What can survey forecasts tell us about informational rigidities?

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Abstract: This paper assesses both the support for and the properties of informational rigidities faced by agents. Specifically, we track the impulse responses of mean forecast errors and disagreement among agents after exogenous structural shocks. Our key contribution is to document that in response to structural shocks, mean forecasts fail to completely adjust on impact, leading to statistically and economically significant deviations from the null of full information: the half life of forecast errors is roughly between 6 months and a year. Importantly, the dynamic process followed by forecast errors following structural shocks is consistent with the predictions of models of informational rigidities. We interpret this finding as providing support for the recent expansion of research into models of informational rigidities. In addition, we document several stylized facts about the conditional responses of forecast errors and disagreement among agents that can be used to differentiate between some of the models of informational rigidities recently proposed. We use a variety of structural shocks, expectation surveys, and robustness checks to establish these facts about informational rigidities.

Keywords: expectations, information rigidity, survey forecasts.

JEL: E3, E4, E5

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1 Introduction

How economic agents form their expectations has long been one of the most fundamental, and most debated, questions in macroeconomics. Indeed, the abandonment of adaptive expectations in favor of rational expectations was one of the defining features in the rebuilding of macroeconomics starting in the 1970s. Yet, even with the advent of rational expectations, research continued to emphasize the fact that, in forming their expectations, agents typically face constraints. For example, Lucas (1972) assumed agents could not observe all prices in the economy. Likewise, Kydland and Prescott (1982) assumed that agents could not differentiate in real time between transitory and permanent productivity shocks. Despite this early interest in the information problems faced by economic agents and their implications for aggregate dynamics, most modern macroeconomic models assume full-information rational expectations on the part of all agents. Yet recent work such as Mankiw and Reis (2002), Woodford (2003) and Sims (2002), has once more revived interest in better understanding the frictions and limitations faced by agents in the acquisition and processing of information.

This renewed interest in the expectations formation process has been spurred by several failures of full information models. For example, Mankiw and Reis (2002) argue that the observed delayed response of inflation to monetary policy shocks is not readily matched by New Keynesian models without the addition of informational rigidities or the counterfactual assumption of price indexation. Similarly, Dupor et al (2007b) show that the differential response of inflation to monetary policy and technology shocks is difficult to reconcile without informational rigidities. In addition, departing from the assumption of full-information can also account for some empirical puzzles. For example, Roberts (1997, 1998) and Adam and Padula (2003) demonstrate that empirical estimates of the slope of the New Keynesian Phillips Curve have the correct sign when conditioning on survey measures of inflation expectations while this is typically not the case under the assumption of full-information rational expectations. Similarly, Romer and Romer (2004) show that monetary policy shocks drawn from the Fed's Taylor rule conditional on its historical forecasts eliminate the price puzzle identified in previous work. Piazzesi and Schneider (2008), Gourinchas and Tornell (2004) and Bachetta et al (2008) all identify links between systematic forecast errors in survey forecasts and puzzles in various financial markets.

Despite this resurgent focus on the nature of the expectations formation process, little consensus exists on how best to model the acquisition and processing of information by agents. In large part, this reflects a lack of convincing empirical evidence on the matter. First, the evidence against the assumption of full-information rational expectations is sparse, often fragile, and most importantly of unclear economic significance. Second, there is even less empirical evidence available to distinguish among competing models of informational rigidities, so macroeconomists seeking to include informational frictions in their models have a multitude of options to consider but little basis upon which to choose a particular specification.

The most traditional approach to testing expectations data relies on testing the null of full information using survey forecasts, typically of inflation, by regressing ex-post inflation on mean inflation forecasts. As surveyed in Pesaran and Weale (2006), this literature has yielded only mixed results, typically finding departures from full information over short time samples but not over longer periods. In addition, this approach has little insight to offer about the dynamic properties of the expectations formation process beyond a test of the null of full information and reveals little about the economic significance of identified departures from full information.[1] A second strand of empirical evidence has focused on evaluating the *implications* of models with informational rigidities relative to those without.[2] These results have also been mixed and are in any case difficult to rely on for making general conclusions about the expectations formation process since this type of evidence is sensitive to the estimation approach as well as to auxiliary modeling assumptions. A third approach documents the costs of collecting and processing information (e.g. Zbaracki et al (2004)). This approach is instrumental in establishing the fact that economic agents face significant informational constraints but cannot address how these constraints affect agents' choices and aggregate dynamics. Finally, the fourth approach studies the properties of disagreement among agents to make inferences about their underlying approaches to expectations formation. For example, Mankiw Reis and Wolfers (2004) note that disagreement among agents is inconsistent with full information but not with models in which agents face informational frictions.[3] They argue that a sticky-information model can reproduce many of the

[1] See Pesaran and Weale (2006) and Mankiw, Reis, and Wolfers (2003) for surveys of this literature.
[2] See Korenok (2005), Andres et al (2005), Kiley (2007), Coibion (2007), Dupor et al (2007a), and Knotek (2007).
[3] It is possible to have forecast dispersion when fully rational agents share the *same* information set but use different forecasting models or have different objective functions. However, Jonung (1981) and others find that agents disagree about current and *past* inflation and perceptions of past inflation are a strong predictor of inflationary expectations so that heterogeneity in expectations is driven to a significant extent by perceptions about current and past conditions. Hence, a bulk of disagreement seems to arise from differential information sets. Probably more importantly, there is potentially no discipline on what rules agents could use and consequently models with heterogeneous forecasting rules

features of expectations data they consider. Branch (2007) similarly makes use of data on disagreement to compare the fit of the sticky information model and a model in which agents may endogenously use heterogeneous forecasting rules.

This paper lays out a new set of stylized facts about the expectations formation process to address the two key issues: do agents have full information, and if not, how do we model their information problem? We make use of three data sets containing survey measures of inflation forecasts: the Michigan Survey of Consumers, the Survey of Professional Forecasters, and the Blue Chip Economic Indicators. Each survey provides mean forecasts of inflation over the next year, as well as measures of the cross-sectional dispersion of agents' forecasts of future inflation. Unlike the previous literature, we study the *conditional* responses of forecast errors and forecast dispersion to identified structural shocks. With this novel approach we can hope to have more power and robustness in distinguishing hypotheses of how expectations are formed. As we discuss later, different models of expectation formation deliver sign restrictions on first and second moments of impulse response functions that can be used to assess the validity of these models. In contrast, these models tend to agree on implications for unconditional moments of expectations (e.g., positive dispersion of forecasts). In this respect, our approach is similar to standard methods of applied macroeconomics that utilize conditional responses of variables to shocks (i.e., impulse response functions) to study and estimate the behavior of empirical models.

Our first stylized fact is that *forecasts fail to adjust one-for-one with the variable being forecasted after structural shocks.* Instead, we find systematic patterns of serially correlated conditional forecast errors, particularly after technology and oil price shocks.[4] Thus, after inflationary (deflationary) shocks, one observes a predictable sequence of serially correlated positive (negative) inflation forecast errors. Over time, forecast errors monotonically converge to zero. This result not only contradicts the null of full-information but does so in exactly the manner predicted by standard models of informational rigidities. In addition, we find that these deviations from full-information are not only statistically significant but also of economically significant

can rationalize any outcome. Thus, we do not formally try to isolate the contribution of heterogeneous forecasting rules to disagreement because we could not formulate a set of falsifiable hypotheses to rule out this theory.

[4] Our baseline structural shocks are monetary policy, technology, and oil price shocks. These are the shocks that explain the largest component of the variance of inflation out of the ones we consider, between thirty and fifty percent jointly depending on the time horizon, which is important for our ability to distinguish models of expectation formation in the data. We also consider other exogenous shock measures, such as fiscal shocks, information shocks, and alternative measures of monetary policy shocks.

magnitudes. For example, the half-lives of conditional percentage forecast errors are between six months and a year. Such a delayed adjustment of average expectations in response to structural shocks is large enough to have important repercussions for macroeconomic dynamics. We interpret these results as demonstrating that informational rigidities are an important component of the expectations formation process for both consumers and professional forecasters. Given the crucial role played by forward-looking behavior in macroeconomics, this has broad implications for understanding and modeling business cycles.

Having documented this novel evidence for informational rigidities in the data, we then turn to the question of how to differentiate between competing models of expectations formation. To do so, we first present contrasting implications of two general types of informational rigidities. The first is the sticky information model of Mankiw and Reis (2002). In this model, agents can update their information only infrequently, but when they do so they acquire complete information about the current and past states.[5] Thus, at any moment in time, this model implies that a fraction of agents will be relying on outdated information. This generates a distribution of information sets across agents based on the last date at which agents acquired new information. An appealing feature of this form of rigidity is that a single form of rigidity can help explain inertia in different macroeconomic variables. These sticky-information models are also able to deliver inertial inflation in response to monetary policy shocks and rapid adjustment of inflation to technology shocks (Mankiw and Reis (2007) and Reis (2008)).

In the second class of models of informational rigidities, which we group under the heading of imperfect information, agents cannot observe the current state perfectly and must thus form a belief about the current state based on the variables that they observe.[6] For example, Woodford (2001) considers a model in which agents observe a noisy signal about the current state. These agents use a Kalman filter to *continuously* update their beliefs about the current state in the face of new signals.[7] Sims (2003) argues that agents face limited information processing

[5] The microfoundations of sticky information are developed in Reis (2006a) for firms and Reis (2006b) for consumers. He shows that when agents face fixed costs to acquiring information, they will update their information sets infrequently and, under certain conditions, exactly in the way proposed in Mankiw and Reis (2002).

[6] Loosely speaking, if one thinks of sticky information as resulting from fixed costs to acquiring information, imperfect information models can be thought of as resulting from convex costs to acquiring information, leading to continuous but incremental information acquisition.

[7] This strand of literature goes back to Lucas (1972) which has an early version of a macroeconomic model with imperfect information.

capacities, and must thus endogenously allocate their attention to different variables.[8] Applying Sims' approach to price-setting decisions, Paciello (2007) and Mackowiak and Wiederholt (2009) show that under rational inattention, firms will pay more attention to technology shocks than monetary policy shocks because the former are more volatile and have greater effect on profits. As a result, firms change prices more rapidly after a technology shock than a monetary policy shock.

These two classes of models share certain important characteristics. First, both models consist of rational expectations agents subject to a specific source of informational rigidity, unlike earlier ad hoc models with adaptive expectations. Second, each model implies that after a shock the average forecast across agents will trail in terms of magnitudes and timing the variable being forecasted, but in each case forecast errors will converge to zero over time. Third, both approaches are consistent with disagreement among agents, i.e. agents have different beliefs about the current and future states. Finally, both are consistent with the differential response of inflation to technology and monetary policy shocks, making them particularly appealing approaches to consider.

Despite these similarities, the two models also make conflicting predictions. For example, in sticky information models, agents update their information sets infrequently and independently of the type of shock hitting the economy. Thus, the convergence rate of percentage forecast errors should be identical across shocks after controlling for the persistence of the inflation rate.[9] In imperfect information models, on the other hand, the convergence rate of percentage forecast errors will depend on the quantitative importance of different shocks. For example, firms should devote more attention to gathering information about shocks that affect profits more. Thus, in general, shocks that play an important role in affecting business cycles should have a faster convergence rate of forecast errors than quantitatively unimportant shocks since agents should pay more attention to more important shocks. Secondly, in the sticky-information model, disagreement, as measured by the cross-sectional variance of forecasts, is predicted to increase after a shock. In the linear imperfect information model that we consider, there should be no increase in disagreement across agents after macroeconomic shocks. In summary, these models offer crisp differential predictions that can be used to assess their empirical validity.

[8] Sims (2003) illustrates how rationally inattentive agents behave much like imperfect agents but differ in that the signal to noise ratio is endogenous.
[9] More precisely, the percentage forecast errors should converge at a common rate determined entirely by the rate of information updating.

Consequently, we study the differences in the conditional responses of percentage forecast errors across agents and shocks and uncover two new findings. Our second stylized fact is that *conditional percentage forecast errors converge at similar rates across different shocks*. In other words, we find little evidence that forecasts adjust more or less rapidly to different shocks. In particular, mean inflation forecasts converge to actual inflation just as rapidly after monetary policy shocks as after technology shocks. This result is consistent with sticky information models, but not necessarily inconsistent with imperfect information models since the latter predict that percentage forecast errors *may* converge at different rates. We show that we can reject the null that differences in convergence rates are as large as that predicted by calibrated imperfect information models such as Mackowiak and Wiederholt (2009), but we cannot ascertain whether this rejection applies to all imperfect information models or the specific calibration used. Thus, our results call for further study of imperfect information models to determine whether their predictions for convergence rates can be reconciled with our empirical results.

Our third stylized fact is that *conditional percentage forecast errors converge at similar rates across agents*. Thus, we find no evidence that professional forecasters' mean forecasts converge more rapidly to actual inflation than consumers' forecasts. This result is not necessarily inconsistent with either imperfect or sticky information models, but it is challenging for epidemiological models of information diffusion, as in Carroll (2003). This approach assumes that information spreads gradually from professional forecasters to consumers, a proposition that is inconsistent with our finding that mean professional forecasts converge no quicker to true values than consumer forecasts. We provide evidence that the tests proposed by Carroll (2003) deliver results that are consistent with this stylized fact.

Finally, following Mankiw, Reis and Wolfers (2004) and Branch (2007), we study the cross-sectional dispersion of forecasts across agents. But unlike these authors, we focus on the conditional response of disagreement among agents to structural shocks. This delivers our fourth stylized fact: *structural shocks do not appear to lead to any discernible increase in disagreement*. This result is remarkably consistent with simple linear imperfect information models but not sticky information models.

The structure of the paper is as follows. In section 2, we present two models of informational rigidity and compare their predictions about conditional forecast errors and the response of the cross-sectional dispersion of beliefs after a shock. In section 3, we present the survey measures that form the backbone of our empirical analysis as well as the shock measures we utilize. Section 4 presents the baseline empirical results. Section 5 includes robustness checks of our results. Section 6 concludes.

2 Two Models of Information Rigidity

2.1 Sticky Information

Reis (2006a) considers the problem of a firm facing a fixed cost to acquiring and processing new information. In the presence of fixed costs, it becomes optimal for firms to update their information infrequently. Under certain conditions, Reis shows that the acquisition of information follows a Poisson process in which, each period, agents face a constant probability λ of not being able to update their information. We refer to λ as the degree of informational rigidity for the sticky information model. Following Mankiw and Reis (2002), we assume that when agents update their information sets, they acquire complete information and form expectations rationally. In periods in which agents do not update their information sets, their expectations and actions continue to be based on their old information. Thus, agents who update their information sets in the same period have the same beliefs and forecasts about macroeconomic variables.

