasted here with the equivalent time series for short-term disagreement.

The charts along with Fig. 1 document three novel facts about forecaster disagreement. First, forecasters disagree both about the short term but also the medium- and long-run prospects of the economy. Second, the disagreement among forecasters is time varying, even for long-term forecasts. Third, the shape of the term structure of disagreement differs markedly across variables. While disagreement at both short- and long-horizons is time varying for all three variables, the ordering of the level of disagreement across horizons differs for each variable. While the professional forecasters in the Blue

[3] There is one exception to this rule. Long-run forecasts were provided in the January 2003 survey instead of the December 2002 survey.

[4] Recall that surveys are taken at the end of the month previous to the publication date. We choose these survey months as they are based on the maximum amount of information about the current quarter available to survey participants.

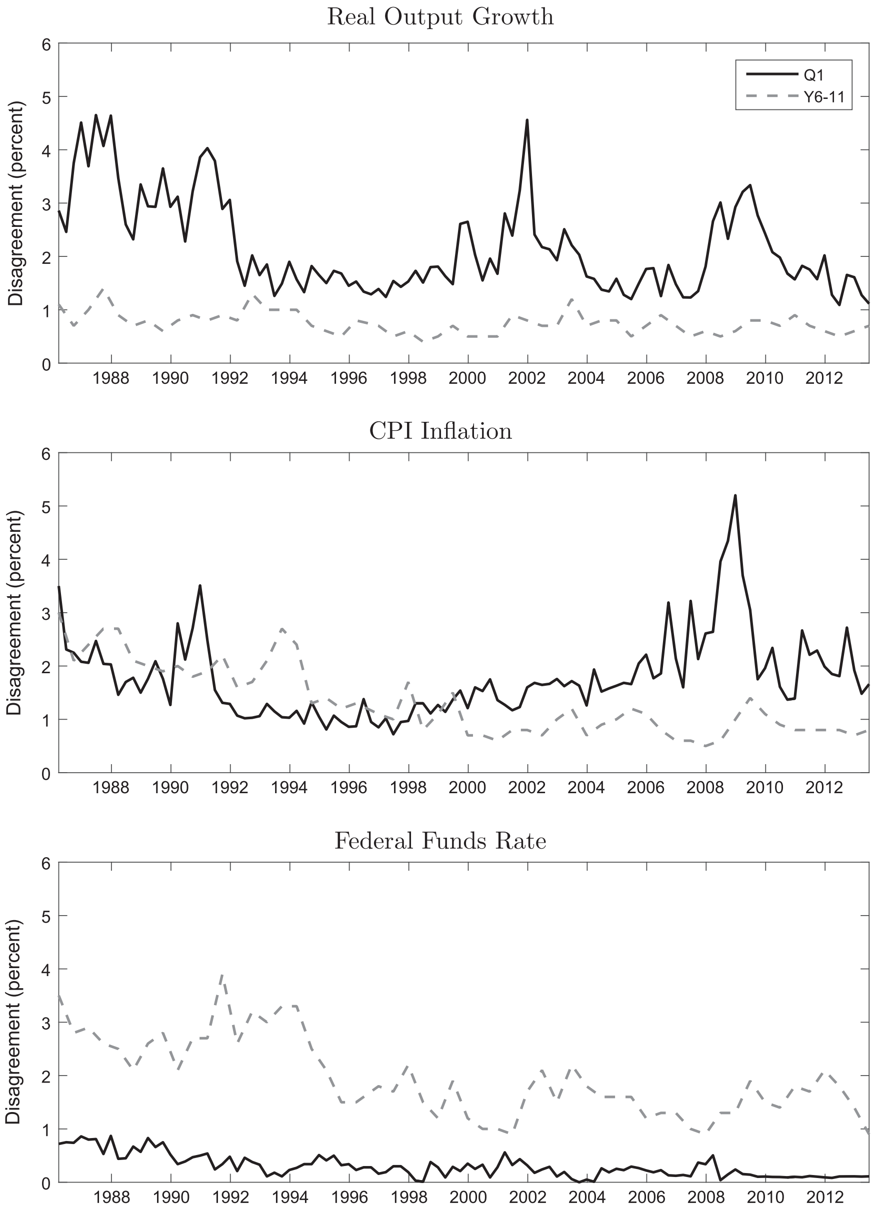


Fig. 2. Time series of disagreement. This figure shows the time series of forecast disagreement as measured by the average forecast of the highest 10 responses minus that of the lowest 10 responses (in percent) for real output growth (top panel), CPI inflation (middle panel), and the federal funds rate (bottom panel) from the Blue Chip Financial Forecasts survey. Q1 denotes the one-quarter ahead forecast while Y6–11 denotes the average forecast for horizons from 6-to-11 years ahead. The sample period is from 1986Q1 to 2013Q2.

Chip survey have disagreed more about output growth in the near term than in the long term over the entire sample from 1986 through 2013, the opposite is true about their forecasts of the federal funds rate. Indeed, while there is typically little disagreement about the federal funds rate in the next quarter, forecasters disagree substantially about the level of short term interest rates in the very long run. Interestingly, for CPI inflation disagreement about the short and long term was at similar levels in the late 1980s and the 1990s, but forecasters started to disagree more about near-term than long-term inflation since around the year 2000. While we only show the time series of disagreement for two different forecast horizons here for simplicity, the left panel of Fig. 1 documents the term structures of average disagreement across all forecast horizons. In summary, our data show striking differences across variables: the term structure of disagreement is downward sloping for real output growth, relatively flat for inflation, and upward sloping for the federal funds rate.

Given the large changes in the monetary landscape during our sample period and the unprecedented economic developments in the wake of the financial crisis, it is important to also document how the term structure of disagreement varies over alternative subsamples. In particular, the period from the mid-1980s to the mid-1990s was characterized by a strong downward trend in expected inflation and policy rates. To assess how this affects our results, in the top panel of Fig. 3

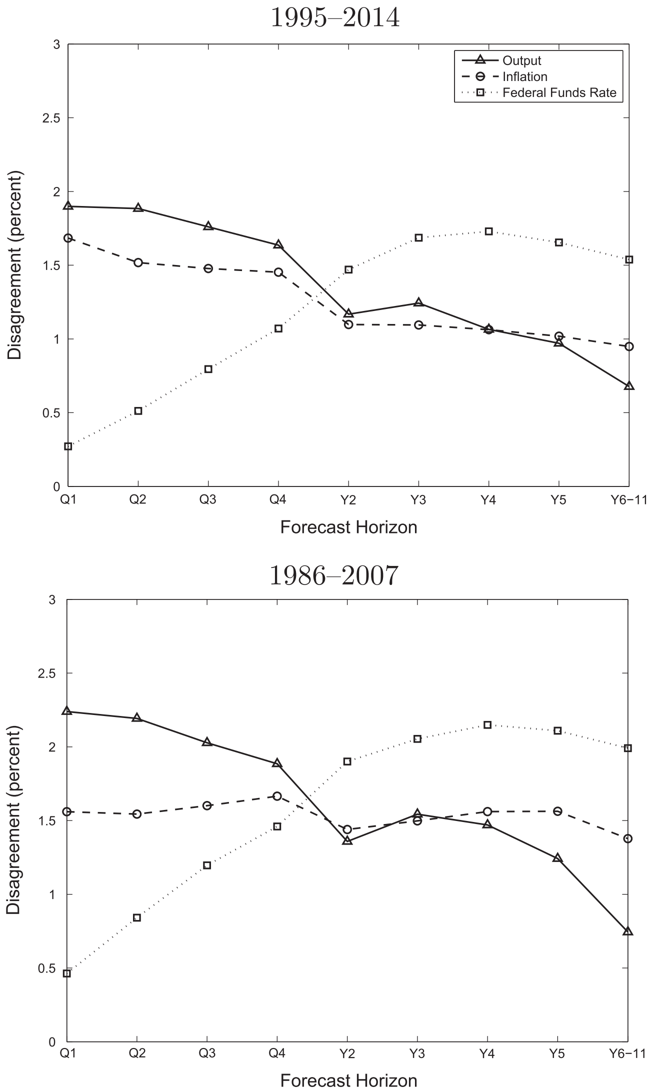


Fig. 3. Term structure of disagreement: subsamples. This figure shows selected statistics for forecast disagreement from the Blue Chip Financial Forecasts survey. Disagreement is defined as the average forecast of the highest 10 responses minus that of the lowest 10 responses of survey participants (in percent). The top and bottom panels show the term structure of disagreement averaged across time for real output growth, CPI inflation, and the federal funds rate for the samples 1995–2014 and 1986–2007, respectively, for various forecast horizons. Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead.

we show the term structure of disagreement for the period 1995–2014. While the level of disagreement is lower across horizons and for all variables the relative shapes of the term structures of disagreement are largely similar to Fig. 1. Over this subsample the term structure of disagreement for inflation is more downward sloping than in the full sample, but remains flatter than the corresponding term structure for real output growth. The bottom panel of Fig. 3 shows the term structures of disagreement excluding the financial crisis and its aftermath. In this case, the resulting term structures are virtually unchanged from their full-sample counterparts. This highlights that disagreement about the policy rate at short horizons has historically been very low even outside the post-financial crisis period that featured “forward guidance” (see Fig. 2). Disagreement at medium and long horizons remained substantial with similar volatility as in the pre-crisis period. This underlines that forecaster disagreement can provide useful information even when the policy rate is near the zero lower bound.[5]

At first sight, the results for real output growth and inflation appear to be at odds with the findings of Lahiri and Sheng (2008) and Patton and Timmermann (2010) who have studied forecast disagreement up to two years into the future using the Consensus Economics survey. These authors argue that disagreement increases with the forecast horizon for both

[5] Andrade et al. (2015) provide more evidence on the evolution of disagreement near the zero lower bound.

variables. In order to understand the differences between their findings and the ones reported here, it is important to highlight the differences between the two sources of survey data. In the Consensus Economics survey the forecast target, i.e. the value of a variable in a particular calendar year, is held fixed across twenty four consecutive monthly forecasts. This implies that while time passes, the forecast horizon is shrinking and the target forecast becomes less and less uncertain as end-of-year inflation or GDP growth rates become partly revealed. In other words, in the Consensus Economics survey that Lahiri and Sheng (2008) and Patton and Timmermann (2010) exploit, the information set available to forecasters decreases with the forecast horizon. This is in contrast to the Blue Chip survey that we study which asks participants for forecasts at constant horizons so that, for a given date, the information set is held constant across forecast horizons. Hence, when interpreting the empirical findings of Lahiri and Sheng (2008) and Patton and Timmermann (2010), it is important to keep in mind that in these two studies, by the nature of the survey they are based on, the information available to forecasters is not the same across forecast horizons. In contrast, in this paper we take the more conventional view that the information set available to forecasters is fixed in any given period and that based on this same information set forecasts at various horizons into the future are made.