Denoting the mean forecast across agents at time t of a variable π_{t+j} j periods ahead as $F_t\pi_{t+j}$, we have

$$F_t\pi_{t+j} = (1-\lambda)\sum\nolimits_{k=0}^{\infty} \lambda^k E_{t-k}\pi_{t+j} \tag{1}$$

The mean forecast is a weighted average of past (rational) expectations of the variable at time $t+j$. Without loss of generality, suppose that the economy is initially in a steady-state, so that all expectations of π are equal to the steady-state value, normalized to zero for simplicity. At time $t=0$, a shock occurs and affects π in a deterministic way (i.e. yields a sequence of inflation rates $\frac{\partial \pi_{t+j}}{\partial shock} = (\pi_{t+j} - 0) = \pi_{t+j}$). There are no other shocks. The impulse response of the average forecast across agents follows

$$\frac{\partial F_t\pi_{t+j}}{\partial shock} = (1-\lambda^{t+1})\pi_{t+j} \quad \forall t \geq 0 \tag{2}$$

The mean forecast depends on the ex-post value of inflation, since when agents update their information sets, they acquire full information. Thus, after an inflationary shock, mean forecasts rise along with inflation. Note that the coefficient is converging to one over time, so mean forecasts converge to the true value. But because the coefficient is less than one, forecast errors will be non-zero and persistent. Defining the forecast error j periods ahead as $FE_{t,t+j} \equiv \pi_{t+j} - F_t\pi_{t+j}$, its impulse response is given by

$$\frac{\partial FE_{t,t+j}}{\partial shock} = \lambda^{t+1}\pi_{t+j} \quad \forall t \geq 0 \tag{3}$$

Forecast errors depend both on the inflation process after the shock, as well as the degree of informational rigidity. Note that when $\lambda = 0$, firms always update their information sets and the forecast error is always zero. As the degree of informational rigidity rises, conditional forecast errors will become increasingly persistent.

The impulse response for forecast errors above also makes clear that the convergence of the forecast error to the true value is independent of the volatility of the shock. Specifically, the percentage forecast error ($\frac{FE_{t,t+j}}{\pi_{t+j}}$) is monotonically decreasing over time at a rate governed by the degree of informational rigidity.[10] Because agents must choose a certain average duration between information updates, this convergence rate is independent of the properties of the shock. In other words, two different kinds of shocks must yield the same convergence rate for mean forecasts.

The sticky information model also makes predictions about the cross-sectional dispersion of beliefs across agents. Define $V_t\pi_{t+j}$ to be the cross-sectional variance of forecasts at time t of π in j periods. Then,

$$V_t\pi_{t+j} = (1-\lambda)\sum\nolimits_{k=0}^{\infty}\lambda^k[E_{t-k}\pi_{t+j} - F_t\pi_{t+j}]^2 \tag{4}$$

In response to a shock at time $t = 0$ out of the steady-state, the impulse response of the cross-sectional variance of forecasts is given by

$$\frac{\partial V_t\pi_{t+j}}{\partial shock} = (1-\lambda^{t+1})\lambda^{t+1}\pi_{t+j}^2 \quad \forall t \geq 0 \tag{5}$$

[10] Note that the percentage forecast error is generally a nonlinear function of current and past shocks, so that the impulse response of percentage forecast errors is actually also a function of past shocks and the persistence of the shocks. To be more precise, it is the ratio of the impulse response of the forecast error to the impulse response of inflation $(\partial FE_{t,t+j}/\partial shock)/(\partial\pi_{t+j}/\partial shock)$ which is only a function of informational rigidity. The same caveat applies for imperfect information models. However, this distinction has little effect on our empirical results in practice, as noted in footnote (28). We are grateful to Mirko Wiederholt for pointing out this distinction.

As long as $\lambda > 0$ and $\pi_{t+j} > 0$, the dispersion, or degree of disagreement across agents, will rise in response to a shock. Over time (assuming inflation converges), the dispersion will return to its steady-state level.[11]

We can summarize the predictions of the sticky-information model as follows:

1. Conditional forecast errors respond to shocks with the same sign as the predicted variable and converge to zero over time.
2. The convergence rate of percentage forecast errors is common across shocks.
3. The dispersion of forecasts should increase after a shock.

2.2 Imperfect Information

Lucas (1972), Cukierman and Wachtel (1979), Woodford (2001) and Sims (2003) develop models where economic agents filter the state of economic fundamentals from a series of signals contaminated with idiosyncratic, agent-specific noise. In contrast to Mankiw and Reis (2002), agents *continuously* track variables and incorporate the most recent information into their decision making. The striking feature of this class of models is that the dispersion of forecasts does not vary in response to a shock in fundamentals. In this section, we present a simple model to illustrate the intuition behind this result.

Suppose that economic agents observe signals about inflation $\omega_{it} = \pi_t + v_{it}$ where π_t is the aggregate level of inflation and $v_{it} \sim iid\ N(0, \Sigma_v)$ is an agent specific shock. Also without loss of generality, suppose that inflation evolves as a random walk $\pi_t = \pi_{t-1} + w_t$ where $w_t \sim iid\ N(0, \Sigma_w)$.[12] Denote the optimal forecast for inflation at time *t* given agent *i*'s information at time *s* with $\pi_{i,t|s}$. Using properties of the Kalman filter, one can show that

$$\pi_{i,t|t} = \pi_{i,t|t-1} + G(\omega_{it} - \pi_{i,t|t-1}), \tag{6}$$

where $G \in (0,1)$ is the gain of the Kalman filter. Note that the gain of the filter does not vary across agents because all agents solve the same Ricatti equation $P = [P - P(P + \Sigma_w)^{-1} P] + \Sigma_v$,

[11] Mankiw, Reis and Wolfers (2003) use this prediction for the behavior of the forecast disagreement to check whether the dynamics of disagreement during the Volcker disinflation are broadly supported by the sticky information model.

[12] This can readily be extended to non-random walk behavior. Our conclusions also do not change if we allow shocks $v_{i,t}$ to be correlated across agents.

where P is the variance of the one-step ahead forecast $\pi_{i,t|t-1}$, and thus obtain the same gain $G = P(P+\Sigma_v)^{-1}$.

The average forecast for the current state of inflation given current information is then given by

$$\begin{aligned} F_t\pi_{i,t|t} &\equiv E_i\pi_{i,t|t} = (1-G)E_i\pi_{i,t|t-1} + GE_i\omega_{it} = (1-G)E_i\pi_{i,t|t-1} + G(E_i\pi_t + E_i v_{it}) \\ &= (1-G)E_i\pi_{i,t|t-1} + G\pi_t = (1-G)E_i\pi_{i,t-1|t-1} + G\pi_t \end{aligned} \quad (7)$$

where $E_i(\cdot)$ indicates that expectation is taken over agents rather than time and the last equality follows from $\pi_{i,t+j|t} = \pi_{i,t|t}$. Then the impulse of the average forecast of inflation to an inflationary shock is $\pi_{t+j|t+j} = G\sum_{k=0}^{j}(1-G)^k\pi_t = [1-(1-G)^j]\pi_t \quad \forall j \geq 0$ where we omit $(1-G)^{j+1}E_i\pi_{i,t|t-1}$ by conditioning on the initial state of beliefs. Since for each agent the forecast for inflation is $\pi_{i,t+j|t} = \pi_{i,t|t}$, the impulse of the average *j*-step ahead forecast has the same properties as the average forecast for the current state.

Similar to the sticky information model, this model predicts that the average forecast will have serially correlated ex-post error equal to $(1-G)^j\pi_t$. Because $G<1$, the forecast error moves in the same direction as the mean forecast does. Note that the forecast error converges to zero with time as $\pi_{t+j|t+j} - \pi_t = (1-G)^j\pi_t \to 0$ with $j \to \infty$. Thus, the impulse response of forecast errors under imperfect information follows the same qualitative pattern as under sticky information. An additional similarity to the sticky information model is that the dynamics of the percentage forecast error in the imperfect information model is only a function of the Kalman filter gain *G* which is governed by the degree of informational rigidity.

Using equation (6), we can derive the law of motion for the dispersion of forecasts across agents: $V_t\pi_{i,t|t} = (1-G)^2V\pi_{i,t|t-1} + G^2V(\pi_t + v_{it}) = (1-G)^2V\pi_{i,t|t-1} + G^2\Sigma_v = (1-G)^2V\pi_{i,t-1|t-1} + G^2\Sigma_v$. Note that $V\pi_{i,t|t}$ does not depend on π_t. This means that the motion of forecast dispersion does not vary with π_t. Again using the fact that *j*-step ahead forecast is based only on the forecast for the current state (here, $\pi_{i,t+j|t} = \pi_{i,t|t}$), we conclude that the dispersion of the *j*-step ahead forecasts does not vary with π_t. Intuitively, because agents continuously update their information sets, the disagreement in their forecasts arises only due to idiosyncratic differences in information sets induced by shocks v_{it}. Since the dispersion of v_{it} does not vary in response to shocks to fundamentals such as π_t, the forecast dispersion does not respond to π_t.[13]

Note that the speed of reacting to signals ω_{it} is increasing in the volatility of fundamentals and decreasing in the volatility of the idiosyncratic shock v_{it}. Likewise, one can show that if the agent's objective function (e.g., profit or utility) is more sensitive to certain types of fundamental shocks (e.g. technology) than to other types of fundamental shocks (e.g., monetary policy), then the reaction to sensitive shocks is stronger (see Mackowiak and Wiederholt (2009)).[14] Thus, unlike the sticky information model, the imperfect information model allows for a differential response of information acquisition to fundamental shocks. For example, agents may learn slowly the true state of monetary policy but may react quickly to shocks in technology.

We can summarize the predictions of the imperfect information model as follows:

1. Conditional forecast errors respond to shocks with the same sign as the predicted variable and converge to zero over time.
2. The convergence rate of percentage forecast errors can be different across shocks.
3. The dispersion of forecasts should not increase after a shock.

Observe that the imperfect information model makes the same qualitative predictions about forecast errors and mean forecasts as the sticky information model. In contrast to the sticky information model, the imperfect information model implies that dispersion of forecasts does not respond to fundamental shocks and the speed of response to shocks can vary across shocks.

3 Data Description

We have described three predictions of each model of informational rigidities. We will test these predictions using three data sets of inflation surveys. The first is the Michigan Survey of Consumers (MSC). The MSC is a nationally representative monthly survey of 500 to 1,300 consumers. Respondents are asked to report their expected inflation rate for the next twelve months. The MSC is collected over the corresponding month. The survey question on inflation

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[13] The dispersion of forecasts can respond to shocks in the imperfect information model if shocks induce conditional heteroskedasticity $\Sigma_{v,t}=\Sigma_v(\pi_t)$, which is similar in spirit to heteroskedasticity analyzed in GARCH models. Cukierman and Wachtel (1979) present such a model. We focus on the model without heteroskedastic effects because it offers sharper predictions.

[14] In general, the speed of learning in imperfect information models will also depend on the persistence of the shocks. However, Mackowiak and Wiederholt (2008) show that the persistence of shocks has ambiguous effects on the speed of learning making these predictions sensitive to the model. We return to this issue in section 4.2.

forecasts begins in January 1978. The second source is the Survey of Professional Forecasters (SPF). This is a quarterly survey of 9 to 40 professional forecasters. The SPF collects quarterly forecasts (for the current quarter and the next four quarters) for a number of macroeconomic variables. We focus on forecasts of average GDP Deflator inflation over the next year for consistency with the MSC forecasts. GDP Deflator inflation forecasts have been collected by the SPF since 1974. The third (proprietary) dataset is the Blue Chip Economic Indicators (BCEI). This is a collection of forecasts from professional forecasters for a similar set of macroeconomic variables as the SPF. The consensus BCEI forecasts are available monthly starting in April 1980 but dispersion measures can only be constructed starting in July 1984. For the BCEI, we focus on forecasts of the CPI. For each dataset, we extract a mean forecast of average inflation over the next year and a measure of the cross-sectional dispersion of those forecasts. We discuss the construction of our data in more detail in Appendix A.[15]

Figure 1 plots the mean forecasts and forecast dispersion series from each survey in Panels A and B respectively. The mean forecasts are highly correlated with each other. We measure dispersion as the log of the cross-sectional standard deviation of inflation forecasts. The standard deviation of MSC is much higher than for professional forecasters. All three measures point to decreasing levels of disagreement since the early 1980s. Table 1 presents correlations of these measures with macroeconomic variables. All three mean inflation forecast measures are highly correlated with inflation and with each other, and, to a lesser extent, with the unemployment rate. They are also slightly negatively correlated with the growth rate of real GDP. The cross-correlation among dispersion measures is lower than for mean forecasts. Nonetheless, these unconditional correlations indicate an apparently strong link between the degree of disagreement among agents and macroeconomic conditions, a point emphasized by Mankiw, Reis and Wolfers (2003).[16] Interestingly, since the mid-1980s, the correlation between disagreement about inflation

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[15] Some readers may find the notion that professional forecasters do not continuously update their information sets as prescribed by the sticky information model intuitively unappealing. However, Mankiw, Reis and Wolfers (2003) argue that the sticky information model should be interpreted more broadly when applied to professional forecasters. For example, professional forecasters often build stories to interpret predictions and these stories may be updated relatively infrequently. In any case, the purpose of this paper is to determine whether sticky information or imperfect information models adequately describe informational rigidities faced by economic agents.

[16] The strong unconditional correlation, however, should not be interpreted in favor of or against models of informational rigidities because there could be forces other than informational imperfections that may lead to comovement of macroeconomic variables and the *level* of uncertainty (e.g., uncertainty shocks as in Bloom (2008)). Furthermore, the strong correlations between macroeconomic variables and the level of forecast disagreement greatly diminish once we remove the trending components in the data. For example, the correlation between the HP-filtered

and the unemployment rate exceeds the correlation of disagreement with the inflation rate for all three survey measures.

Because the predictions made by the two models are all conditional on a macroeconomic shock, a key element of our analysis is the selection and identification of shocks. There is a long literature on identifying exogenous structural shocks to the economy, giving us a wide range of measures to consider.[17] We considered the following shocks from the literature:

a) Monetary policy shocks, identified from a VAR.[18]
b) Technology shocks, identified using long-run restrictions as in Gali (1999).
c) Oil shocks, identified as in Hamilton (1996).
d) Information shocks, identified as in Beaudry and Portier (2006).
e) Confidence shocks, identified as in Barsky and Sims (2008).
f) Fiscal shocks, from Romer and Romer (2007).

Appendix B discusses the details of each approach.[19] Table 2 presents the cross-correlation matrix for these shocks. Most shock measures are largely uncorrelated with one another, consistent with their interpretations as exogenous structural shocks to the economy. The highest correlations are between the confidence shock of Barsky and Sims and the information shock of Beaudry and Portier, which indicates that there is some overlap between the two shock series, as well as between the confidence shock and the oil price shock.

Our selection criterion for shocks is to focus primarily on the three shocks which account for the largest component of the variance of inflation. Table 3 presents a variance decomposition of inflation into the orthogonalized components of these shocks.[20] The most important shock in

forecast disagreement in the MSC and the HP-filtered unemployment rate is 0.14, which is not statistically different from zero, while the same correlation for the raw data is 0.65, which is significantly different from zero. We find similar results for correlations between other macroeconomic variables and the level of forecast disagreement.

[17] The main advantage of studying responses to structural shocks rather than reduced-form shocks is that by comparing responses across shocks we have additional tests of models with information frictions. For example, we can test whether forecast errors converge at the same rate across shocks. However, as we demonstrate in Monte Carlo simulations (Appendix C), composite and unidentified shocks may be attractive because they explain a large fraction of variation in inflation and hence can provide more precise estimates and more power tests. In sections 5.2-5.3, we consider responses to a composite shock as well as to unidentified inflation innovations.

[18] In section 5.1, we experiment with monetary policy shocks from Romer and Romer (2004) and find similar results.

[19] All of our structural shocks are constructed using final data. While this data is unavailable to agents in real time, this is not an issue for our analysis. If it is difficult for agents to perceive shocks using real-time data, this is a form of imperfect information and will be revealed in our empirical results.

[20] The ordering has no qualitative effect on the results since the shocks are already largely orthogonal to one another.

terms of explaining the volatility of inflation appears to be technology shocks, as identified using long-run restrictions by Gali (1999), accounting for approximately twenty-five to thirty-five percent of the variance of inflation. The next two most quantitatively important shocks are monetary policy and oil price shocks. Monetary policy shocks account for up to five percent of the variance of inflation, while oil price shocks account for up to twenty percent. Each of the remaining three shocks, information, confidence, and fiscal, accounts for less than five percent of the variance of inflation. It is worth noting that despite our inclusion of six shock measures, these jointly account for only about half of the variance of inflation, leaving much of the volatility unexplained by these structural shocks.

Given these shocks, we can consider the impulse response of inflation to each shock as well as the predicted response of forecast errors and dispersion measures from the models.[21] For our three baseline shocks, monetary policy, technology and oil shocks, we plot the impulse response of annual inflation based on the whole sample, as well as predicted responses from the sticky information model in Figure 2. In response to monetary policy shocks, inflation follows the well-known delayed response, reaching its minimum approximately two years after the interest rate increase. In response to such a shock, the sticky information model predicts a negative forecast error, as mean forecasts should decline more slowly than actual inflation. Forecast dispersion, on the other hand, should rise as disagreement increases between those who have observed the shock and those who have not. Disagreement disappears as more and more agents learn about the shock. In response to a positive technology shock, the response of inflation is much more rapid and more precisely estimated. Forecast errors are predicted to decline by the sticky information model while dispersion should rise. Finally, oil price shocks lead to an increase in inflation. With informational rigidities, this yields a prediction of positive forecast errors after the shock. Imperfect information models would predict a qualitatively similar path of forecast errors, but no response of dispersion after each shock.

[21] Impulse responses of inflation to monetary policy and technology shocks come from including inflation in each VAR, while the response to oil shocks (following Kilian (2007)) comes from estimating an AR(2) process for inflation augmented with current oil shocks plus 6 lags of the oil shock. All standard errors are bootstrapped. Inflation measures used are the PCE price index for monetary shocks, GDP deflator for technology shocks, and CPI for oil shocks. The distribution of predicted forecast errors and dispersion responses are based on the bootstrapped distribution of inflation responses. We set λ=0.75 to generate predictions under sticky-information.

4 Empirical Analysis

We begin the empirical analysis with a preliminary check on the response of mean forecasts to the exogenous shocks. The question here is whether forecasts move in a manner which is generally consistent with the ex-post path of inflation. We estimate the following equation for each type of shock k and for each measure of mean year-ahead (h = 4 or 12) inflation forecasts:

$$F_t\pi_{t+h} = c + \sum_{i=1}^{I} \beta_i F_{t-i}\pi_{t-i+h} + \sum_{j=0}^{J} \gamma_j \varepsilon_{t-j}^{k} + v_t \qquad (8)$$

This equation is similar to the specification estimated in Romer and Romer (2004).[22,23] We then plot the impulse responses to a one standard-deviation increase in the exogenous shock, along with 95% confidence intervals in Figure 3.[24] Lag lengths (I and J) are selected based on the BIC allowing for a maximum lag length of a year and a half for each specification. For each specification, the sample used is given by the longest overlapping period of time for which the dependent variable and the structural shock are available, except in the case of monetary policy shocks when we restrict the estimation to start in 1984. In addition, when both forecasts and shocks are available on a monthly basis, we use h = 12, otherwise we set h = 4.

In response to monetary policy shocks, the MSC, SPF and BCEI have responses of mean forecasts which are very imprecisely estimated.[25] In response to technology shocks, we see a much

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[22] Note that our procedure has two steps (estimate shocks and then regress the variable of interest on these estimated shocks) and one generally has to appropriately adjust standard errors in the second step, which corresponds to our equation (8) and similar specifications considered later in the text. This adjustment, however, is not necessary in our analysis. Our null hypothesis is that the shocks have no effect on the mean forecast, forecast error, and forecast dispersion, i.e. $\gamma_j = 0$ for all j. Pagan (1984) shows that under this null it is not necessary to adjust standard errors. In cases where we test for equality of persistence across forecasters and shocks, we bias our inference against finding equality since using generated regressors leads to an understatement of sampling uncertainty. The key advantage of the two-step procedure is that we always use the same shock for all choices of the dependent variable, whereas a one-step VAR procedure would yield different shock series depending on which set of forecasts was included in the VAR. Furthermore, as we discuss in the analysis of conditional responses of forecast disagreement to structural shocks, in some specifications we must use the absolute value of the shock which makes the one-step approach particularly cumbersome.

[23] In this and subsequent specifications, we include one structural shock at a time and do not take into account potential feedback from the dependent variable to the structural shock and possible serial correlation in the shocks. Table 2 documents that the shocks are largely orthogonal to one another so there is no omitted variable bias when we consider one shock at a time. We also experimented with VAR specifications which include all shocks as well as allow for serial correlation in structural shock and feedback from the dependent variable so that we can study responses to orthogonalized innovations to the shock measures. Although the standard errors were slightly larger because we estimated more parameters, the results from VAR-type exercises were remarkably consistent with the single equation estimates and hence are not reported.

[24] Confidence intervals for impulse responses are generated based on 1,000 draws from the asymptotic distribution of parameter estimates of equation (8), from which we extract our distribution of impulse responses.

[25] Note that the fact that the mean forecasts do not significantly respond to monetary policy shocks does not necessarily mean that economic agents ignore these shocks. The response of actual inflation to monetary policy

more pronounced response of inflation forecasts: for all three survey measures, forecasts of future inflation fall and the decline is statistically significant. In response to oil shocks, we also see statistically significant increases in inflation forecasts, consistent with the inflation process after such shocks. Importantly, agents do adjust their forecasts in response to shocks and thus we may be confident that the shocks, particularly technology and oil price shocks, contain genuinely new information and that they create meaningful variation in information sets suitable for our analysis.

4.1 Response of Forecast Errors to Shocks

The responses of mean forecasts tell us little about informational rigidities but simply indicate that mean forecasts go in the same direction as actual inflation. This result would be expected to hold under full information as well as the models with informational rigidities considered here. A more relevant test for the importance of informational rigidities is looking at the response of forecast errors conditional on an exogenous shock. The presence of informational rigidities, be they sticky information or imperfect information, implies that we should observe persistent conditional forecast errors whereas full information implies that forecast errors will be zero after the time of the shock. Forecast errors are generated using real-time data of inflation measures.[26] To estimate the response of forecast errors, we run the following regression:

$$\pi_t - F_{t-h}\pi_t = c + \sum_{i=1}^{I} \beta_i (\pi_{t-i} - F_{t-i-h}\pi_{t-i}) + \sum_{j=0}^{J} \gamma_j \varepsilon_{t-j}^{k} + v_t \tag{9}$$

where h = 4 for quarterly data and h = 12 for monthly data. We plot the impulse responses and associated standard errors for forecast errors starting a year after the shock.[27] The results are presented in Figure 4.

For monetary policy shocks, there is only limited evidence of serially correlated forecast errors. MSC and BCEI forecast errors are negative, as would be expected under informational rigidities, but these are (marginally for MSC) insignificant at the 5% level. SPF forecast errors are positive, but these are statistically insignificant as well. For technology shocks, on the other hand,

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shocks is fairly weak, especially in the short time samples available here, and thus one may expect that mean forecasts should have a weak response too. It is likely that with these weak responses we cannot clearly discern the effect of monetary policy shocks, a point we demonstrate in Appendix C.

[26] For the MSC, we use the PCE price index as the measure of inflation, for the BCEI, we use the CPI and for SPF, we use the GNP deflator prior to 1992, the implicit GDP price deflator from 1992 to 1995, and the chained GDP price index starting in 1996. This reflects the different measures forecasted by SPF over time. Each inflation series is real-time data. Specifically, we use the level of inflation that was available six months after the inflation date. This is to avoid identifying revisions in price indexes as forecast errors.

[27] The response of forecast errors in the first year reflects only variation in inflation, since the date of the forecasts precedes that of the shock. Thus, we do not include these in the impulse responses.

forecast errors are persistently negative and statistically significant for all 3 survey measures. This indicates significant departures from full information, since inflation forecasts are responding more slowly than actual inflation. With oil shocks, the evidence again strongly points to informational rigidities: forecast errors are all positive and two out of three are statistically significant. Finally, all forecast errors converge to zero, so agents' forecasts correctly converge to the true values over time.

These results point to the potential importance of informational rigidities on the part of both consumers and professional forecasters. In response to technology and oil price shocks, we find clear evidence that forecasts fail to adjust one-for-one with ex-post inflation. This is particularly important since these two shocks appear to play such an important role in explaining inflation volatility. On the other hand, the results for monetary policy shocks are mixed. This could be interpreted in one of at least three ways. One may take this as evidence suggesting that monetary policy shocks are observed (and fully processed) by all and are thus not subject to informational rigidities. A second interpretation would simply question whether monetary policy shocks are shocks at all, as done in Cochrane (1994). A third interpretation is that because monetary policy shocks play such a small role in explaining the volatility of inflation (and hence inflation expectations) and because the contemporaneous and short-run responses of actual inflation to monetary policy shocks are weak, there is little hope of being able to clearly discern the response of forecast errors to this shock.

To assess the validity of the latter, we ran Monte Carlo experiments in which inflation is driven by two shocks, with details in Appendix C. We constructed measures of forecast errors and dispersion under the null of sticky-information and applied our empirical approach to estimating the impulse response of forecast errors and dispersion to one of the shocks. When the shocks are quantitatively important, i.e. account for more than five percent of the volatility of inflation, our 2-step approach can consistently recover the correct dynamics of forecast errors and forecast dispersion. However, when the shock accounts for less than five percent of the inflation variance, we are unable to precisely estimate the response of forecast errors to this shock in similar time samples as those available from survey measures. Similar results held with disagreement responses. Thus, the fact that monetary policy shocks account for such a small fraction of the inflation variance (less than five percent) is a likely source of the difference in the estimated response of forecast errors relative to oil price and technology shocks, which each account for a substantial component of the volatility in inflation.

Further support for this idea is provided in section 5.2, where we find that composite shocks (a linear combination of monetary policy, technology, and oil price shocks) also deliver impulse responses of conditional forecast errors that are consistent with models of informational rigidities. We also show in section 5.3 that unidentified inflationary innovations (i.e. those shocks to inflation that are not associated with monetary policy, technology or oil prices) yield similar results. Thus we find a clear pattern that in response to quantitatively important shocks, forecast errors are serially correlated and closely follow the predictions of models of informational rigidities. We interpret this as providing robust statistical evidence of departures from the null of full information. In the next section, we discuss the economic significance of the results.

4.2 Persistence of Conditional Percentage Forecast Errors

In this section, we consider another set of predictions of the two models. Sticky information implies that for a common set of agents, percentage forecast errors after a shock will decline monotonically at the same rate for all shocks. The persistence of conditional percentage forecast errors in this model hinges only on the degree of informational rigidity which is captured by the parameter λ. For imperfect information agents, on the other hand, the persistence of conditional percentage forecast errors may differ across shocks. This reflects the fact that the weight placed on a signal correlated with a shock depends positively on the quantitative importance of the shock (or more generally on the benefit of paying attention to the shock, as in rational inattention models). In our simple linear imperfect information model as well as in the more sophisticated model of Mackowiak and Wiederholt (2008), the persistence of the percentage forecast errors is only a function of the informational rigidity which is captured by the Kalman filter gain or bits of attention allocated to tracking a variable. We estimate the persistence of conditional percentage forecast errors in response to different shocks and ask whether this persistence is common across shocks and agents.

To do so, we first run the following regression:

$$\frac{(\pi_t - F_{t-h}\pi_t)}{\pi_t} = c + \sum\nolimits_{i=1}^{I} \beta_i \frac{(\pi_{t-i} - F_{t-i-h}\pi_{t-i})}{\pi_{t-i}} + \sum\nolimits_{j=0}^{J} \gamma_j \varepsilon_{t-j}^{k} + v_t \qquad (10)$$

again selecting I and J using the BIC criterion, using one-year ahead forecasts, and individually for each shock and survey measure. Using the coefficients estimated from equation 10, we extract the impulse response of the percentage forecast error to the shock. The persistence of the conditional percentage forecast error is measured using the parameter θ which minimizes the squared distance between the estimated impulse response and the geometrically declining process governed by θ (i.e. θ^j for $j \geq 0$).[28] Results are presented in Table 4.[29] In addition to the three structural shocks, we also present results in response to the unexplained inflation innovations, as defined in section 5.3.