In addition to Lahiri and Sheng (2008) and Patton and Timmermann (2010), a few other papers have studied various aspects of the disagreement among forecasters. Mankiw et al. (2003) document that the disagreement about US inflation expectations up to 17 months ahead from various surveys of consumers and professional forecasters (not including the Blue Chip survey) is time varying. They also study the correlation of inflation disagreement with changes in macroeconomic variables such as inflation and GDP growth and find weak evidence of such correlations. Dovern et al. (2012) study the behavior of forecasts for real GDP growth, inflation, and short-term interest rates over the next year for the G7 countries. Their analysis is based on the Consensus Economics survey of professional forecasters which is also employed by Lahiri and Sheng (2008) and Patton and Timmermann (2010) for the US. Since that survey does not provide fixed-horizon forecasts for real GDP and inflation, Dovern et al. (2012) approximate these using the reported fixed-target forecasts. Based on their constructed series, they conclude that short-term disagreement differs across the three variables and across G7 countries. Wright (2011) documents that disagreement of one-year ahead inflation forecasts from the Consensus Economics survey is correlated with nominal term premia in a number of countries. He measures disagreement as the cross-sectional standard deviation of individual inflation forecasts and argues that this variable captures inflation uncertainty. Using data on individual point as well as density forecasts from the US Survey of Professional Forecasters, Zarnowitz and Lambros (1987) study the relationship between consensus forecasts and measures of uncertainty while Rich and Tracy (2010) show that disagreement about US inflation is not systematically related to measures of inflation uncertainty. Boero et al. (2008) study the relationship between forecast uncertainty and disagreement up to two years into the future for a UK survey of professional forecasts and find a sustained reduction of inflation uncertainty after the introduction of a formal inflation targeting regime by the Bank of England.

One common thread among the papers cited above is that they all study disagreement at horizons of at most two years into the future. To the best of our knowledge, this paper is the first documenting facts about the whole term structure of disagreement including the long run. As we will argue in the next section, these new facts about long-term forecasts provide information that is important for differentiating between various models of expectation formation.

3. Modeling disagreement

In this section we introduce a generalized model of informational frictions which extends the Mankiw and Reis (2002) sticky information framework in two crucial dimensions. First, it allows for a multivariate setup, where agents update information about individual variables at different points in time. Second, macroeconomic variables are driven by unobserved short-term and long-term components, introducing an additional filtering problem for the agents. A key aspect of our setup is that no agent has informational advantages over any other: every agent faces the same probability of updating and agents agree on the model of the economy and on the model parameters. As a result, in a long enough sample no agent will systematically forecast better than other agents. Again, we emphasize that our approach is conceptually distinct from those with differences in prior beliefs or differences in the interpretation of signals (e.g., Lahiri and Sheng, 2008; Patton and Timmermann, 2010). As our results show, such forms of heterogeneity are not necessary to generate fundamental disagreement. We think that these are appealing properties in light of the widely documented result that it is difficult to beat consensus forecasts of both survey participants and econometric models (see e.g. Bauer et al., 2003 or Stock and Watson, 2004).

3.1. A generalized imperfect information model

The true state of the macroeconomy is captured by the random vector $z_t = (g_t, \pi_t, i_t)'$ representing real output growth, g_t, inflation, π_t, and the central-bank policy rate i_t. The data generating process for these state variables is,

$$z_t = (I_3 - \Phi)\mu_t + \Phi z_{t-1} + v_t^z, \tag{1}$$

$$\mu_t = \mu_{t-1} + v_t^{\mu}, \tag{2}$$

with initial conditions z_0 and μ_0. We define the elements of μ_t as $\mu_t = \left(\overline{g}_t, \overline{\pi}_t, \overline{i}_t\right)'$. We assume all of the eigenvalues of the matrix Φ are inside the unit circle[6] and v_t^z and v_t^μ are *i.i.d.* Gaussian innovations which are mutually independent with variance–covariance matrices Σ^z and Σ^μ, respectively. Consequently, the variable μ_t plays the role of the "long-run" component in the sense that $\lim_{h\to\infty}\mathbb{E}\left[z_{t+h}|z_t,\mu_t,z_{t-1},\mu_{t-1}\ldots\right]=\mu_t$. In the following sections we will compare our model to that of one without shifting endpoints (i.e., Eq. (1) with $\mu_t=\mu \ \ \forall t$).

The unobserved data can then be written in the compact form,

$$X_t = FX_{t-1}+\epsilon_t, \tag{3}$$

where $X_t=(z_t{}',\mu_t{}')'$, and ϵ_t are *i.i.d.* Gaussian innovations with variance matrix Σ^ϵ and

$$F=\begin{bmatrix}\Phi & (I_3-\Phi)\\ 0 & I_3\end{bmatrix}, \quad \Sigma^\epsilon=\begin{bmatrix}I_3 & (I_3-\Phi)\\ 0 & I_3\end{bmatrix}\begin{bmatrix}\Sigma^z & 0\\ 0 & \Sigma^\mu\end{bmatrix}\begin{bmatrix}I_3 & (I_3-\Phi)\\ 0 & I_3\end{bmatrix}'. \tag{4}$$

There are N agents in our model. If output growth, inflation and the policy rate in z_t are fully observable in every period, each agent j observes the data $\{y_t : t=1,\ldots,T\}$ where

$$y_t = H'X_t, \qquad H=[I_3 \,\vdots\, 0_{3\times 3}]'. \tag{5}$$

Our baseline model is characterized by a form of sticky information about the current state of the economy. In particular, at any point in time individual agents may observe only a subset of variables in y_{jt}: the kth element of y_{jt} is only observed with a fixed probability λ_k. Under these assumptions, the dimension of the observation matrix in Eq. (5), H_{jt}, changes across agents and across time depending on which elements of z_t are observed by forecaster j. Note that previous formulations of the sticky information model have only used a univariate censoring variable so that agents observe simultaneously all elements of y_t when they are allowed to update their information set. The flexibility in our model is consistent with Andrade and Le Bihan (2013), which shows micro-data evidence that the probability of updating a forecast varies across macroeconomic variables. Then at each point in time for the kth variable, $\lfloor n\lambda_k \rfloor$ agents are randomly chosen from a discrete uniform distribution where $\lfloor\cdot\rfloor$ represents the integer part of the expression. These selected agents use the (perfectly observed) current value of the kth element of z_t when updating their forecasts. Thus, at any point in time, only a fraction of agents will observe a particular element of z_t. When agents do not observe the full vector z_t they use the Kalman filter with missing observations (see e.g., Harvey, 1989). Each agent then updates its Kalman filter estimate of the states using,

$$X_{t|jt} = X_{t|j(t-1)} + P_{t|j(t-1)}H_{jt}\left(H_{jt}'\,P_{t|j(t-1)}H_{jt}+\Sigma^\eta\right)^{-1}\left(y_{jt}-H_{jt}'\,X_{t|j(t-1)}\right) \tag{6}$$

$$P_{t|jt} = P_{t|j(t-1)} - P_{t|j(t-1)}H_{jt}\left(H_{jt}'\,P_{t|j(t-1)}H_{jt}+\Sigma^\eta\right)^{-1}H_{jt}'\,P_{t|j(t-1)} \tag{7}$$

$$P_{t|j(t-1)} = FP_{(t-1)|j(t-1)}F'+\Sigma^\epsilon \tag{8}$$

with initial conditions $X_{0|j0}$ and $P_{0|j0}$. This implies that in our generalized sticky information model, when agents observe an element of z_t they do not necessarily observe all past observations of the same variable.[7] Under this specification, disagreement about the current and future states of the macroeconomy depends on both the current and the past history of all agents' observations of z_t. Given this structure, we assume each agent has full knowledge of the parameters defined in Eq. (4) and produces forecasts for $z_{t+h}, h\in\mathbb{Z}_+$, conditional on $\Omega_{jt}=\left\{y_{jt},y_{j(t-1)},\ldots\right\}$ based on the Kalman filter,

$$\mathbb{E}[z_{t+h}|\Omega_{jt}] = H'F^h X_{t|jt}, \qquad H=[I_3 \,\vdots\, 0_{3\times 3}]'. \tag{9}$$

If no element of z_t is observed then $X_{t|jt}=X_{t|j(t-1)}$ and $P_{t|jt}=P_{t|j(t-1)}$.

3.2. Model properties and predictions

This section provides a discussion of the properties of the model as well as its predictions for the term structure of disagreement.

3.2.1. Discussion of the model

The model of imperfect information considered in this paper incorporates two important informational constraints that forecasters face. First, agents in the model do not perfectly observe at all times the current state of the economy, as represented by the vector X_t in the previous section. Second, agents have to infer to what extent changes in the observed

[6] Note that in our setting the matrix Φ is otherwise unrestricted. A different setting, such as a dynamic stochastic general equilibrium model, would imply restrictions on this matrix.

[7] This differs from previous implementations in the literature where a fraction of agents are able to observe the full time series up to the current date. In a multivariate model with different values of λ_k for each series, calibrating the model using that approach would be computationally infeasible. We discuss the robustness of our results to our choice of formulation in Section 4.4.

variables are due to transitory shocks, as represented by the innovation v_t^z, or reflect changes to the slow-moving permanent components, as captured by the innovation v_t^μ.

The sticky information model captures the costs of processing the information available to produce a forecast update. A narrow interpretation of the sticky information model, as a model of infrequent acquisition of information, best characterizes households' behavior, but not of professional forecasters which have access to a constant flow of information – see for example (Carroll, 2003). Here we follow (Mankiw and Reis, 2002) and interpret the model as capturing the fact that even professional forecasters have limited resources for *processing* newly acquired information into forecast updates so that updating their forecast is costly. So, despite the availability of new information about the current state of the economy, forecasters may not incorporate it into their forecasts and report forecasts similar to what they would have reported had they not updated their information set.[8] Last, most forecasters in the Blue Chip survey have other business tasks than just providing a forecast. As such, the sticky-information model might be viewed as a simple model of "rational inattention", where the infrequent forecast update reflects resource allocation within firms.