The first notable feature of the results in Table 4 is that the point estimates of θ are all in the neighborhood of 0.5-0.75 so that the half-life of percentage forecast errors is approximately six months to a year. This is very close to the level of informational rigidity imposed by Mankiw and Reis (2002) which delivers economically significant implications from sticky information. In the context of rational inattention models, our estimates correspond approximately to bits of information flow being between 0.2 and 0.5, which is similar to the values derived in the calibrated model of Mackowiak and Wiederholt (2009).[30] Thus, our estimates of the persistence of conditional percentage forecast errors are such that these informational rigidities play a quantitatively important role in macroeconomic dynamics: in short, *informational rigidity is both statistically and economically significant*.

Turning to the differences in estimated levels of informational rigidity across shocks and agents, we provide two key results. First, *we find little evidence that the persistence of conditional percentage forecast errors differs across shocks for each survey measure*. For consumers, the persistence of conditional percentage forecast errors after monetary policy shocks is somewhat lower than that after technology and oil price shocks. For SPF, the persistence is almost identical

[28] We normalize the initial value of the impulse response of conditional forecast errors to be one. Standard errors are extracted by drawing from the empirical distribution of parameter estimates of (10), calculating impulse responses and solving for θ for each impulse response. As with forecast errors, we only include the responses starting a year after the shock. We use the impulse responses over the subsequent two years to generate estimates of θ. An alternative approach, consistent with footnote 10, is to estimate impulse responses of forecast errors and inflation separately, then generate the impulse response of percentage forecast errors by taking the ratio of the two. We found that this approach yields qualitatively similar results (although slightly higher point estimates of informational rigidity) as the ones found from estimating equation (10) above, so we present results only for the simpler case.

[29] Note that although impulse responses may be imprecisely estimated, we estimate the parameter θ quite precisely because we utilize the information contained in the full path of the response.

[30] This conversion is done by using the model of Mackowiak and Wiederholt (2008) in the case of AR(1) shocks. Their model implies that the persistence of conditional percentage forecast errors (our θ) is given by $1/2^{2\kappa}$ where κ is bits of information flow.

across shocks while for BCEI forecasts, the persistence of forecast errors is somewhat lower after oil price shocks than after monetary and technology shocks. Overall, the persistence of conditional percentage forecast errors across shocks is quite similar for each survey measure. We cannot reject the pairwise nulls of equality of estimated θ's across shocks and agents in almost all cases nor can we reject the null that the estimated convergence rates are identical across shocks and types of forecasts.[31] This result is broadly consistent with the null of sticky-information, but is not necessarily inconsistent with imperfect information models. In the latter, convergence rates, which depend on the volatility and persistence of shocks (and more generally how they impact profits or utility), may but need not differ across shocks. However, the calibrated rational inattention model of Mackowiak and Wiederholt (2009) yields more precise and testable predictions. These authors consider a model in which consumers and firms are rational inattention agents and find that, after calibrating the persistence and volatility of monetary policy and technology shocks, these agents should pay more attention to technology than monetary policy shocks, primarily because the latter are less volatile than the former. For MSC, we can reject (*p*-value of 0.012) the prediction of the imperfect information model calibrated as in Mackowiak and Wiederholt (2009) that forecasts respond more rapidly to technology shocks than monetary policy shocks, but not for professional forecasters (*p*-values of 0.90 and 0.44 for SPF and BCEI respectively). However, we can consistently reject the stronger hypothesis that the difference in convergence rates between monetary policy shocks and technology shocks for all types of forecasts is as large as that predicted by their calibration.[32] Thus, while we find little evidence for this phenomenon, our results only contradict the joint hypothesis of rational inattention within the specific model and calibration that they propose, but not the null of rational inattention per se. We interpret this result as pointing to the need for further research into imperfect information models to ascertain whether their predictions for convergence rates can be reconciled with our empirical estimates.

[31] We can reject the null of equality for the response to monetary policy shocks in MSC vs. SPF and the response of MSC to monetary policy shocks vs. the unidentified shock. When testing the null that all convergence rates are identical, we get a *p*-value of 0.099 and a *p*-value of 0.59 when we exclude the MSC response to monetary policy shocks. For these tests, we use seemingly unrelated regressions to account for the possible co-dependence of estimated parameters across shocks and forecasters.

[32] For this comparison, we apply the calibrated learning rates for consumers of Mackowiak and Wiederholt (2009) to MSC estimates, and their calibrated rates for firms to SPF and BCEI. Note however that generated regressors in this case will tend to bias us toward rejecting the null.

Secondly, *we find no evidence that consumers acquire information in a less efficient manner than professional forecasters*. Our estimates indicate that forecast errors by consumers are actually less persistent than those of SPF forecasters (though mostly not statistically significantly so) and approximately as persistent as those of BCEI forecasters. Note that this is at odds with the results of Carroll (2003), who proposed and provided empirical evidence in the U.S. for an epidemiological model of information diffusion from professional forecasters to consumers which implied that mean forecasts of consumers would respond more slowly than those of professional forecasters. Our estimates indicate, on the other hand, that the persistence of consumers' conditional percentage forecast errors is no higher than that of professional forecasters in response to the monetary, technology, and oil price shocks. Furthermore, we find the same pattern for unidentified shocks. Hence, consumers' forecasts, on average, respond to all shocks at least as rapidly as professional forecasters.

To reconcile our results with Carroll (2003), we revisit the evidence that he provides using a longer time sample and an additional measure of professional forecasts. First, he argues that the mean squared error (MSE) of SPF forecasts of future CPI inflation is substantially less than that of consumer forecasts. However, Carroll uses *core* CPI inflation to calculate forecast errors rather than the general CPI index. This is important since the SPF forecasts he uses are for the general CPI index, and consumers responding to the Michigan Survey of Consumers are unlikely to exclude food and energy prices when forecasting inflation. When we calculate MSE's of SPF and Michigan forecasts using the general CPI index, we find that consumer forecasts actually lead to *lower* MSE's than either the SPF or BCEI forecasts of the CPI, both over the time period considered by Carroll (1981:3-2000:2) and the longer time sample now available (1981:3-2007:3).[33] Secondly, Carroll uses Granger causality tests and finds that SPF forecasts Granger-cause consumer forecasts but that the reverse is not true. While we can reproduce this result over his time sample, we find no evidence that Blue Chip forecasts Granger-cause Michigan consumer forecasts. In addition, over the longer sample of 1981:3-2007:3, we find that neither the SPF nor the BCEI Granger-cause consumer forecasts. Thus, the Granger-causality results are limited to SPF forecasts over a specific time period; over a longer sample and using additional measures of professional forecasts, we find no evidence that professional forecasts Granger-cause consumer

[33] Taylor (1999) and Mehra (2002) similarly conclude that Michigan consumer forecasts lead to similar, or even smaller, MSE's than the Survey of Professional Forecasters.

forecasts. Thus, the tests proposed by Carroll (2003) are actually consistent with our results that consumer forecasts respond just as rapidly to shocks as professional forecasts.

4.3 Response of Forecast Dispersion to Shocks

We now turn to the response of the dispersion of inflation forecasts to the same shocks. The following estimation equation is used:

$$\ln \sigma(F_t \pi_{t+h}) = c + \sum_{i=1}^{I} \beta_i \ln \sigma(F_{t-i} \pi_{t-i+h}) + \sum_{j=0}^{J} \gamma_j \, | \varepsilon_{t-k}^{k} | + v_t \tag{11}$$

where $\ln \sigma(F_t \pi_{t+h})$ is the logarithm of the cross-sectional standard deviation of inflation forecasts over the next year.[34] We include the absolute value of the shock because the predicted response of forecast dispersion in the sticky information model is invariant to whether the shock is positive or negative.

Figure 5 plots the impulse responses of the forecast dispersion measures for each survey in response to the exogenous shocks, along with 95% confidence intervals. In addition, we plot the predicted response of dispersion from the sticky information model.[35] In response to monetary policy and technology shocks, we find no evidence that forecast dispersion rises after these shocks for any of the survey measures.[36] In response to oil price shocks, the dispersion of forecasts of consumers displays a statistically significant and highly persistent increase after the shock. No such response is apparent for the SPF or the BCEI. Thus, for professional forecasters, our results are consistent with imperfect information: professional forecasters can adequately be modeled as continuously tracking economic indicators without observing the underlying state perfectly. For

[34] Taking the logarithm serves two purposes. First, the distribution of forecast dispersion is highly skewed and rare observations in the right tail of the distribution can greatly distort the estimates. The logarithmic transformation makes the dispersion bell-shaped, attenuates the adverse effects of episodes with extreme variability in forecasts, and hence improves the finite sample properties of our estimates. Second, we can interpret impulse responses as percent deviations from steady state forecast dispersion.

[35] The predicted response of dispersion under the null of sticky-information is constructed as follows: *i*) estimate the response of inflation to each shock using univariate regressions using the same inflation measure and time sample as in the corresponding regression for dispersion, *ii*) using the inflation response, compute the predicted path of the cross-sectional standard deviation of forecasts according to sticky information following equation (5) and the corresponding estimated degrees of informational rigidity from Table 4, *iii*) normalize the response of the cross-sectional standard deviation of forecasts by the mean of the cross-sectional standard deviation of forecasts over the relevant time period to convert the response to percentage changes comparable to the impulse responses of the log of the cross-sectional standard deviation of forecasts.

[36] It must be noted that this result is sensitive to the time period for monetary policy shocks. If one uses data starting in the late 1970s, monetary policy shocks (in absolute value) lead to a *permanent* increase in dispersion of SPF forecasts. We choose to focus on the post 1984 period for monetary policy shocks because FFR shocks are extremely noisy between 1979 and 1982, reflecting the fact that the Fed abandoned targeting the federal funds rate over this period. Thus, we are concerned that the identified FFR shocks prior to 1984 are not adequate measures of monetary policy innovations. None of the other results are sensitive to the time period.

consumers, the results are somewhat mixed. While monetary and technology shocks do not lead to significant changes in forecast dispersion, oil price shocks seem to lead to highly persistent increases in disagreement. Thus, although we cannot unanimously favor either representation of the informational rigidities facing consumers, the preponderance of evidence suggests that *disagreement in forecasts does not respond to structural shocks*. Furthermore, not only are our point estimates close to zero but we can also reject the null of sticky-information in five out of the nine impulse responses (and in five out of six cases when shocks have the strongest effect on inflation).[37]

5 Robustness Analysis

In this section, we investigate the robustness of our results to several issues. First, we allow for an alternative set of shocks. Second, we generate a composite shock that aggregates our three baseline structural shocks and study the response of forecast errors and forecast dispersion to this composite shock. Third, we present the response of forecast errors and dispersion to the unidentified component of inflation innovations.[38]

5.1 Alternative Shock Measures

In this section, we reproduce the forecast error and forecast dispersion tests for three alternative shocks. First, we use the Romer and Romer (2004) measures of innovations to the FFR. These are available monthly from April 1970 until December 1996. Second, we use the information shocks of Beaudry and Portier (2006), which capture changes in stock prices that have no contemporaneous effect on TFP. These are designed to represent expected changes in TFP and cause temporary decreases in inflation. Third, we use the fiscal shocks of Romer and Romer (2007) which provide a sequence of exogenous tax changes and have temporary deflationary effects.[39] All three shocks are deflationary, so both models of informational rigidities would predict a sequence of negative forecast errors after the shock.

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[37] Mankiw, Reis and Wolfers (2003) analyze the dynamics of forecast disagreement during the Volcker disinflation. Although they find that disagreement moved broadly in line with the prediction of the sticky information model during this specific episode, the sticky information model predicted much greater movements in disagreement than was observed in the data. The interpretation of this episode, however, is complicated by the secular decline in the forecast disagreement (see footnote 16) which coincided with the Volcker disinflation.

[38] In Coibion and Gorodnichenko (2008), we reproduced our baseline estimates for forecasts of the unemployment rate rather than inflation. We found similar qualitative results.

[39] We do not present results for confidence shocks because these seem to have no discernible effects on inflation. Thus, one could not tell whether informational rigidities would imply positive or negative conditional responses of

The results for the forecast errors are provided in Figure 6. While most of the forecast errors go in the expected direction, almost none of the responses are statistically significantly different from zero. Given the strong evidence for informational rigidities found for the more quantitatively important (for inflation) technology and oil price shocks, it is unclear whether one should interpret this lack of a response of forecast errors as being consistent with full information or as reflecting the fact that, because these shocks account for such a small component of the variance of inflation, it is unlikely that one will be able to precisely estimate the response of forecast errors in small samples (as illustrated in Appendix C). The results for the response of dispersion in forecasts to the absolute value of each exogenous shock are provided in Figure 7. Overall, there is little evidence of changes in disagreement after these structural shocks and, in four of nine impulse responses, we reject the null of the predicted path from the sticky information model.

5.2 Composite Shock

The Monte Carlo exercise in Appendix C illustrates that when shocks explain only a small fraction of the variance of inflation, the conditional response of forecast errors and forecast dispersion will tend to be imprecisely estimated. Indeed, this seemed to be the case for forecast errors after monetary policy shocks in the baseline estimation. As an alternative approach designed to minimize this issue, we develop a composite shock which is an aggregate of the individual identified shocks and present responses of forecast errors and dispersion to this shock.

To do so, we first run an AR(4) on real-time CPI inflation, the residuals of which we interpret as inflation innovations. We then regress these innovations on the monetary policy shocks, the technology shocks and the oil price shocks. The predictable component of the inflation innovation we define as the composite shock. By construction, these innovations are inflationary. Figure 8 presents the conditional response of forecast errors and forecast dispersion to the composite shock, estimated as in sections 4.1 and 4.3, for all three survey measures. For every survey measure, the response of forecast errors is positive and highly significant. Each survey delivers a positive sequence of monotonically declining forecast errors, as predicted by models of informational rigidities. As found in the baseline results, the response of consumers to shocks is at

forecast errors. We find these shocks lead to positive responses of forecast errors for MSC, (marginally) negative for BCEI, and insignificant for SPF. There is no statistically significant response of dispersion for any of the surveys to the absolute value of these shocks.

least as quick as that of professional forecasters. The response of dispersion to the (absolute value of) composite shock is also largely consistent with our baseline results. For MSC and SPF, we cannot reject the null of no response in dispersion to the composite shock. For BCEI, there is a small statistically significant response of dispersion, but we can also strongly reject the null of the sticky-information model.

5.3 Unidentified Inflationary Innovations

While all of our analysis has focused on the conditional response of forecast measures to identified shocks, Table 3 indicates that only half of the inflation volatility is accounted for by these shocks. One could, of course, consider additional shock measures (markup shocks, preference shocks, etc) from the literature. Instead, we now consider the impulse response of forecast errors and forecast dispersion to unidentified inflation innovations. Specifically, we estimate an AR(4) process for real-time inflation, then regress the residuals on the monetary policy shocks, technology shocks, and oil price shocks. The residuals from this second regression we call the unidentified innovations to inflation.[40] By construction, these innovations are inflationary, and should thus lead to positive forecast errors if informational rigidities are present. Importantly, these shocks have a large quantitative effect on inflation and since neither imperfect information nor sticky information models restrict us to using only structural shocks, we can have an additional powerful test for these two models.

Figure 9 presents the conditional response of forecast errors and forecast dispersion to these unidentified inflation innovations, using the same approach as in sections 4.1 and 4.3. For all three survey measures, the response of forecast errors is positive and statistically significant, although less precisely estimated than in the case of the composite shock. All of the impulse responses also monotonically decline to zero. We interpret this as indicating that the evidence for informational rigidities is not limited to the structural innovations considered before but extends more generally to all innovations to inflation, as long as these account for a large enough fraction of the inflation variance. The response of dispersion to these unidentified innovations is consistent across survey measures: we find no evidence that dispersion changes after these shocks and we reject the null of sticky information in each case.

[40] Note that these unidentified innovations include the alternative shocks from section 5.1. Controlling for these shocks as well has no effect on the results.

6 Conclusion

Recent work utilizing informational rigidities offers potential explanations for some important macroeconomic puzzles. Yet direct empirical evidence for informational rigidities has been limited, thereby raising fundamental questions about the validity of these models. Previous research on survey measures has focused on testing the null of full information. While these tests are informative, they have yielded mixed results and do not address the key issue of the dynamic behavior of forecast errors after shocks. Our results instead paint a clear picture: after structural shocks, agents fail to adjust their forecasts by a sufficient amount, inducing a non-zero response of forecast errors. As time goes by, forecast errors converge monotonically to the full information outcome. This evidence is particularly strong for structural shocks which have a significant quantitative effect on the variable being forecasted. In addition, the estimated persistence of conditional percentage forecast errors is large, implying that informational rigidities are both statistically and economically significant. We interpret these results as providing a robust empirical basis for models of informational rigidities that has previously been sorely lacking.

The conditional response of forecast errors to structural shocks also uncovers some stylized facts about informational rigidities across shocks and agent types. First, we find no evidence that consumers' forecasts adjust more gradually than professional forecasts after a shock. This fact is inconsistent with epidemiological models of information diffusion from professional forecasters to consumers (as in Carroll (2003)). Second, the convergence rate of percentage forecast errors is broadly similar for all shocks as predicted by the sticky information model but not necessarily inconsistent with the imperfect information model. Third, our results on the conditional response of the dispersion of forecasts across agents to shocks point primarily to imperfect information as the most adequate representation of informational rigidities. For both professional forecasters and consumers, we find broad support for the prediction of imperfect information models that disagreement is independent of structural shocks.

Understanding the formation of expectations is central in many fields of economics. However the dearth of direct evidence on how economic agents form expectations as well as the role of informational frictions in this process has limited progress in addressing this fundamental question. We provide a set of stylized facts about responses of expectations to shocks and shed new light on the mechanisms and types of informational rigidities faced by economic agents. Our evidence calls for deeper theoretical analysis of informational frictions to fully reconcile the theory with the data. Further study of the behavior of disagreement among agents is likely to be fruitful for better understanding the nature of informational rigidities affecting agents.

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Table 1: Correlations of Survey Measures with Macroeconomic Variables

Panel A: Mean Forecasts of Inflation

	MSC	SPF	BCEI
MSC	1.00		
SPF	0.89	1.00	
BCEI	0.89	0.98	1.00
Unemployment	0.37	0.63	0.60
RGDP Growth	-0.24	-0.10	-0.18
Inflation	0.87	0.86	0.85

Panel B: Dispersion of Inflation Forecasts

	MSC	SPF	BCEI
MSC	1.00		
SPF	0.45	1.00	
BCEI	0.47	0.58	1.00
Unemployment	0.68	0.51	0.42
RGDP Growth	-0.21	0.04	-0.04
Inflation	0.31	0.24	0.26

Note: Correlations are over common samples. For Panel A, data is from 1980Q2-2007Q3. For Panel B, data is from 1984Q3-2007Q3. Inflation is measured using log-difference of GDP Deflator.

Table 2: Correlation of exogenous macroeconomic shocks

	VAR FFR	Gali Technology	Hamilton Oil	Beaudry Information	Barsky Confidence	Romers Fiscal
FFR	1.00	0.01	-0.03	-0.06	0.02	-0.11
Oil	0.01	1.00	-0.19	-0.10	0.17	-0.05
Tech	-0.03	-0.19	1.00	-0.16	-0.29	0.03
Information	-0.06	-0.10	-0.16	1.00	0.30	0.09
Confidence	0.02	0.17	-0.29	0.30	1.00	-0.02
Fiscal	-0.11	-0.05	0.03	0.09	-0.02	1.00

Note: The sample runs from 1984Q3 until 2007Q3.

Table 3: Variance Decomposition of Inflation

Quarters	FFR	Tech	Oil	Info	Confidence	Fiscal	Unexplained
1	0.3	27.6	1.6	0.3	0.8	2.4	67.0
2	4.4	34.6	1.4	0.6	1.9	1.8	55.2
3	5.0	34.9	2.1	2.4	1.7	1.8	52.1
4	4.6	33.0	2.3	2.3	2.9	1.7	53.3
8	3.3	27.3	15.3	2.1	2.5	1.2	48.3
12	3.0	25.1	18.7	2.2	2.4	1.3	47.2
16	2.9	24.3	19.7	2.3	2.3	1.3	47.3
20	2.8	24.0	20.0	2.2	2.3	1.3	47.3

Note: Data is from 1980Q1 until 2006Q2. 4 lags in VAR, Cholesky decomposition as ordered in table. Variables are: 1) FFR: monetary policy shocks, 2) Tech: technology shocks identified a la Gali (1999), 3) Info: information shocks a la Beaudry and Portier (2006), 4) Confidence: Confidence shocks a la Barsky and Sims (2008), 5) Fiscal: fiscal shocks from Romer and Romer (2007), 6) Oil: oil price shocks from Hamilton (1996), 7) Inflation: annualized quarterly log change in the implicit GDP deflator.

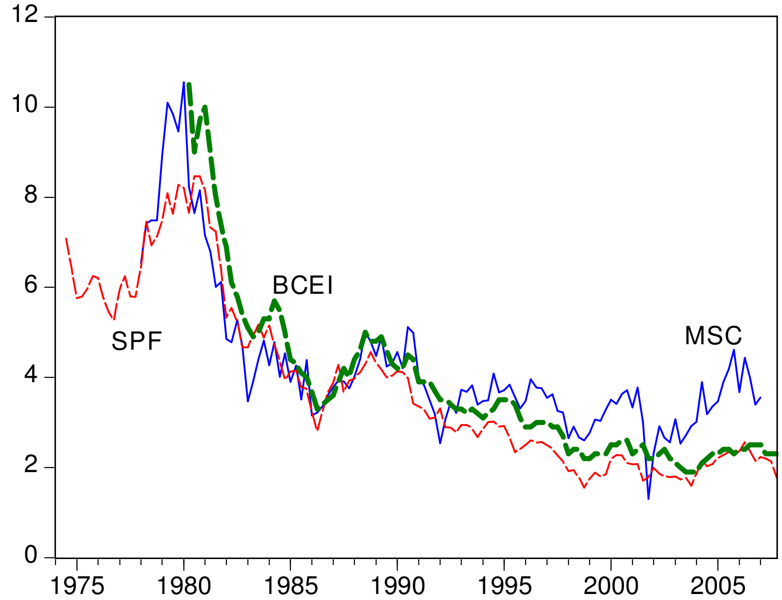
Table 4: Persistence of Conditional Percentage Forecast Errors

	MSC	SPF	BCEI
FFR Shock	0.48	0.78	0.59
	(0.10)	(0.11)	(0.21)
Technology Shock	0.65	0.75	0.62
	(0.07)	(0.09)	(0.21)
Oil Price Shock	0.65	0.79	0.49
	(0.09)	(0.09)	(0.27)
Unidentified Shock	0.76	0.79	0.82
	(0.09)	(0.08)	(0.14)

Note: These are estimates of θ, the persistence of conditional forecast errors, as described in section 4.2. All estimates correspond to quarterly frequency. Standard errors are in parentheses. Standard errors are computed using 1,000 Monte Carlo simulations of the impulse responses based on draws from the estimated asymptotic distribution of parameters in equation (10). The unidentified shock is described in section 5.3.

Figure 1: Plots of Survey Measures of Inflation Forecasts

Panel A: Mean Forecasts of Inflation over Next Year



Panel B: (Log) Cross-sectional Standard Deviation of Inflation Forecasts over Next Year

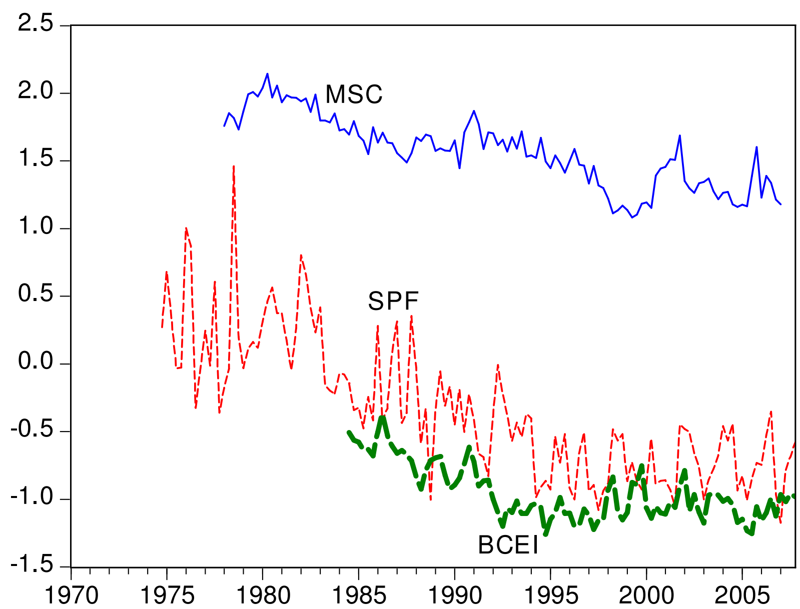
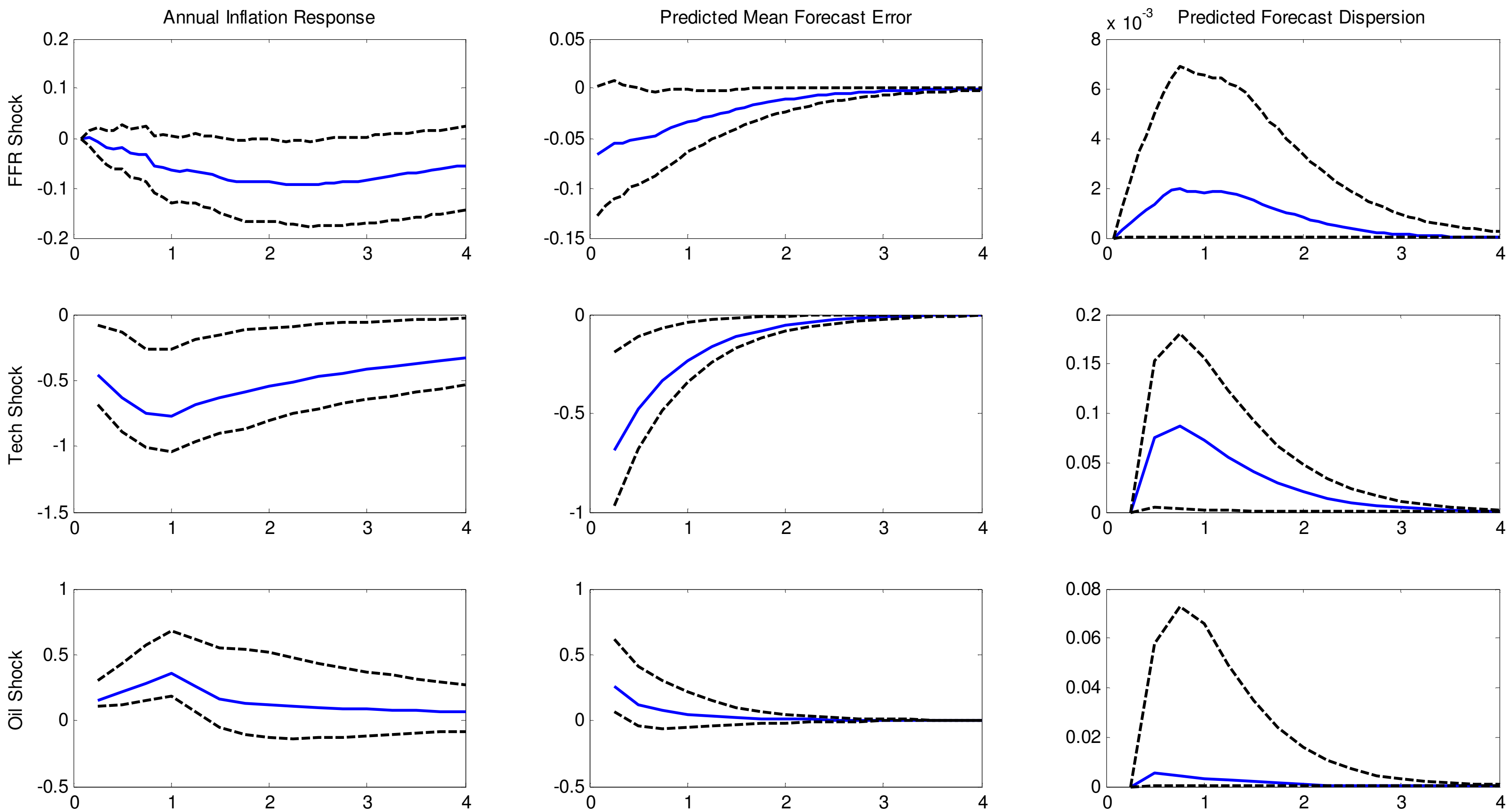
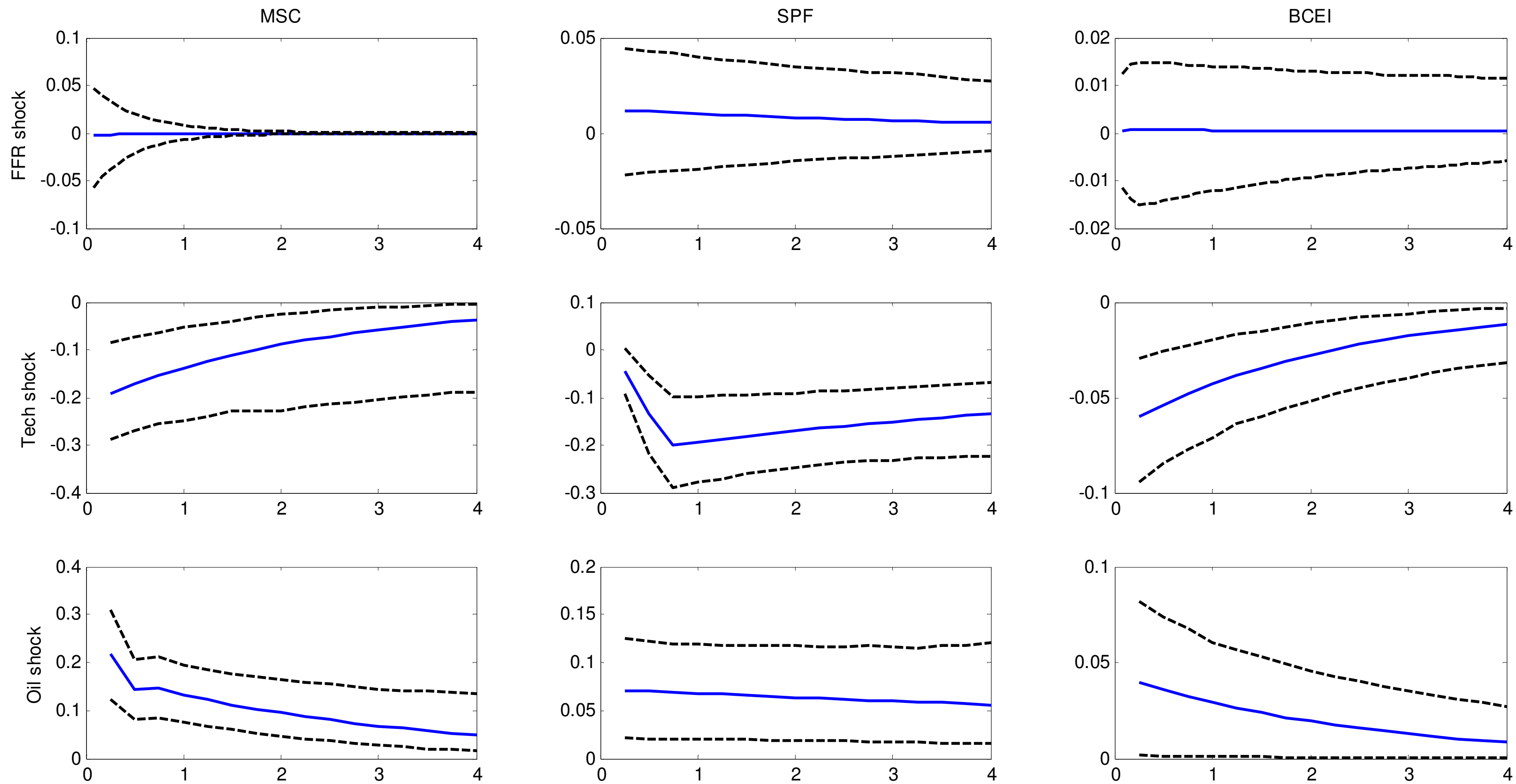