The second constraint implies that agents optimally use different components of the signals they observe for short-term versus long-term forecasts. In particular, they need to filter from the observed data the highly volatile temporary factors from the slow-moving permanent components of the variables of interest. This decomposition into permanent and transitory elements has a long and widespread tradition in theoretical and empirical macroeconomic research. For instance, the seminal real-business cycle model in Kydland and Prescott (1982) considers such a decomposition of productivity growth. More recently, Cogley and Sbordone (2008) model inflation as having a permanent and a transitory component. Gürkaynak et al. (2005) study the consequences of such a specification of inflation for the term structure of interest rates. Moreover, several studies show that a time-varying drift captures well both the dynamic properties of variables such as real GDP growth (Stock and Watson, 1989; Cogley and Sargent, 2005; Laubach and Williams, 2003), the inflation rate (Stock and Watson, 2007; Cogley et al., 2010), and the federal funds rate (Kozicki and Tinsley, 2001; Gürkaynak et al., 2005) as well as the slow movements of their consensus long-term expectations (Edge et al., 2007; Kozicki and Tinsley, 2012).

3.2.2. *Predictions of the model about forecaster disagreement*

We now review the main properties of the disagreement that the model presented in the previous section generates. To simplify the discussion, we assume here that the economy is populated by a continuum of forecasters and that at date t each agent had access to an infinite sequence of observations. Under sticky information, the h-step ahead optimal forecast of agent j derived from Eq. (6) is

$$z_{t+h|jt} = H'F^h\left[X_{t|j(t-1)} + B_{jt}(X_t - X_{t|j(t-1)})\right] = H'F^h Z_{jt}, \tag{10}$$

with $B_{jt} = P_{t|j(t-1)}H_{jt}\left(H_{jt}'\, P_{t|j(t-1)}H_{jt}\right)^{-1}H_{jt}'$. Using $\mathrm{V}(Z_{jt}) = \mathrm{V}\left[\mathbb{E}(Z_{jt}|B_{jt})\right] + \mathbb{E}\left[\mathrm{V}(Z_{jt}|B_{jt})\right]$, the cross-sectional variance of forecasts can be decomposed into

$$V_{ht}^z = H'F^h(X_t - \overline{X}_{t|(t-1)})\mathbf{V}^B(X_t - \overline{X}_{t|(t-1)})'\left(H'F^h\right)' + H'F^h(I - \overline{B})\mathbf{V}_{1t}^X(I - \overline{B})'\left(H'F^h\right)', \tag{11}$$

where $\overline{X}_{t|(t-1)} = \mathbb{E}(X_{t|j(t-1)}|t)$, $\overline{B} = \mathbb{E}(B_{jt}|t)$, and where $\mathbf{V}_{1t}^X = \mathrm{V}(X_{t|jt-1}|t)$ stands for the cross-sectional variance of agents' predictions in $t-1$ for the state vector at date t, $X_{t|j(t-1)}$ and $\mathbf{V}^B = \mathrm{V}(B_{jt}|t)$ denotes the cross-sectional heterogeneity of agents' updating matrices in t, B_{jt}, which is constant when one assumes that at date t each agent had access to an infinite sequence of observations $\{z_{jt}, z_{j(t-1)}, \ldots\}$.

Based on Eq. (11), we analyze how the model can potentially explain the observed term structures of disagreement. We discuss the implications for the time variation of disagreement at the end of this section. First and foremost, it is important to emphasize the simple point that if all agents update each period, there is no disagreement. Since it is difficult to argue that important economic variables such as interest rates and stock prices are not observed continuously, then we can immediately rule out separate univariate models for each of our three variables. One essential feature of a multivariate framework is that it does not require infrequent updating for each variable in the system in order to generate disagreement for all the variables.

To build further intuition for the mechanisms which drive our empirical results, let us start from the simplest possible model and progressively add features as needed to explain the facts. Consider a simple univariate model without shifting endpoints, so that all the terms in Eq. (11) are scalars and $|F| < 1$. Then, it is immediate to see that: (i) for $h \to \infty$, disagreement tends to zero and (ii) the term structure of disagreement is monotonically decreasing with the forecast horizon ($F^{2h}\downarrow 0$). If we add shifting endpoints, the maximum eigenvalue of F is now equal to one. From Eq. (11) it is easy to see that disagreement in the long-run is positive. However, it can be shown that this model can only generate an upward sloping term structure of disagreement for unreasonably large values of the variance of the innovation to the long-run component. Instead, it appears more natural to assume that the diagonal elements of Σ^z are much larger than those of Σ^μ in a pointwise comparison, since the long-term component is meant to capture a slow moving trend. This is another reason why a

[8] Andrade and Le Bihan (2013) provide micro-data evidence consistent with this interpretation of the sticky-information model that professional forecasters update infrequently their forecasts.

univariate model would not be able to generate the different observed shapes of the term structure under these reasonable assumptions.

Consider instead a multivariate model without shifting endpoints. As apparent already from the discussion above this model cannot generate long-term disagreement. However, specific choices for F and the probabilities of observing the current realization of each variable can deliver any shape of disagreement in the short-run. Intuitively, as the forecast horizon h increases, some of the off-diagonal elements of F may increase or decrease, generating different patterns of disagreement for different variables. Finally, augmenting this model with shifting endpoints would then inherit these properties along with generating positive fundamental disagreement.

Lastly, the literature has measured the sticky information model's success by its ability to generate time variation of disagreement (Mankiw and Reis, 2010). The time variation in disagreement comes from two sources: (i) the average gap between state realizations and forecasters' state predictions, $(X_t - \overline{X}_{t|(t-1)})$, with bigger underlying shocks at date t increasing disagreement at all horizons; and (ii) the induced time varying cross-sectional dispersion of agents' predictions in $t-1$ for the state vector at date t, $\mathbf{V}^X_{1t}$.

3.3. Calibration

The generalized imperfect information model introduced in the previous section appears to have the ability to replicate the key features of our new set of facts. However, it is important to assess the performance of the model in reproducing these facts when parameter values are “reasonable” in the sense of being consistent with the properties of the data. For example, a high level of fundamental disagreement could be generated by a model featuring a highly volatile drift, μ_t. However, this would be inconsistent with the relatively low volatility of long-term consensus forecasts. Because we aim to evaluate the model's ability to predict the observed term structure of disagreement and its variation over time, we use minimal information on disagreement in calibrating the parameters. In particular, we use short-term disagreement only in order to calibrate the degree of information frictions.

Our interpretation of the model is that neither the ‘econometrician’ nor the agents perfectly observe the current state of the macroeconomy at all points in time. In more detail, the econometrician's observation equation is

$$\mathcal{Y}_t = H'X_t + \tilde{\eta}_t, \tag{12}$$

where $\mathcal{Y}_t$ are the actual output growth, inflation and interest rate data. In contrast with the agents in the model, the econometrician collects new information about the state z_t in every period, but she only observes a noisy measure of the true state, with observation error $\tilde{\eta}_t$, normally distributed with variance matrix $\tilde{\Sigma}^\eta$. We then choose the model parameters to minimize the negative of the Gaussian log-likelihood function,

$$\mathcal{L}(\theta_1, \tilde{\Sigma}^\eta; \mathcal{Y}_1, \ldots, \mathcal{Y}_T) = -\sum_{t=1}^{T} \log\Big((2\pi)^{-3/2} |H'\tilde{P}_{t|(t-1)}H + \tilde{\Sigma}^\eta|^{-1/2} \times \exp\Big\{-\frac{1}{2}\Big(\mathcal{Y}_t - H'\tilde{X}_{t|(t-1)}\Big)'\Big(H'\tilde{P}_{t|(t-1)}H + \tilde{\Sigma}^\eta\Big)^{-1}\Big(\mathcal{Y}_t - H'\tilde{X}_{t|(t-1)}\Big)\Big\}\Big),$$

where $\theta_1 = (\Phi, \Sigma^z, \Sigma^\mu)$ defines the model's structural parameters. However, it is straightforward to observe that the model's parameters are not identified using only realized data. First, additional restrictions would be needed to identify the volatility of the drift and the volatility of the short term shocks. Second, additional information is needed to pin down the parameters related to information stickiness. As we noted in Section 2.1, we do not observe the medium- or long-term forecasts of individual forecasters which precludes full maximum likelihood estimation of the model. To this end we propose choosing parameters that minimize the following criterion function

$$\mathcal{C}(\theta_1, \theta_2, \tilde{\Sigma}^\eta; \alpha) = \mathcal{L}(\theta_1, \tilde{\Sigma}^\eta; \mathcal{Y}_1, \ldots, \mathcal{Y}_T) + \alpha \cdot \mathcal{P}(\theta_1, \theta_2; \mathcal{S}_1, \ldots, \mathcal{S}_T),$$

where $\theta_2 = (\lambda_g, \lambda_\pi, \lambda_i)'$ and $\mathcal{S}_t$ are the BCFF survey data at time t. The second term in the criterion function is a penalization term. Its role is to discipline the parameters by introducing a penalty when observed moments from the survey forecasts are “far” from the corresponding model-implied moments:

$$\mathcal{P}(\theta_1, \theta_2; \mathcal{S}_1, \ldots, \mathcal{S}_T) = \big(g(\theta_1, \theta_2) - g_S(\mathcal{S}_1, \ldots, \mathcal{S}_T)\big)' W \big(g(\theta_1, \theta_2) - g_S(\mathcal{S}_1, \ldots, \mathcal{S}_T)\big),$$

where W is a positive semi-definite weighting matrix and $g_S(\mathcal{S}_1, \ldots, \mathcal{S}_T)$ is a collection of moments from the data.

We use real GNP and GDP data as provided by the Bureau of Economic Analysis, headline CPI from the Bureau of Labor Statistics and the federal funds rate from the H.15 data provided by the Board of Governors of the Federal Reserve. The data are quarterly from 1955Q1 to 2013Q2. We use 15 sample moments from the BCFF survey (5 sample moments for each of the three variables). The data are quarterly from 1986Q1 to 2013Q2 and include the following: our disagreement measure for the one-quarter ahead forecast only; the standard deviation of consensus forecast for one- and four-quarters ahead along with two-years ahead and six-to-eleven years ahead.