Figure 2: Impulse Response of Inflation to Shocks and Predicted Responses of Conditional Forecast Errors and Forecast Dispersion to Shocks



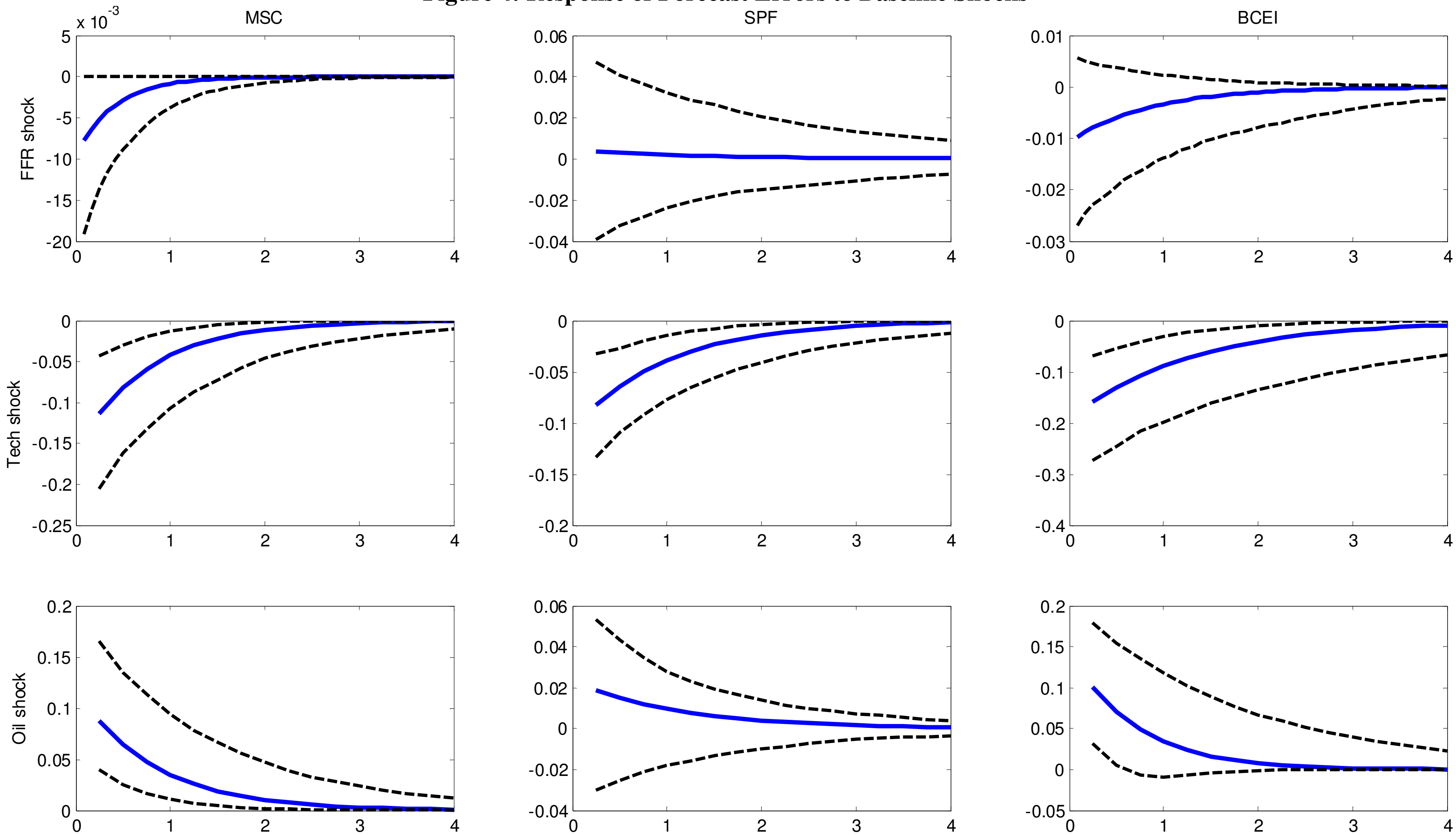
Note: Horizontal axis shows time in years. Inflation responses to one standard deviation oil and technology shocks are based on quarterly data. Inflation response to a one standard deviation FFR shock is based on monthly data. Technology shocks are identified using Gali (1999) long run restrictions. FFR shocks are identified recursively from a five variable VAR with inflation, unemployment rate, inflation in the commodity price index, index of industrial production and fed funds rate. Oil price shocks are taken from Hamilton (1996). Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. Predicted responses are from a sticky information model. We assume that agents update their information once a year on average, following Mankiw and Reis (2002), which implies λ=0.75. See section 4 for details.

Figure 3: Response of Mean Forecasts to Baseline Shocks



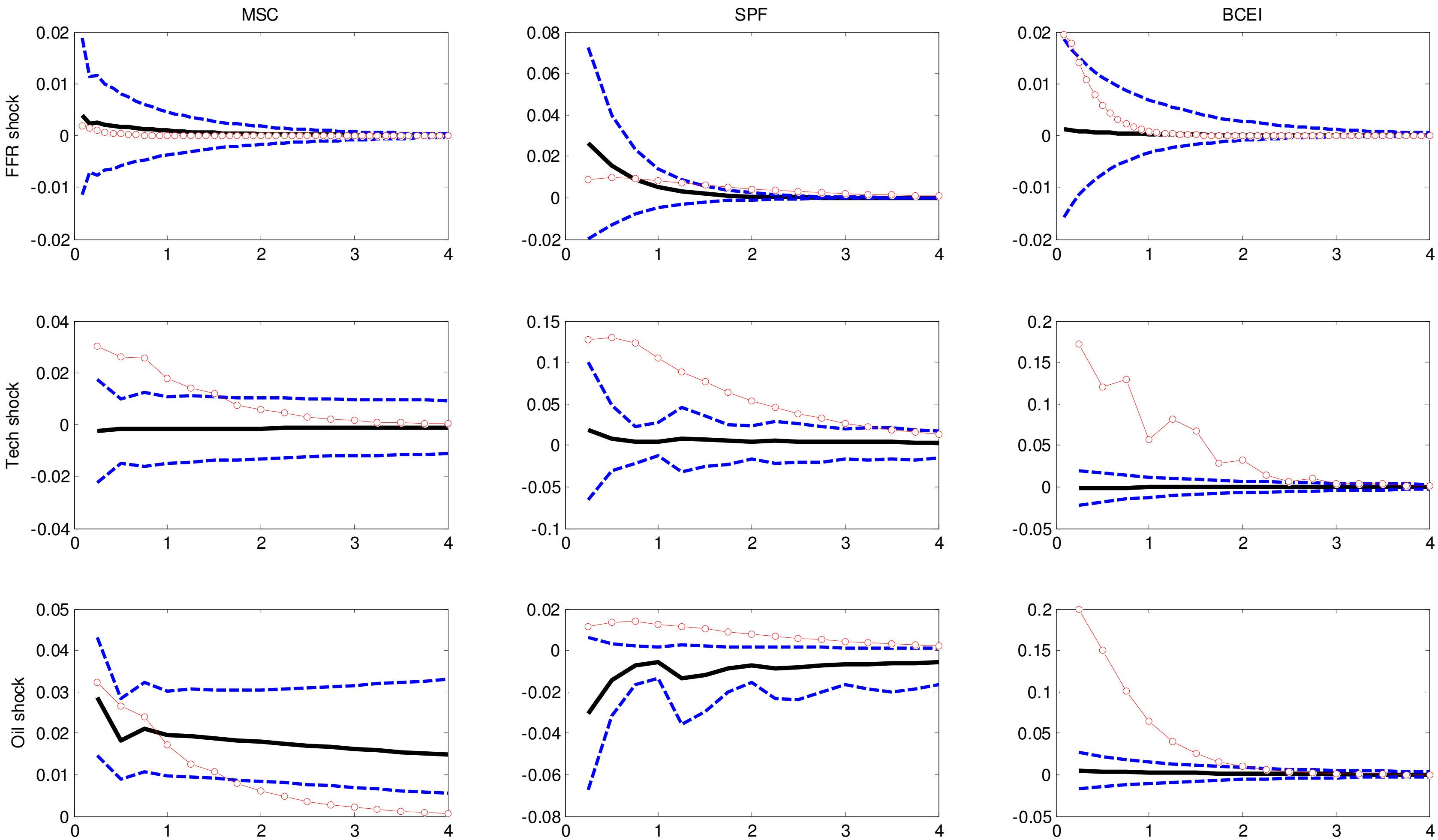
Note: Horizontal axis shows time in years. Technology shocks are identified using Gali (1999) long run restrictions. FFR shocks are identified recursively from a five variable VAR with inflation, unemployment rate, inflation in the commodity price index, index of industrial production and fed funds rate (monthly data). Oil price shocks are taken from Hamilton (1996). Responses of MSC and BCEI forecasts to FFR shocks are based on monthly data. Responses in all other panels are based on quarterly data. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. See section 4 for details.