The corresponding model-implied statistics are constructed by the function $g(\theta_1, \theta_2)$ via a simulation approach: we simulate the model using $T=120$ (approximately the length of the survey data sample) and choose $N=50$ (consistent with number of participants in the survey) across 100 simulations in our optimization procedure. We choose a diagonal

Table 1
Results of calibration for $\alpha = 50$. *Sticky information model.* This table provides the calibrated parameters for $\alpha = 50$ as discussed in Section 4.1 of the paper. $|\cdot|$ designates the modulus of a complex number. Results are based on 2500 simulations. The sample period is from 1986Q1 to 2013Q2.

Φ	Σ^z	sqrt(diag($\tilde{\Sigma}^\eta$))
$\begin{bmatrix} 0.392 & -0.478 & -0.142 \\ 0.122 & 0.939 & -0.024 \\ 0.146 & 0.087 & 0.931 \end{bmatrix}$	$\begin{bmatrix} 3.736 & -0.065 & 0.564 \\ -0.065 & 0.911 & 0.347 \\ 0.564 & 0.347 & 0.635 \end{bmatrix}$	$\begin{bmatrix} 2.586 \\ 1.355 \\ 0.000 \end{bmatrix}$
$\lvert \mathrm{eig}(\Phi) \rvert$	Σ^μ	λ
$\begin{bmatrix} 0.920 \\ 0.674 \\ 0.674 \end{bmatrix}$	$\begin{bmatrix} 0.007 & 0.012 & 0.022 \\ 0.012 & 0.021 & 0.039 \\ 0.022 & 0.039 & 0.073 \end{bmatrix}$	$\begin{bmatrix} 0.260 \\ 0.260 \\ 1.000 \end{bmatrix}$

weighting matrix which places a weight of 1 on short-term disagreement and a weight of 0.1 on the standard deviation of consensus forecasts at the selected horizons. The weight matrix is selected so as to choose parameter values such that, as closely as possible, the level of the model-implied one-quarter ahead disagreement is consistent with the data without generating excessively volatile consensus forecasts. We can then evaluate the performance of the model to match the term structure of disagreement using the least amount of disagreement data to do so. Very loosely, the model is "normalized" so that the shortest-horizon forecast disagreement is approximately correct.

We would then like to solve $\min_{\theta_1,\theta_2,\tilde{\Sigma}^\eta} \mathcal{C}(\theta_1, \theta_2, \tilde{\Sigma}^\eta)$. The final input necessary to the model calibration is the choice of initial conditions. As we have information about the dispersion in agents' expectations at the beginning of the sample, we use the March 1986 BCFF survey to provide initial conditions for both $z_{t|jt}$ and $\mu_{t|jt}$. For the former, we use the forecasts for the first quarter of 1986 from the March 1986 BCFF survey as a "nowcast". For the latter, we do not observe individual long-term forecasts, so instead we scale the initial conditions from the nowcast to replicate the 6-to-11 years ahead disagreement measured by the top-10 average minus the bottom-10 average in the same survey.[9]

It should be emphasized that we do not interpret the variation in initial conditions as a reflection of different priors about the structural parameters of the economy, but rather as a result of past observation errors that occurred prior to our sample period. Regardless, in the next section we show that removing the influence of the initial conditions does not alter the main conclusions implied by the model.

4. Results

In this section we use our calibrated parameters to assess the model's ability to reproduce the new stylized facts from Section 2. The section starts by briefly discussing the values of the calibrated parameters. Section 4.2 discusses the implications for the term structure of disagreement (Facts 1 and 2). In Section 4.3 the corresponding results for the time variation and co-movement of disagreement across variables (Fact 3) are shown. Finally, Section 4.4 presents a number of robustness checks, including an alternative specification for information frictions.

4.1. Calibration results

We discuss the calibrated parameters corresponding to a value of $\alpha = 50$. We view this as our "baseline" calibration as it ensures that the volatility of model-implied consensus forecasts matches the data well across horizons. We discuss in Section 4.4 that model-implied disagreement is largely insensitive to variations in α.

Table 1 presents the calibrated parameters for the baseline specification. Recall that agents' ability to observe the elements of the state vector z_t depends on three independent random censoring processes: the λ parameters govern the degree of information stickiness for each variable in this model. The calibrated values for λ correspond to 13, 13 and 50 out of 50 agents observing the current realization of real output growth, CPI inflation and the federal funds rate, respectively, in each period. Thus, in our baseline model all agents observe the federal funds rate perfectly. This result is striking since the calibration puts, a priori, no restriction on λ_i, while in reality, the policy rate can be perfectly observed in real time. For output growth and inflation the calibrated λs imply an average frequency of updating for Blue Chip forecasters of slightly less than four quarters, in line with the results of Mankiw et al. (2003). The consistency of the results is quite remarkable, given the different data and methodology used in this study. In more detail, Mankiw et al. (2003) find that a sticky information model of inflation forecasts with an average frequency of update of about 12 months can predict fairly closely the observed dispersion of one-year inflation expectations for households (Michigan survey). In order to match the

[9] The March 1986 survey only includes forecasts for 45 participants. The additional 5 agents in our model are endowed with initial conditions equal to the median of the survey data.

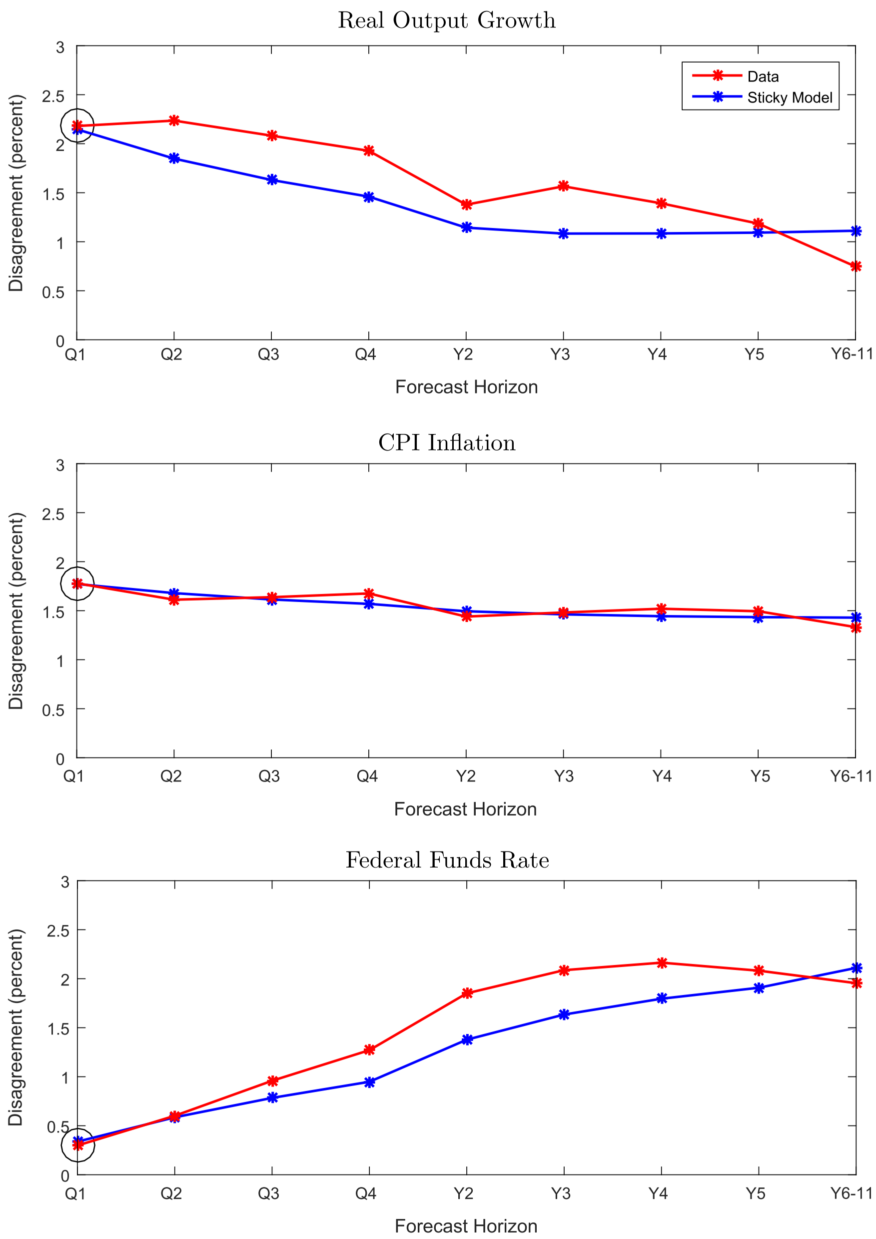


Fig. 4. Term structure of disagreement. *Sticky information model.* This figure displays the model-implied (time) average of disagreement across different horizons for the generalized sticky information model (blue) calibrated with $\alpha = 50$ along with the Blue Chip Financial Forecasts survey (red). Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. Open circles designate survey moments used to form the penalization term $\mathcal{P}(\theta_1, \theta_2; \mathcal{S}_1, \ldots, \mathcal{S}_T)$. Results are based on 2500 simulations. All statistics are measured in percent. The sample period is from 1986Q1 to 2013Q2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

disagreement of professional forecasters (Livingston Survey) the same model requires an average frequency of updating of about 10 months, which indeed is not too different. Another important finding is that the variance of the calibrated long-term component (Σ^{μ}) is substantially lower for all three variables relative to the corresponding variance of the short-term component (Σ^{z}). This accords with our interpretation of μ_t as capturing slow-moving drifts in the economy's fundamentals.

4.2. The model-implied term structure of disagreement

In Fig. 4 we show the model-implied term structure of disagreement along with the disagreement observed in the data. The calibrated model does a remarkable job replicating the different shapes of the observed term structure of disagreement for the three variables. In fact, the term structure of disagreement for CPI inflation is matched almost perfectly. The model-implied term structure is downward sloping for output growth, approximately flat for CPI inflation, and upward sloping for the federal funds rate. It is important to emphasize that we only use one quarter ahead disagreement (designated by the open circle in each graph) in the calibration. In sum, our sticky information model can reproduce Facts 1 and 2 for parameter values that are consistent with the actual and survey data.

As discussed in Section 3.2.2, the shape of the term structure of disagreement is determined jointly by all of the parameters of the model. Therefore it is difficult to give a precise description of the underlying mechanism which generates the results. However, we can provide a heuristic explanation of how each is generated by revisiting the parameter values from Table 1. The downward slope in the term structure for real output growth can be explained by the fact that it displays fairly volatile temporary shocks and is observed with a fairly high amount of stickiness. This explains the high level of disagreement in the short term and the fact that forecasts at longer horizons respond less to changes in observed real output, delivering relatively low disagreement at medium- to long-term horizons. CPI inflation is also infrequently observed but, at the same time, its long-term component is relatively more volatile than its temporary component when compared to output growth. Accordingly, this results in a relatively flat term structure of disagreement. Finally, the federal funds rate is perfectly observed and, given its estimated persistence, is predicted well using only its past value. As a result, there is minimal disagreement at short horizons. At longer horizons, though, disagreement about future real output growth, CPI inflation and the long-term level of the federal funds rate (i.e., $\bar{i}_t$) generate disagreement about the federal funds rate forecasts. In the left panels of Fig. 5 we add 95% confidence intervals around the term structure of disagreement. These plots show that even allowing for variation across simulations, the shapes of the term structure of disagreement mimic those in the data.

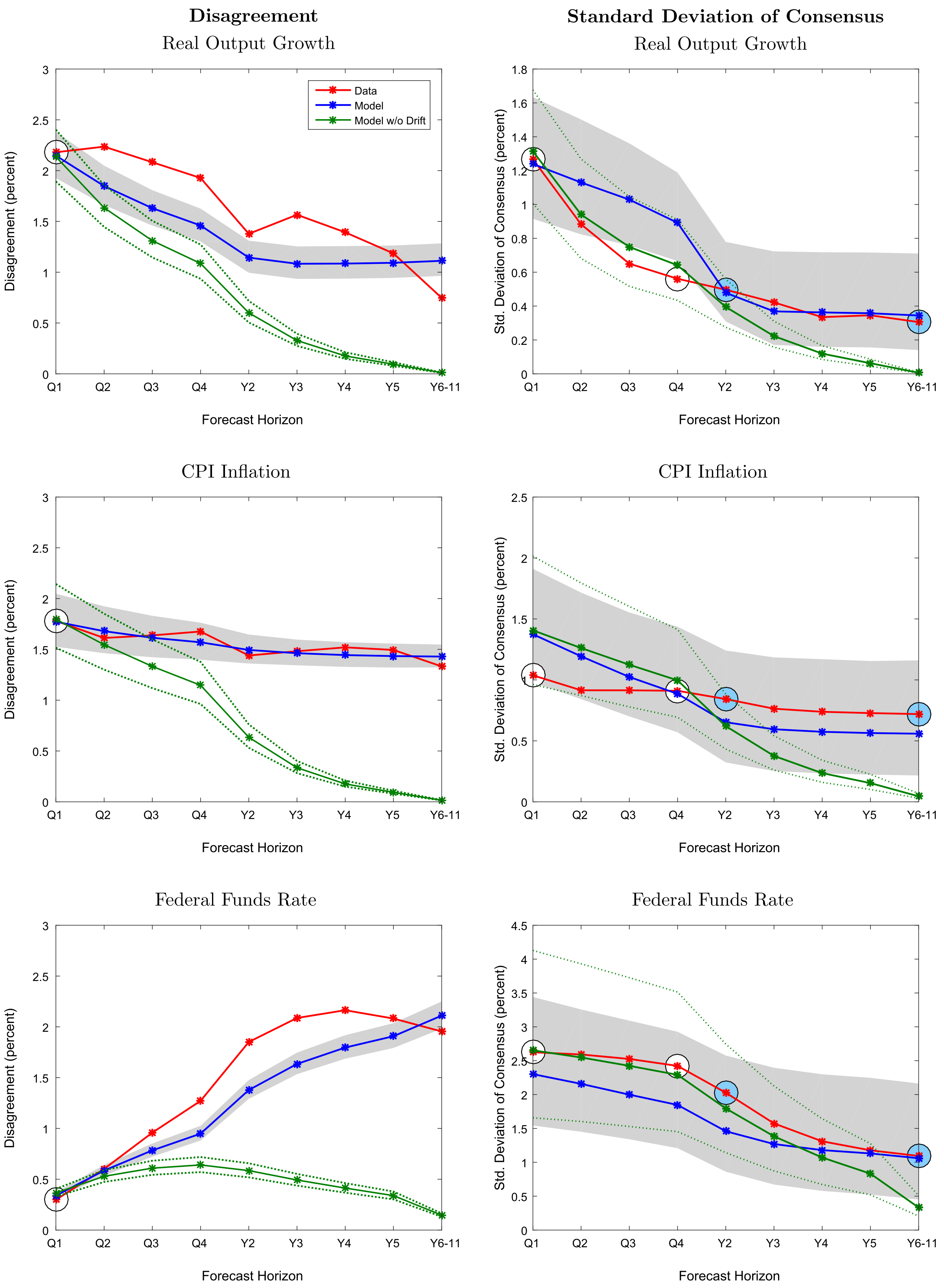
Of course, the results on the model-implied term structures of disagreement may come at the cost of unrealistically volatile forecasts. We now compare the model performance in terms of the variability of model-implied consensus forecasts which we also use in the calibration. The right panels of Fig. 5 present the standard deviation of consensus forecasts from the BCFF survey along with the model-implied standard deviations. The model captures well the term structure of consensus forecast volatility for all three variables, as shown by the fact that the standard deviation of consensus forecasts falls within the 95% confidence bands indicated by the shaded area with the exception of the three-quarter ahead and four-quarter ahead forecasts of real output growth.

As discussed in Section 3.2.2, disagreement in the medium-to-long run depends on agents' disagreement about the decomposition into temporary and long-term factors for all three variables. To highlight this last point, the left panel of Fig. 5 also shows term structures of disagreement for the model without shifting endpoints, shown by the green line. We calibrate this model using the same method as for the model with shifting endpoints. We use the same moments of disagreement (one-quarter ahead only for each variable) but only the one-quarter and four-quarter ahead standard deviations of consensus forecasts, as this model cannot generate variability in long-term forecasts. As before, the circles indicate the moments that are used in the calibration. The open white circles highlight the moments used in the calibration for both models, and the light blue circles single out the moments used only in the calibration of the model with shifting endpoints. The model without shifting endpoints clearly falls short at explaining disagreement for all but the shortest horizons. As expected, for long horizons the disagreement implied by this model approaches zero for all variables. Of note, the model with shifting endpoints provides a better fit to disagreement at horizons above one year without compromising the fit of short-term disagreement. This improved performance is not entirely obvious as the model with shifting endpoints has six more parameters, but the calibration imposes six additional restrictions which discipline the volatility of the model-implied longer-term consensus forecasts. In terms of the volatility of consensus forecasts, the model without shifting endpoints has a comparable fit at short to intermediate horizons. Furthermore, the model without shifting endpoints consistently implies a volatility of consensus forecasts which is too low at longer horizons. These results confirm our analysis in Section 3.2.2. In summary, the introduction of shifting endpoints results in a dramatic improvement of the fit of the term structure of disagreement, especially for horizons above one year. We conclude that the presence of a slow-moving, low-frequency component in the DGP is vital to replicating the first two facts about forecast disagreement.

4.3. The model-implied second moments of disagreement

We next turn to a discussion of the third fact related to the time variance and correlation of disagreement. One argument frequently used in favor of the sticky information model is that, even with a continuum of agents, the model will produce time variation of disagreement. The left panels of Fig. 6 show the standard deviation (hereafter, volatility) of disagreement from the BCFF data and its model-implied counterpart. The right column of the figure shows the pairwise time series

Fig. 5. Disagreement and standard deviation of forecasts. *Sticky information model.* The first column displays the model-implied disagreement for the generalized sticky information model (blue) and the sticky information model without shifting endpoints (green) calibrated with $\alpha = 50$ along with the Blue Chip Financial Forecasts survey (red). The second column displays the corresponding standard deviation of consensus forecasts. Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. Open white circles designate survey moments used to form the penalization term $\mathcal{P}(\theta_1, \theta_2; \mathcal{S}_1, \ldots, \mathcal{S}_T)$ for the model without shifting endpoints. Open white and light blue circles designate survey moments used to form the penalization term for the generalized sticky information model. Model-implied 95% confidence intervals for the model with and without shifting endpoints are designated by shaded regions and dotted lines, respectively. Results are based on 2500 simulations. All statistics are measured in percent. The sample period is from 1986Q1 to 2013Q2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)



Disagreement
Real Output Growth
Data
Model
Model w/o Drift
Disagreement (percent)
Forecast Horizon
Standard Deviation of Consensus
Real Output Growth
Std. Deviation of Consensus (percent)
Forecast Horizon
CPI Inflation
Disagreement (percent)
Forecast Horizon
CPI Inflation
Std. Deviation of Consensus (percent)
Forecast Horizon
Federal Funds Rate
Disagreement (percent)
Forecast Horizon
Federal Funds Rate
Std. Deviation of Consensus (percent)
Forecast Horizon
Q1
Q2
Q3
Q4
Y2
Y3
Y4
Y5
Y6-11

correlations of disagreement for different horizons for both the model and the data. We start by briefly discussing the properties of these correlations in the data. First, note that in the survey there is a substantial degree of correlation among the three time series of disagreement at various horizons. An interesting exception is the correlation between disagreement about CPI inflation and the federal funds rate at the one-quarter ahead horizon which is much lower than the corresponding correlation at medium- and long-horizons.[10] In contrast, the same correlation between the federal funds rate and output growth disagreements equals 60 percent in the data. Consequently, the small amount of short-term disagreement observed for the federal funds rate appears to be to a large extent driven by disagreement about near term-growth prospects. At long horizons, the correlation between disagreement about the federal funds rate and CPI inflation (real output growth) forecasts is more than 80 (60) percent correlated in the data. Hence, long term disagreement about the federal funds rate is clearly driven by disagreement about the determinants of interest rate policy. Further discussion of this issue is provided in Section 5. Finally, note that the time series of disagreement about real output growth and inflation are positively correlated at all forecast horizons including the long term.

The left panels of the figure show the model-implied volatility of disagreement for each variable. The sticky information model captures well the volatility of disagreement about near-term inflation forecasts. However, the model fails to fully match the behavior of the survey data at medium and long horizons. This emphasizes the importance of using the entire term structure of disagreement for model evaluation. The term structure of correlations of disagreement across the three variables, shown in the right column of Fig. 6, matches the correlations observed in the data quite closely. This is all the more remarkable given that the survey moments used in the calibration are only marginal moments of disagreement and consensus forecasts. These results provide an additional motivation for adopting a multivariate framework to study the evolution of survey forecasts as the correlations of disagreement across variables are clearly non-zero in general.