Figure 4: Response of Forecast Errors to Baseline Shocks



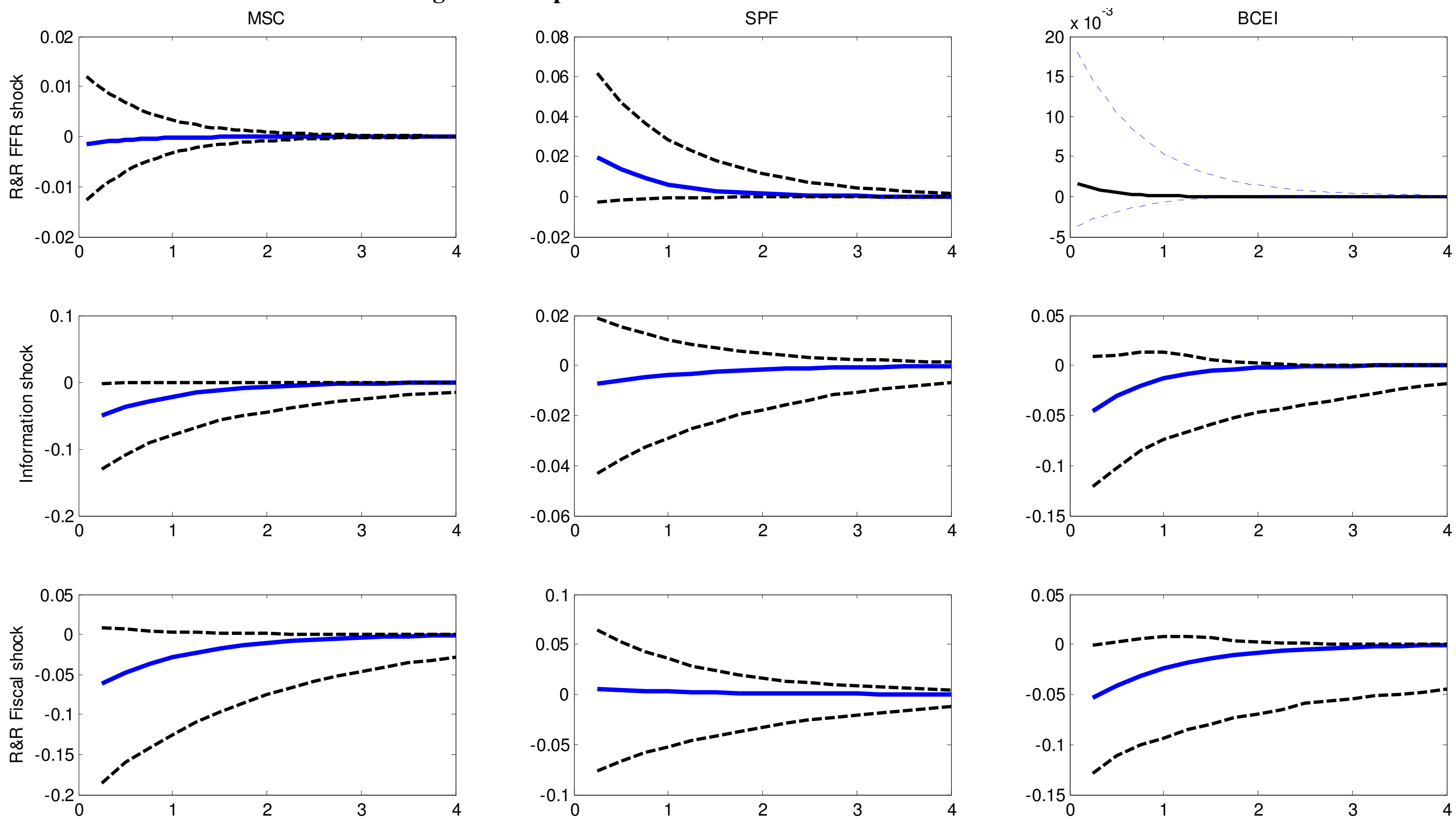
Note: Horizontal axis shows time in years. Technology shocks are identified using Gali (1999) long run restrictions. FFR shocks are identified recursively from a five variable VAR with inflation, unemployment rate, inflation in the commodity price index, index of industrial production and fed funds rate (monthly data). Oil price shocks are taken from Hamilton (1996). Responses of MSC and BCEI forecasts to FFR shocks are based on monthly data. Responses in all other panels are based on quarterly data. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. Responses of forecast errors begin one year after innovation. See section 4.1 for details.

Figure 5: Response of Forecast Dispersion to Baseline Shocks



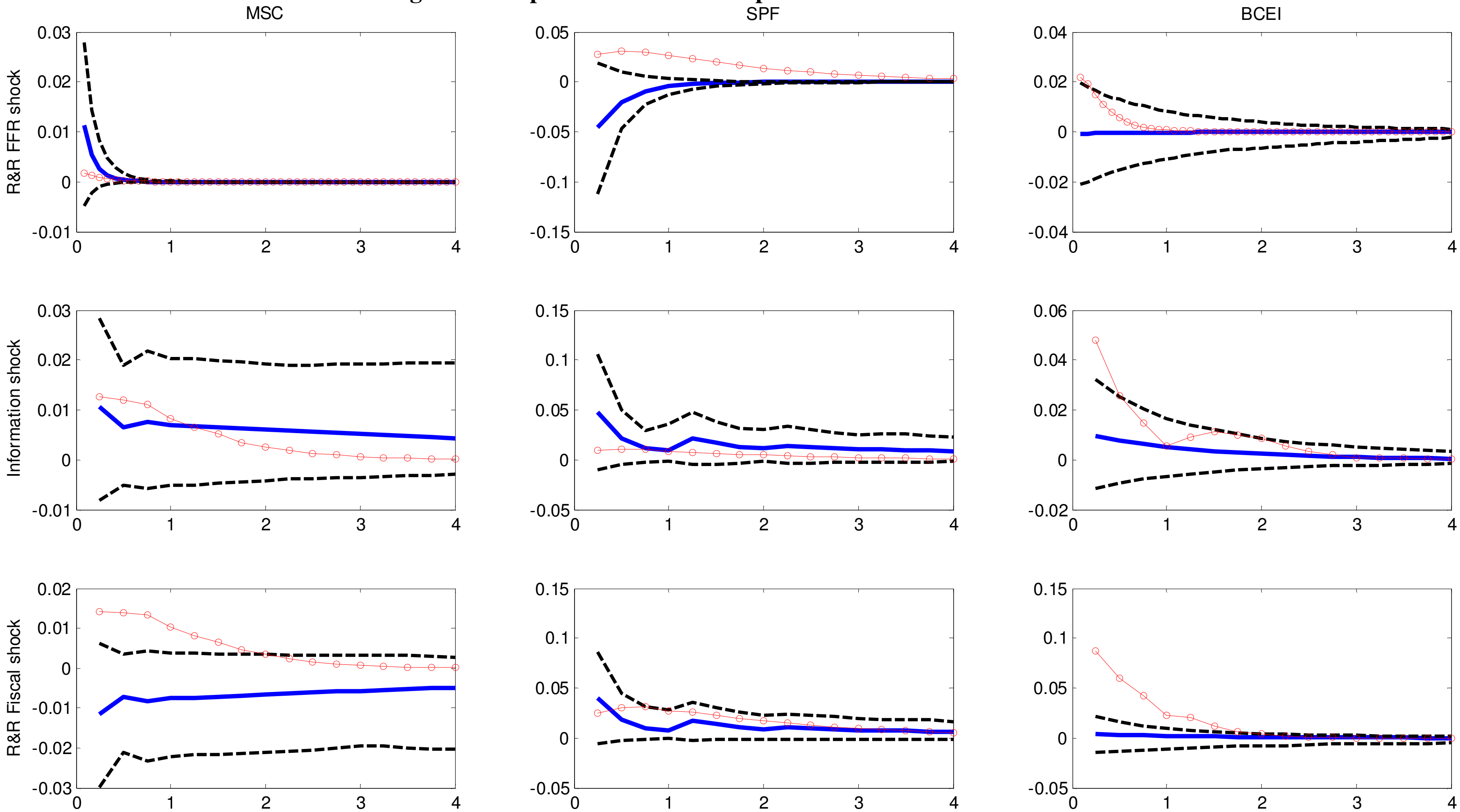
Note: Horizontal axis shows time in years. Technology shocks are identified using Gali (1999) long run restrictions. FFR shocks are identified recursively from a five variable VAR with inflation, unemployment rate, inflation in the commodity price index, index of industrial production and fed funds rate (monthly data). Oil price shocks are taken from Hamilton (1996). Responses of MSC and BCEI forecasts to FFR shocks are based on monthly data. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. Thin red lines with circles are the predicted response of cross-sectional forecast dispersion under the sticky information model. Responses in all other panels are based on quarterly data. See section 4.3 for details.

Figure 6: Response of Forecast Errors to Alternative Shocks



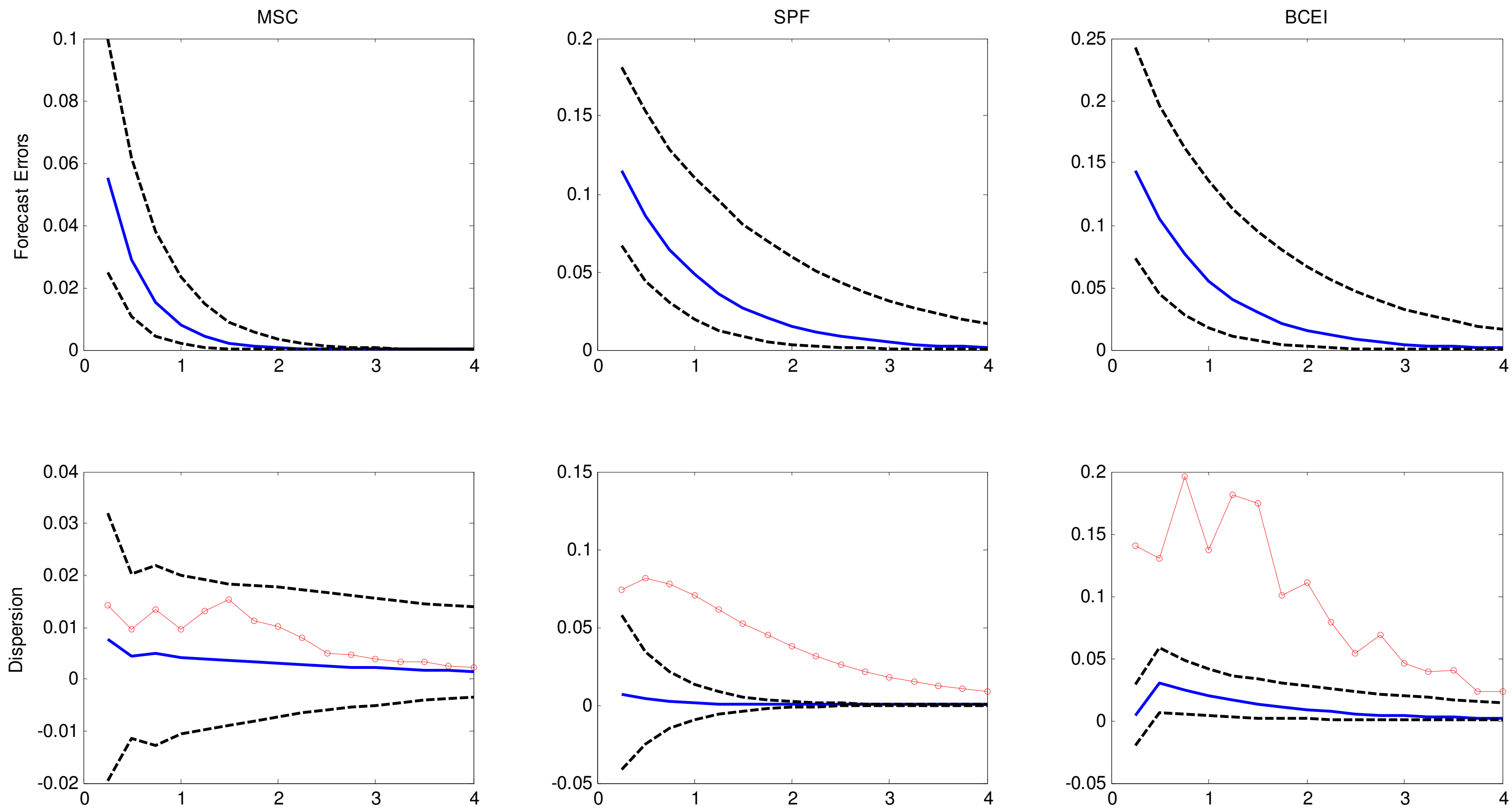
Note: Horizontal axis shows time in years. Information shocks are identified using Beaudry and Portier (2006) short-run restrictions. FFR shocks are taken from Romer and Romer (2004). Fiscal shocks are taken from Romer and Romer (2007). Responses of MSC and BCEI forecasts to FFR shocks are based on monthly data. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. Responses in all other panels are based on quarterly data. See section 5.1 for details.

Figure 7: Response of Forecast Dispersion to Alternative Shocks



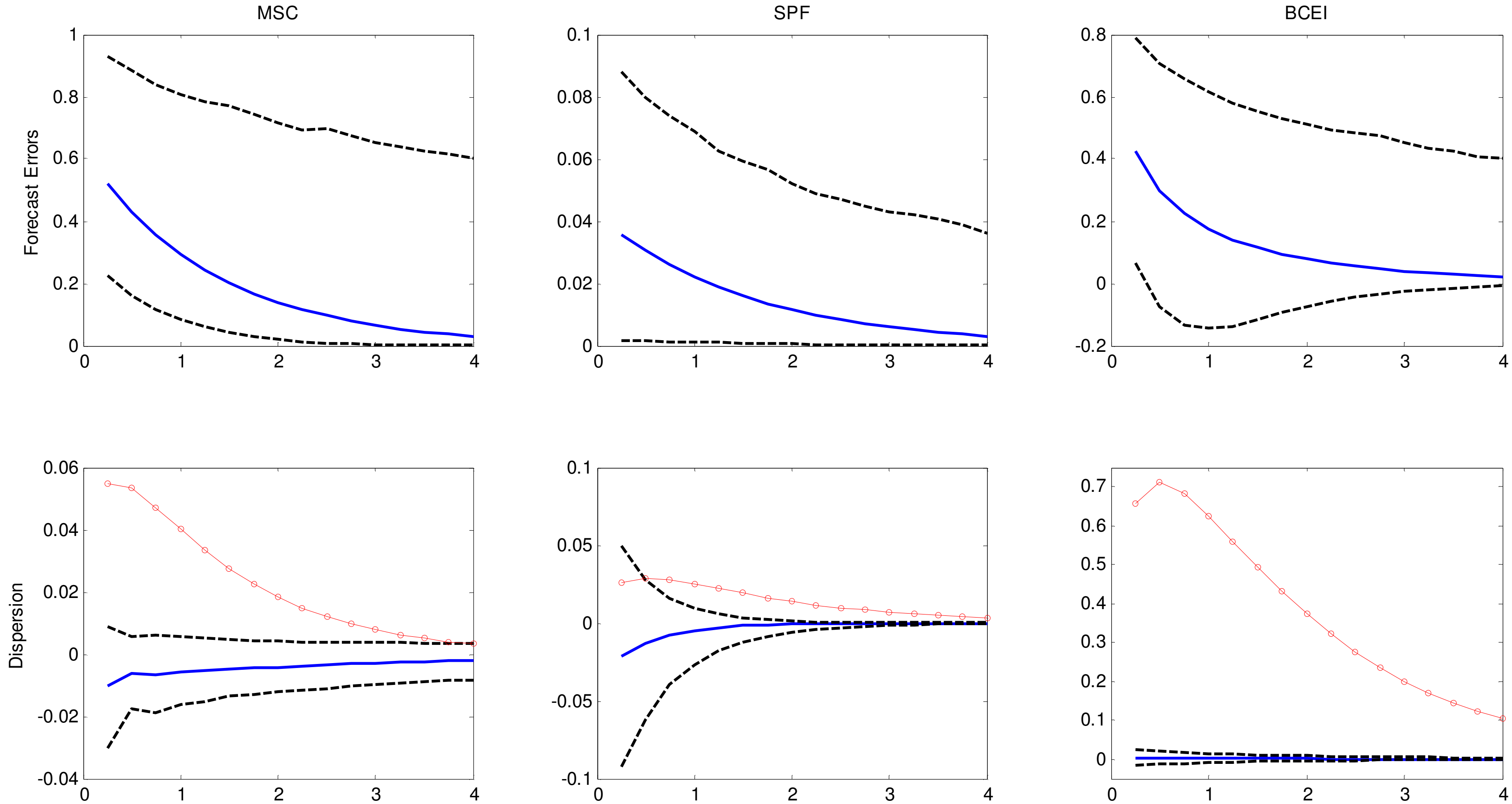
Note: Horizontal axis shows time in years. Information shocks are identified using Beaudry and Portier (2006) short-run restrictions. FFR shocks are taken from Romer and Romer (2004). Fiscal shocks are taken from Romer and Romer (2007). Responses of MSC forecasts to FFR shocks are based on monthly data. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. Thin red lines with circles are the predicted response of cross-sectional forecast dispersion under the sticky information model. Responses in all other panels are based on quarterly data. See section 5.1 for details.