4.4. Robustness and additional results

In this section, we assess the robustness of our findings relative to a number of dimensions: (1) an alternative model of information frictions; (2) the role of the initial conditions; (3) the choice of the penalty parameter; (4) the role of observation error for the econometrician; (5) the model-implied disagreement about short-term real interest rates; and (6) the results for the sticky information model relative to an implementation where agents observe the full history of a variable when they update. We discuss these qualitatively, in turn, and relegate some of the corresponding tables and figures to the Supplementary appendix in order to conserve space.

As mentioned in the Introduction, as an alternative to our baseline assumption of sticky information, we consider a model specification where agents observe a noisy signal of the current state of the economy (the noisy information model, Sims, 2003; Woodford et al., 2003). Noisy information models are commonly used in macroeconomics and finance. In addition, they have been shown to be able to account for the sluggish adjustment of the consensus forecasts to macroeconomic shocks (see Coibion and Gorodnichenko, 2012). Similar to Eq. (12) for the econometrician, agents observe in every period noisy observations about the state z_t

$$y_{jt} = H'X_t + \eta_t. \tag{13}$$

The observation error η_t is normally distributed with variance matrix Σ^{η}. As in our baseline model, agents update their estimates of the state using the Kalman filter.[11] The model is calibrated using the methodology discussed in Section 3.3. As in the case of the sticky information model, the calibrated parameters imply that the policy rate is perfectly observed, while output growth and inflation are fairly noisy. The estimated structural parameters are very close to our baseline sticky information specification. In Fig. 7 we show the model-implied term structure of disagreement for both sticky and noisy information models, along with the disagreement observed in the data. Perhaps surprisingly, the two models have very similar implications for the average term structure of disagreement, suggesting that the specific formulation of the information friction is not so important along this dimension. However, the models' predictions are quite different when it comes to explaining the time variation of disagreement (shown in Supplementary appendix). Although the noisy information specification qualitatively matches the different shapes of the term structure of the volatility of disagreement, it is not capable of explaining the levels observed in the data. This is not surprising as the time variance of disagreement goes to zero when the number of forecasters goes to infinity in this model. The sticky information model outperforms along this dimension.

As discussed in Section 3.3, we choose initial conditions to match the observed short-term and long-term forecaster disagreement at the beginning of our sample. However, since we only use average one-quarter-ahead disagreement in our objective function, it is useful to examine the time series path of model-implied long-term disagreement (shown in Supplementary appendix). To do so, we repeatedly simulate the model based on the calibrated parameters and compute the average path across simulations along with a 95% confidence interval. Our baseline sticky information model closely mimics

[10] The correlations in disagreement display similar patterns even if the post-crisis period is omitted.

[11] For further details about the properties of the noisy information specification along with additional empirical results see the Supplementary appendix.

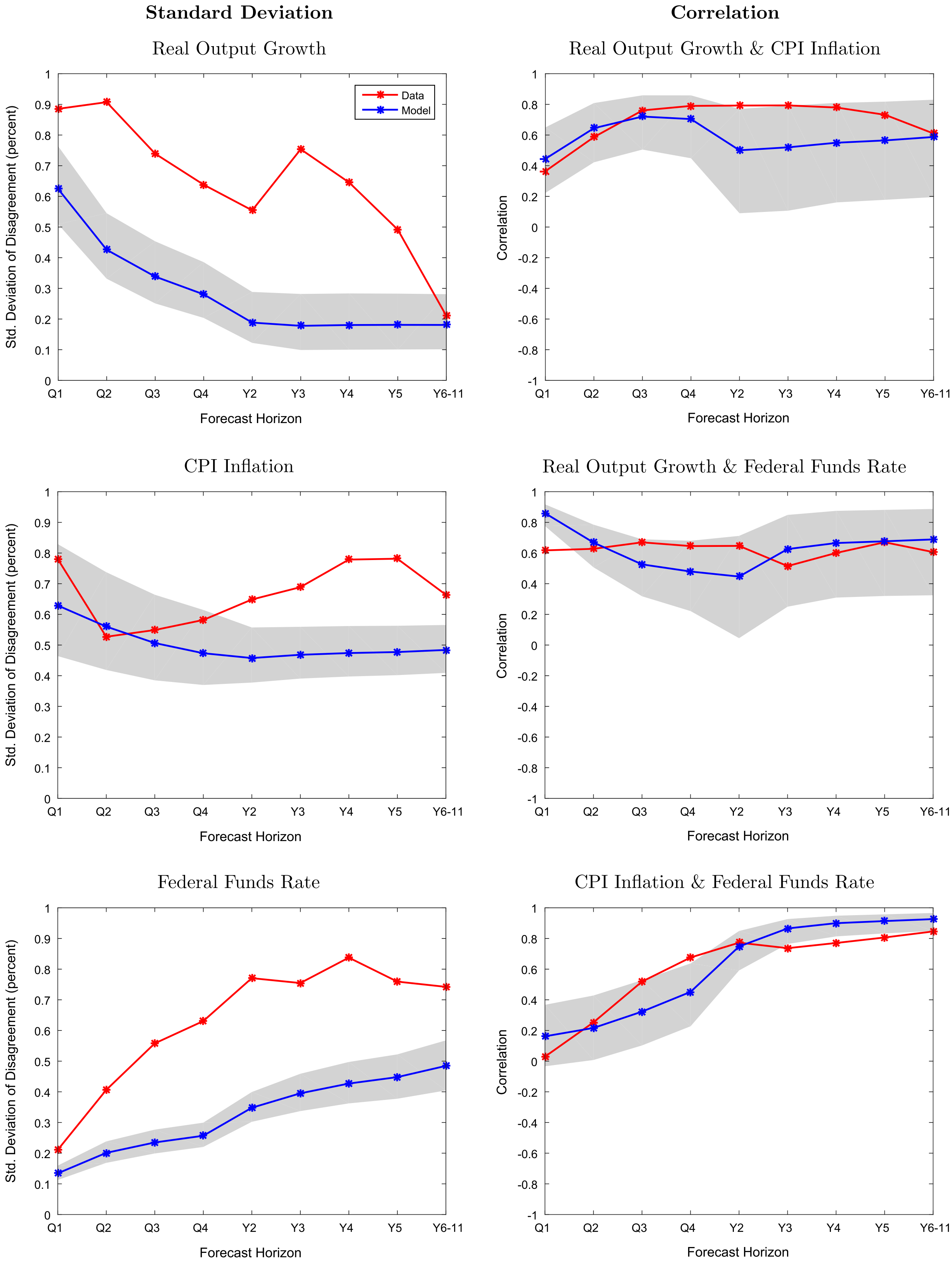


Fig. 6. Second moments of disagreement. *Sticky information model.* The first column displays the model-implied (time) standard deviation of disagreement for the generalized sticky information model calibrated with $\alpha = 50$ (blue) along with the Blue Chip Financial Forecasts survey (red). The second column displays the corresponding correlation of disagreement between variables. Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. Model-implied 95% confidence intervals are designated by shaded regions. Results are based on 2500 simulations. All statistics are measured in percent. The sample period is from 1986Q1 to 2013Q2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

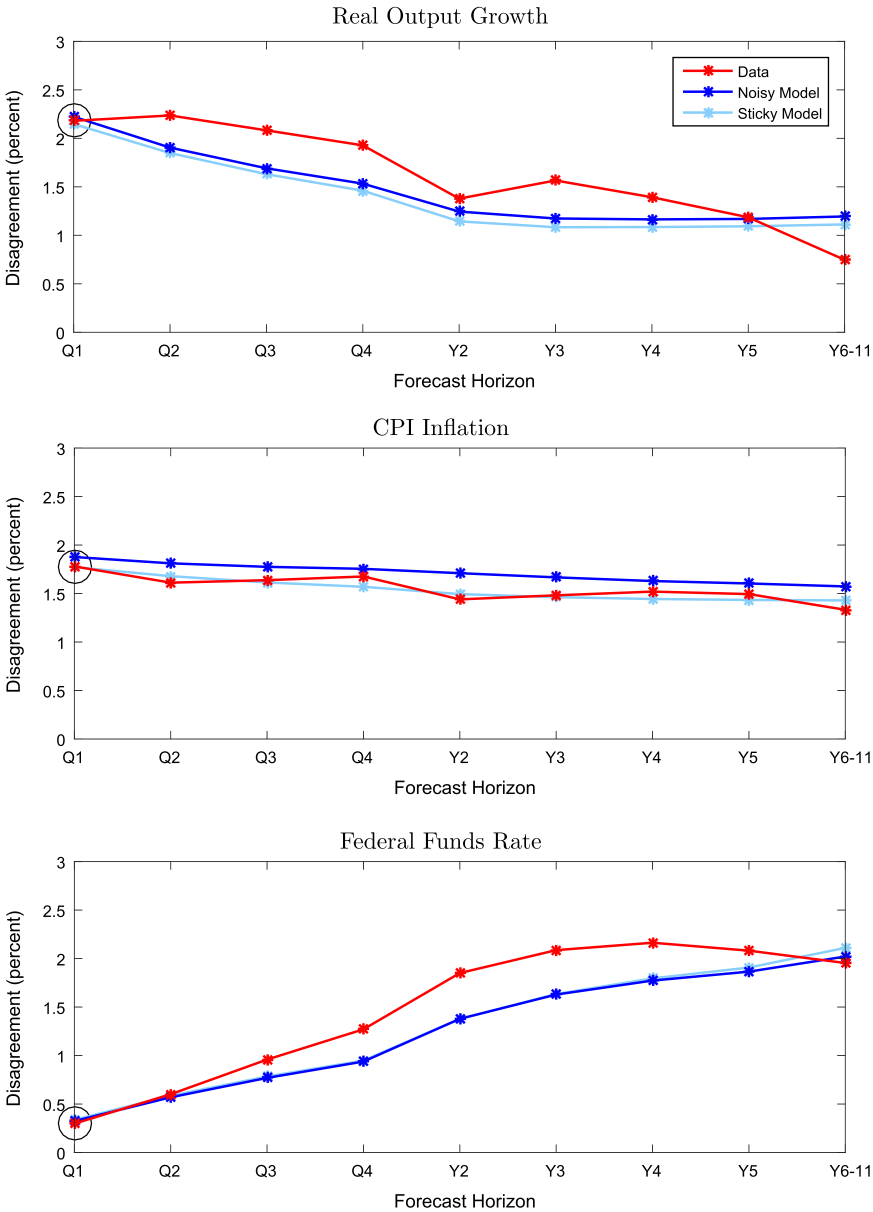


Fig. 7. Term structure of disagreement. *Noisy and sticky information models*. This figure displays the model-implied (time) average of disagreement across different horizons for the generalized noisy information model (dark blue) and the generalized sticky information model (light blue) calibrated with $\alpha = 50$ along with the Blue Chip Financial Forecasts survey (red). Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. Open circles designate survey moments used to form the penalization term $\mathcal{P}(\theta_1, \theta_2; \mathcal{S}_1, \ldots, \mathcal{S}_T)$. Results for the noisy and sticky information models are based on 5000 and 2500 simulations, respectively. All statistics are measured in percent. The sample period is from 1986Q1 to 2013Q2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

the low-frequency trend of observed long-term disagreement including the gradual decline in disagreement for CPI and the federal funds rate seen in the first part of the sample.

While our choice of initial conditions better represents the actual survey data it is important to emphasize that the main results are not driven by this initialization. To show this we simulate our baseline model for 240 periods (twice the original simulation sample size) and discard the first 120 observations of the simulated paths (shown in Supplementary appendix). The long-run disagreement implied by these paths is slightly lower for all three variables but the shapes of the term structure of disagreement and the standard deviation of consensus forecasts are virtually unchanged.

As noted above, we have chosen $\alpha = 50$ as the penalty parameter in our baseline specification. This choice guarantees that the target moments are matched reasonably well by the respective model. At the same time, a higher value of α might compromise the ability of the model to fit the actual data, as measured by the likelihood. To address this issue, results for the

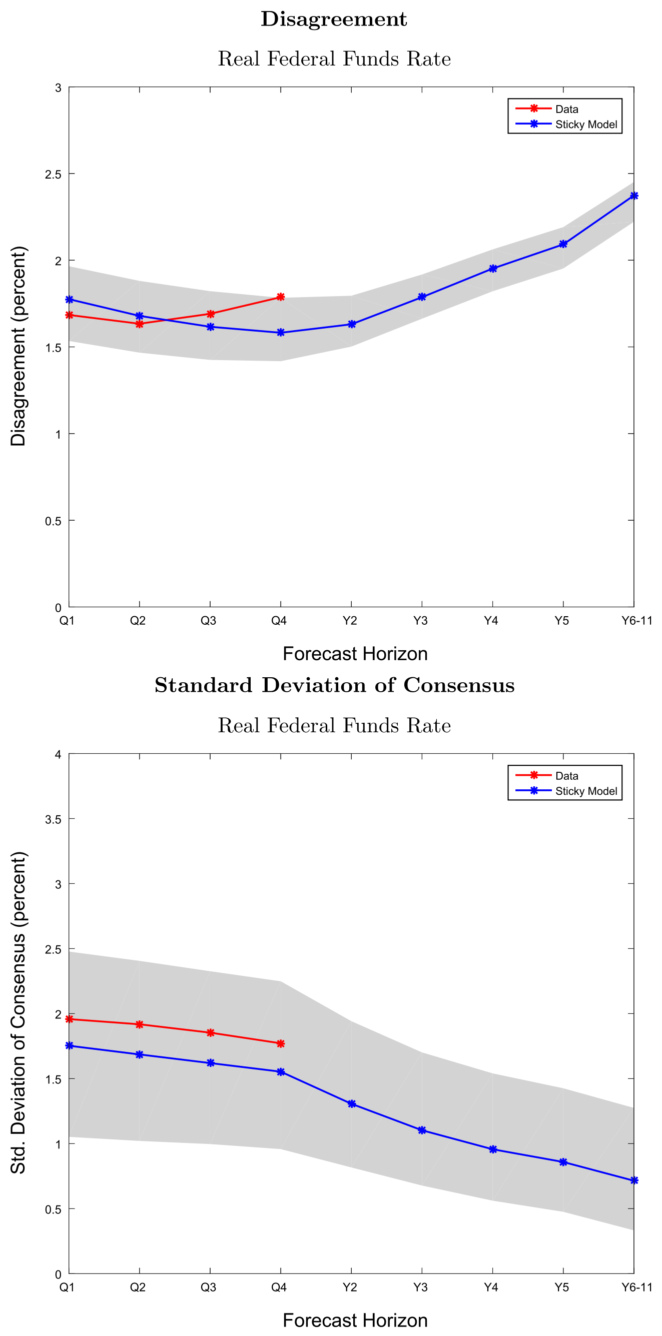


Fig. 8. Disagreement and standard deviation of real interest rate forecasts. *Sticky information model.* The top chart displays the model implied disagreement for the generalized sticky information model (blue) calibrated with $\alpha = 50$ along with the Blue Chip Financial Forecasts survey (red). The bottom chart displays the corresponding standard deviation of consensus forecasts. Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. Model-implied 95% confidence intervals are designated by shaded regions. Results are based on 2500 simulations. All statistics are measured in percent. The sample period is from 1986Q1– to 2013Q2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

model calibrated with values of $\alpha = 1$ and $\alpha = 10$ are also provided. For these values, the calibrated parameters are similar to those where $\alpha = 50$. More importantly, they imply term structures of disagreement that are close to the baseline. However, not surprisingly, small penalty parameters imply standard deviations of consensus forecasts that do not match the survey data as well as when $\alpha = 50$.

Recall that the calibration allows for measurement error in the observation equation for the econometrician which only affects the likelihood component of the objective function in Section 3.3. One implication of this choice is that the filtered states z_t could be much smoother than the actual observed variables y_t if the observation error is large. In order to evaluate the role of this additional degree of freedom for the main results, the model is also calibrated assuming that the econometrician observes y_t perfectly. These results are very similar to the baseline calibration.

As an additional robustness check we exploit the fact that individual forecasts at shorter horizons are observed, in order to construct forecasts and disagreement about real short-term interest rates, defined as the federal funds rate less CPI inflation. Because the disagreement about these two series is correlated at longer than one-quarter-ahead horizons, it is not clear that the model-implied disagreement about real rates should match that observed in the data. That said, as shown in Fig. 8, our baseline model produces levels of disagreement and standard deviations of consensus forecasts that are near the actual data (available only out to four quarters). Interestingly, the model-implied term structures of disagreement about real rates are "U-shaped", declining at short horizons before rising at longer horizons.

We discussed in Section 3.1 that our generalized sticky information model differs from that in the previous literature. Agents in our model, when allowed to update, only observe the current value for an element of z_t rather than the entire history of that variable up to time t. The standard formulation, where agents observe the full history of a variable when they are allowed to update, is computationally infeasible to calibrate in our multivariate model if no restrictions on the λ vector are imposed. One class of restrictions which alleviates the computational difficulties is to set $\lambda = 1$ for the federal funds rate and to introduce a common censoring process for both real output growth and CPI inflation. In other words, when an agent updates they observe the entire history of all three variables up to that point in time. This special case coincides with the calibrated values of λ presented in Table 1. In unreported results, we confirm that the term structure of disagreement and other implied moments of the forecast distribution are essentially the same in this specification when agents observe the full history of a variable when they update.

5. Monetary policy rules

We have thus far presented a reduced-form model used by the agents to produce forecasts. In this section we provide a structural interpretation of these forecasts in terms of simple monetary policy rules.[12] We consider the following class of monetary policy rules:

$$i_t = \rho \cdot i_{t-1} + (1-\rho) \cdot i_t^\star + \varepsilon_t, \tag{14}$$

$$i_t^\star = \bar{i}_t + \varphi_\pi \cdot (\pi_t - \overline{\pi}_t) + \varphi_g \cdot \left(g_t - \overline{g}_t\right) \tag{15}$$

This is a fairly general class of rules which embeds many popular specifications suggested in the literature. Here, ρ plays the role of determining the degree of interest-rate smoothing. The rule has a time-varying intercept, $(1-\rho) \cdot \bar{i}_t$, reflecting low-frequency movements in the interest rate. Finally, this class of rules embeds a time-varying inflation target, as measured by $\overline{\pi}_t$, and similarly a long-run equilibrium growth rate given by $\overline{g}_t$. Consistent with the underlying assumption that we have made throughout the paper, agents agree about the coefficients of the policy rule $\left(\rho, \varphi_\pi, \varphi_g\right)$. Consequently, disagreement about the path of i_t will depend only on disagreement about the paths of z_t and μ_t.[13]

This section provides results from three different exercises. First, we discuss a monetary policy rule with coefficients similar to those found in the empirical literature (e.g., Clarida et al., 2000) and investigate the implications for forecaster disagreement. Second, we show that our reduced-form model, to a high degree of approximation, is consistent with the rule in Eqs. (14) and (15) with similarly "reasonable" coefficients of the policy rule. Third, we evaluate the role of the different components in the monetary policy rule in explaining the observed dispersion of federal funds rate forecasts at various horizons with a particular focus on longer horizons.

Each agent j in the model forms interest-rate forecasts based on a linear combination of the elements of $z_{t|jt}$ and $\mu_{t|jt}$ governed by (powers of) the matrix F in Eq. (4). An alternative class of interest-rate forecasts is based on the rule above. Given the calibrated value of F, the parameters $\left(\rho, \varphi_\pi, \varphi_g\right)$ are chosen to best approximate the reduced-form forecasts implied by F. Both the reduced form interest rate forecasts and those based on the policy rule are linear combinations of z_t and μ_t. However, the policy rule constrains this linear combination to be a function of only three parameters. This is an over-identified system of equations which is solved via a minimum distance approach.

The top chart of Fig. 9 shows the model-implied forecaster disagreement based on different policy rules. In all simulations, the individual forecasts for output growth, inflation and $\mu_{t|jt}$, needed to compute individual forecast path for the federal funds rate, are computed using the reduced-form model. The solid black line shows the implied disagreement using a rule with coefficients $\rho = 0.90$, $\varphi_\pi = 2.0$, and $\varphi_g = 0.5$. This rule broadly follows the actual disagreement especially at short to medium horizons but overshoots at the longest horizon. As discussed in Section 4, the high degree of persistence in the federal funds rate is an important factor in explaining the upward slope in the term structure of disagreement. To further illustrate this point the same rule with ρ set equal to zero is shown as a dashed black line. This rule implies a downward

[12] This is potentially in line with Carvalho and Nechio (2014) who show that professional forecasters and at least some subgroups of households survey participants form their expectations up to one year about the future path of interest rates, inflation, and unemployment in a way that is consistent with simple monetary policy rules.