Figure 8: Response of forecast errors and forecast dispersion to composite shock



Note: Horizontal axis shows time in years. The composite shock is the predictable component of inflation residuals from AR(4) when regressed on monetary policy, technology, and oil price shocks. Response of forecast errors begins one year after the shock. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. Thin red lines with circles are the predicted response of cross-sectional forecast dispersion under the sticky information model. Responses in all panels are based on quarterly data. See section 5.2 for details.

Figure 9: Response of forecast errors and forecast dispersion to unidentified inflation innovations



Note: Horizontal axis shows time in years. Unidentified inflation innovations are the unpredictable component of inflation residuals from AR(4) when regressed on monetary policy, technology, and oil price shocks. Response of forecast errors begins one year after the shock. All responses are to one standard deviation shocks. Dashed lines are 95% confidence intervals based on 10,000 bootstrap replications. In figures with dispersion responses, thin red lines with circles are the predicted response of cross-sectional forecast dispersion under the sticky information model. Responses in all panels are based on quarterly data. See section 5.3 for details.

Appendix A: Description of survey measures and construction of data series.
Michigan Survey of Consumers

The samples for the Surveys of Consumers are statistically designed to be representative of all American households, excluding those in Alaska and Hawaii. Each month, a minimum of 500 interviews are conducted by telephone. After a series of questions, consumers are asked, "During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?" If consumers answer that prices go up or down, the surveyor asks the follow-up question "By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?" The follow-up question first appeared in the questionnaire in January 1978. The data were taken from http://www.sca.isr.umich.edu/main.php. In our calculations of the mean forecast and the standard deviation of forecasts, we excluded responses suggesting that inflation or deflation can be above 49%. This truncation eliminates extreme implausible responses. See "Procedure to Estimate Price Expectations" (http://www.sca.isr.umich.edu/documents.php?c=i) for more details on the sensitivity of mean and variance to different truncation thresholds. No answers are imputed to respondents who had difficulties predicting inflation. We drop all survey responses suggesting that inflation or deflation may exceed 49%.

Survey of Professional Forecasters

The forecasts for the Survey of Professional Forecasters are provided by the Federal Reserve Bank of Philadelphia. The survey began in 1968:Q4. The data set contains the 31 economic variables currently included in the survey. Some variables were added in 1981:Q3 and later in 2003:Q4 and in 2007:Q1. The year-ahead forecast for CPI and price deflators became available 1981Q3 and 1974Q3 respectively. SPF forecasts are collected in the middle of the quarter. Forecasts for the quarterly and annual level of the GDP price index are seasonally adjusted. The base year varies. Prior to 1996, GDP implicit deflator. Prior to 1992, GNP deflator. Annual forecasts are for the annual average. For every survey period, we compute forecast dispersion as the log of the standard deviation of the individual forecasts. See http://www.philadelphiafed.org/econ/spf/ for more details.

Blue Chip Economic Indicators

Blue Chip Economic Indicators surveys economic forecasters at approximately 50 banks, corporations, and consulting firms. Blue Chip Economic Indicators started to collect inflation forecasts in the second quarter of 1980 and reported consensus (median) forecast for next four to seven quarters. We use the consensus forecast in our estimations. Blue Chip Economic Indicators also reported individual forecasts for the current and the next year. We constructed the standard deviation of one-year-ahead forecasts by taking a weighted average of the cross-sectional standard deviation of current-year forecast and the standard deviation of next-year forecasts. The weights correspond to the next 12 months (i.e. for January survey, we use weight of 11/12 on this year and 1/12 on next year, for February survey, we use weight of 10/12 on this year and 2/12 on next year). Because the number of forecasters included in monthly surveys has a strong seasonal pattern, we seasonally adjust the standard deviation measure. The dispersion measure runs from July 1984 to November 2007.

Appendix B: Description of Identified Shocks

R&R FFR shocks are shocks to monetary policy identified in Romer and Romer (2004). These shocks are identified as deviations of fed funds rate from its target rate, conditional on Greenbook forecasts. Data is available at http://elsa.berkeley.edu/~cromer/index.shtml from Jan. 1966 to Dec. 1996.

R&R fiscal shocks are exogenous tax changes as a share of GDP, from Romer and Romer (2007) who use narrative approach to identify exogenous changes in taxes. Data is quarterly from 1947Q1 to 2006Q2.

Oil price shocks are taken from Hamilton (1996) who identifies (WTI) oil price shocks as episodes when oil price exceeds the maximum oil price over the last twelve months. When this is the case, the shock is the difference between the current price and the maximum over the last twelve months, and zero otherwise. We take logs of all prices. Data is quarterly from 1950 until the end of 2007.

Monetary policy shocks identified from a VAR are based on a five variable vector autoregression with twelve lags estimated on the data running from January 1957 to November 2007. Variables included in the VAR are personal consumption expenditures deflator, index of industrial production, change in the index of commodity prices, unemployment rate and Fed Funds rate. Following Bernanke and Blinder (1992), monetary policy shock is identified recursively using Cholesky decomposition and ordering the fed funds rate last. This restriction amounts to assuming that monetary policy shocks do not affect contemporaneously the variables ordered before the Fed Funds rate.

Technology shocks are identified as in Gali (1999) who uses long-run restrictions. The estimation sample covers 1952Q2 through 2007Q3. Labor productivity and hours are defined as in Gali (1999). Technology shocks are identified from the restriction that only technology shocks have long run effect on productivity. To estimate the impulse response of inflation to a technology shock, we estimate a trivariate VAR(4) on quarterly data for the change in labor productivity, change in hours, and inflation rate of the GDP deflator.

Information shocks are identified as in Beaudry and Portier (2006). We use the short-run restrictions imposed on the residuals of a bivariate VAR(4) which includes total factor productivity (TFP) and the S&P500 price index. As discussed in Beaudry and Portier (2006), the short run restriction imposes that TFP does not respond to an information shock contemporaneously while the stock market does. The estimation sample covers 1951Q1 through 2006Q4.

Confidence shocks are identified as in Barsky and Sims (2008). We use a trivariate VAR(4) with the relative forecast for economic conditions for next five years reported in the Michigan Survey of Consumers (Table 16), log of real consumption of nondurables and services, and the log of real GDP. The confidence shock is identified using recursive ordering of the variables where expectations about economic conditions are ordered first. The survey measure begins in January 1978 and ends in August 2007. We use the quarterly average in the VAR.

Appendix C: Monte Carlo Experiments

While the conditional responses of forecast errors to technology and oil price shocks are remarkably consistent with the presence of informational rigidities, the evidence of serial correlation in forecast errors after monetary policy shocks is much weaker. One reason why this could occur is that monetary policy shocks account for a very small fraction of the inflation volatility, making it difficult to precisely estimate the response of forecast errors in short time sample. We also want to examine the ability of our empirical strategy to recover the sticky-information data generating process. In this appendix, we develop a Monte Carlo simulation which replicates our two primary tests—the conditional responses of forecast errors and forecast dispersions—in response to shocks which differ in their quantitative magnitudes.

In each simulation, we let inflation follow an AR(1) process $\pi_t = \rho\pi_{t-1} + \varepsilon_t$ where the shock ε_t is the sum of two independent innovations: $\varepsilon_t = \varepsilon_t^{(1)} + \varepsilon_t^{(2)}$. Agents form expectations rationally but update them infrequently following a Poisson process in which $1-\lambda$ is the probability of updating their information set each period, as in the sticky information model of Mankiw and Reis (2002). Thus, the mean forecast and the forecast dispersion of next-period inflation at time *t* follow equations (1) and (4).

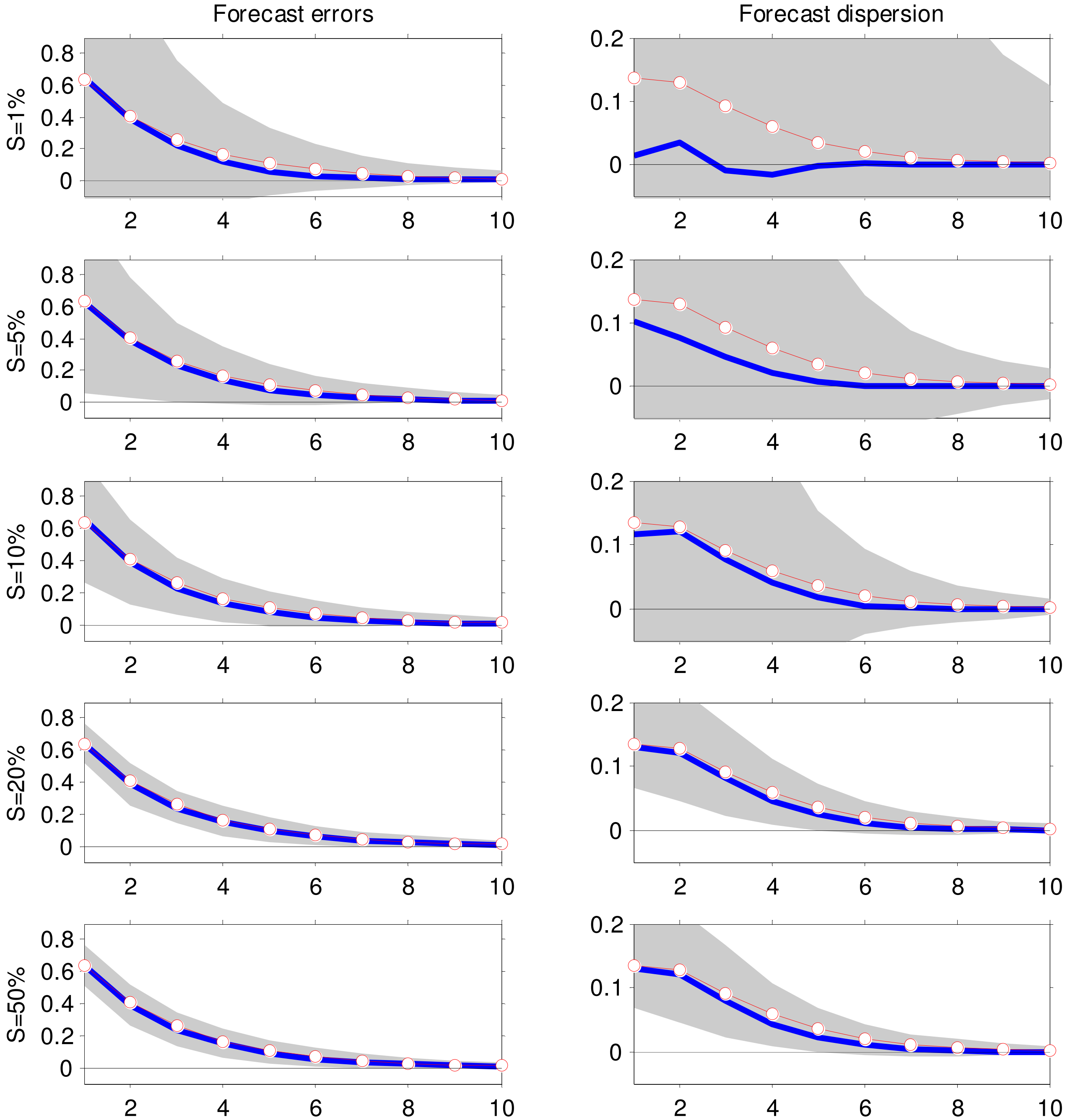
We simulate this model 10,000 times, with each simulation having 1,150 times periods. We set $\rho = 0.85$ and the variance of the total shock to inflation to be $\sigma_\varepsilon^2 = 1.005$ to match estimates of an AR(1) process for GDP deflator inflation from 1979Q1 to 2007Q3.[41] Following Mankiw and Reis (2002), we set the degree of informational rigidity λ to 0.75, implying that agents update their information once a year on average. In each simulation, we estimate the response of forecast errors to innovations $\varepsilon_t^{(1)}$, as done in sections 4.1 and 4.3, using the final *T*=150 periods of the simulation. The key parameter that varies across simulations is the fraction of the inflation variance accounted for by the innovation used to derive impulse responses ($\varepsilon_t^{(1)}$). We consider five values: S =1%, 5%, 10%, 20% and 50%.

Results of the Monte Carlo exercise are presented in Figure A1. We find that the mean estimated response for forecast errors is close to the response predicted by the model for all choices of *S*. For the response of forecast dispersion, small values of *S* (S < 5%) tend to yield a fairly poor match of the theoretical response. When we increase the sample size *T*, the discrepancy between the mean estimated and model-predicted responses for forecast dispersion vanish. Hence, our approach can asymptotically recover the true responses of the data generating process. However, if structural innovations account for a small fraction of the inflation variance (below 10%), precisely estimating the conditional response of forecast dispersion could be too demanding on the data in short samples. We view this as a being a plausible interpretation for why our estimation fails to uncover a significant response of forecast errors to monetary policy shocks. Hence, we put more weight on oil and technology shocks and also investigate the behavior of expectations in response to composite and unidentified shocks. We also find that the coverage rates for confidence intervals are close to nominal sizes when *S* > 5%.

The key message of these Monte Carlo experiments is that in small samples our approach can consistently and precisely estimate the responses of forecast errors and forecast dispersion to quantitatively important shocks and it is less successful when shocks explain only a small fraction (below 5-10%) of variation.

[41] Results are similar when we use alternative ARMA models for the inflation.

Figure A1. Monte Carlo Simulations of Conditional Forecast Error and Conditional Forecast Dispersion Responses to Innovations.



Notes: Thin solid red line with circles is the theoretically predicted response in the sticky information model. Thick solid blue line is the mean estimated response in the Monte Carlo simulations. Shaded region is the 90% distribution of the simulated responses. *S* is the fraction of the inflation variance accounted for by the innovation used in the estimation. Each experiment has 10,000 simulations.