[13] It could also depend on disagreement about future deviations from this rule, ε_{t+h}. Here we focus on sources of disagreement that we can observe with the BCFF survey.

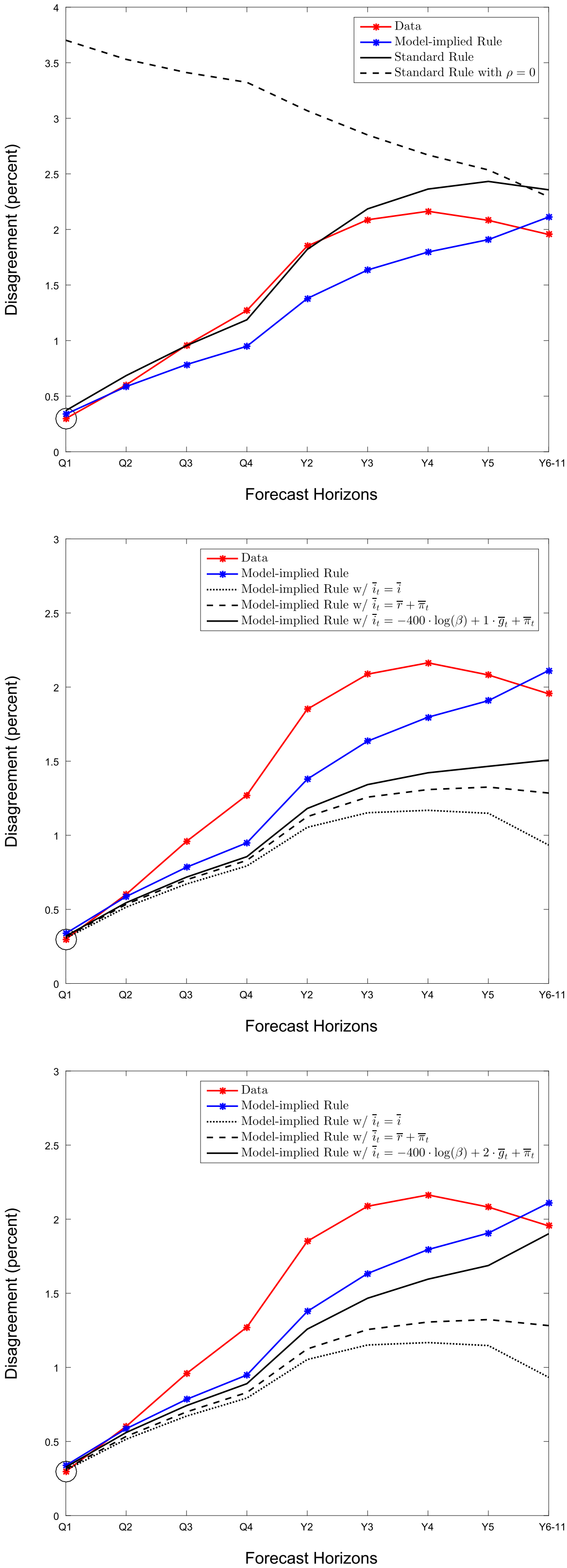


Fig. 9. Monetary policy rules. *Sticky information model*. This figure shows the results of the analysis discussed in Section 5. The top chart displays the model-implied disagreement for different values of $(\rho, \varphi_\pi, \varphi_g)$ along with the Blue Chip Financial Forecasts survey (red). The "standard rule" is given by $(\rho, \varphi_\pi, \varphi_g) = (0.90, 2.0, 0.5)$. The bottom charts show model-implied disagreement for different specifications of $\bar{i}_t$. Q1–Q4 denote the one- through four-quarter ahead forecasts, Y2–Y5 denote the two- through five-year forecasts, and Y6–11 captures the average forecast for horizons from 6-to-11 years ahead. Open circles designate survey moments used to form the penalization term $\mathcal{P}(\theta_1, \theta_2; \mathcal{S}_1, \ldots, \mathcal{S}_T)$. Results are based on 1000 simulations. All statistics are measured in percent. The sample period is from 1986Q1 to 2013Q2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

sloping term structure of disagreement with very high levels at short to medium horizons. Hence, the observed term structure of disagreement for the federal funds rate implies that forecasters perceive a high degree of interest-rate smoothing in the policy function.

The blue line in Fig. 9 is our model-implied structural rule. Despite the fact that we calibrate F from the data based on a reduced-form model, the interest-rate forecasting rule used by our agents is perfectly approximated by a monetary policy rule with "reasonable" parameters (see Fig. 4).[14] The corresponding coefficients are

$$\tilde{\rho} = 0.98, \quad (1-\tilde{\rho}) \cdot \tilde{\varphi}_\pi = 0.24, \quad (1-\tilde{\rho}) \cdot \tilde{\varphi}_g = 0.30. \tag{16}$$

As we have shown, our model is able to capture well the shape of the term structure of disagreement about the federal funds rate. In the third exercise we evaluate which features of our model-implied structural rule explain this disagreement. We focus on the sources of disagreement about the federal funds rate in the long run, which boils down to decomposing disagreement about $\bar{i}_t$. For example, a pertinent question is to what extent disagreement about the policy rate in the long run reflects disagreement about the real rate of interest or about the inflation target. On the one hand, disagreement about the real interest rate is likely to reflect differences in market participants' views about the long-run growth potential of the economy, which has received substantial attention in the recent discussion about "secular stagnation" in the U.S. On the other hand, disagreement about the inflation target can be viewed as a measure of the degree of credibility of the Federal Reserve.

Because our model is reduced form, to identify the factors behind the observed disagreement we require further assumptions. To that end, we consider a series of counterfactuals that link the long-run mean of the policy rate to the long-run means of output growth and inflation using the Fisher equation:

$$\begin{aligned} \bar{i}_t &= \bar{r}_t + \bar{\pi}_t \\ &= \beta_t + \sigma^{-1}\bar{g}_t + \bar{\pi}_t \end{aligned} \tag{17}$$

where $\bar{r}_t$ is the real short rate, β_t can be interpreted as the discount rate, and σ is the intertemporal elasticity of substitution. In these counterfactuals we present different term structures of disagreement based on counterfactual interest rate forecasts obtained by sequentially introducing sources of disagreement about the long-run mean of the policy rate using Eq. (17). For example, we can compute the counterfactual disagreement about the long-run policy rate that would obtain if market participants only disagreed about the inflation target but not about the long-run real rate by assuming that $\bar{i}_t = \bar{r} + \bar{\pi}_t$.

The bottom panels of Fig. 9 provide these decompositions. The red and blue solid lines again represent the term structures of disagreement observed in the data and in the model where $\bar{i}_t$ is time varying according to Eqs. (1) and (2) and the parameters reported in Table 1, respectively. The dotted line, in turn, provides the term structure of disagreement under the restriction that the long-run mean of the policy rate is constant, that is, $\bar{i}_t = \bar{i}$. While this rule is able to generate an upward-sloping term structure of disagreement, the level of disagreement is fairly small compared to the data at medium-to-long horizons. The fact that this rule generates positive disagreement at the longest horizon reflects persistent disagreement about output and inflation gaps in the policy rule rather than disagreement about the long-run value of the real interest rate or the inflation target. The dashed line shows the disagreement about the long-run policy rate that would obtain from a counterfactual where market participants only disagree about the inflation target, that is, $\bar{i}_t = \bar{r} + \bar{\pi}_t$. While this brings long-run policy rate disagreement closer to the observed value, a sizable wedge remains. Finally, the black solid line represents a third counterfactual where disagreement about the long-run policy rate reflects both disagreement about the inflation target and the long-run real short rate, that is, Eq. (17) with $\beta_t = \beta$. In the middle panel we set $\sigma = 1$ which further closes the gap to the data but leaves some small amount of residual disagreement about the long-run policy rate unexplained. For example, this could potentially reflect time variation in agents' preferences (i.e. the discount factor β) or other factors. In the bottom panel we consider a lower value for the intertemporal elasticity of substitution, namely $\sigma = 0.5$, which is near values commonly used in the macroeconomics literature. In this case, disagreement about the long-run policy rate is nearly fully explained by disagreement about the inflation target and long-run growth. In sum, these counterfactuals suggest that disagreement about both the inflation target and the value of the long-run real interest rate play a meaningful role in explaining the long-run disagreement about the policy rate. The more general takeaway from these exercises is that interest rate smoothing and the presence of a time-varying intercept in the policy rule are both important factors driving the observed term structure of disagreement about the future path of the federal funds rate.

6. Conclusion

This paper documents a novel set of facts about disagreement among professional forecasters: (1) forecasters disagree at all horizons including the very long run; (2) the term structure of disagreement differs markedly across variables: it is downward sloping for real output growth, relatively flat for CPI inflation, and upward sloping for the federal funds rate; (3) disagreement is time varying at all horizons including the very long run. We present an imperfect information model of

[14] The norm of the minimum distance criterion function based on one-quarter ahead forecasts is of the order 10^{-10}. Differences in model-implied disagreement between the reduced-form and structural rules are, at most, of the order 10^{-3}.

expectation formation featuring information stickiness. This model is able to replicate the observed term structure of disagreement. Our analysis shows that what is important is an economic environment with the following features: first, the state of the economy is comprised of unobserved transitory and persistent components which agents must disentangle; second, agents must also take into account the dynamic interaction between variables. Explicitly incorporating these elements in the expectation formation process are critical to explaining the term structure of disagreement. An important aspect of our modeling framework is that no agent has informational advantages over any other and agents have rational expectations and full knowledge about the structure of the economy. Perhaps surprisingly, since the sticky information model is often advocated because it generates time variation in disagreement, our model produces insufficiently volatile disagreement at longer horizons. That said, the model does considerably better at matching the volatility of disagreement at shorter horizons. This emphasizes the importance of using the entire term structure of disagreement for model evaluation.

Several extensions to our model could be introduced to overcome this limitation. One approach would be to relax the assumption that agents do not have full knowledge of the DGP, for example, if they must learn about the parameters. An alternative approach would be to endow the model with endogenously generated time variation in the precision of signals that depends on the state of the economy as in Van Nieuwerburgh and Veldkamp (2006). Finally, having shown that our proposed model of expectation formation matches various important features of survey forecasts, one avenue for future research would be to embed the model in a general equilibrium setup.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jmoneco.2016.08.007.

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