Abstract: We propose a new method to test the null of full-information rational expectations which is informative about alternative models subject to informational rigidities and can quantify the economic significance of departures from the null. Applying this method to both U.S. and cross-country data of professional forecasters yields pervasive evidence of informational rigidities that can be explained by models of imperfect information. Furthermore, the proposed method sheds new light on the implications of policies such as inflation-targeting and those leading to the Great Moderation on the expectations formation process. Finally, we document evidence of state-dependence in the expectations formation process.

Keywords: Expectations, Information Rigidity, Survey Forecasts.
JEL codes: E3, E4, E5.
I Introduction

Expectations matter. How much to consume versus save, what price to set, and whether to hire or fire workers are just some of the fundamental decisions underlying macroeconomic dynamics that hinge upon agents’ expectations of the future. Yet how those expectations are formed, and how best to model this process, remains an open question. From the simple automats of adaptive expectations to the all-knowing agents of modern full-information rational expectations models, macroeconomists have considered a wide variety of frameworks to model the expectations formation process, yielding radically different results for macroeconomic dynamics and policy implications. Recent work on rational expectations models with informational frictions such as Mankiw and Reis (2002), Woodford (2001), Sims (2003) and Gorodnichenko (2008) has emphasized how informational rigidities can account for otherwise puzzling empirical findings but these same frictions can also lead to policy prescriptions that differ from those under models with full-information.\(^1\) Despite a growing body of work studying the implications of possible departures from full-information rational expectations, the empirical evidence against this common assumption underlying most modern macroeconomic models has been limited. In particular, while statistical evidence against the null is commonly uncovered, the economic significance of these rejections remains unclear.

Building from the predictions of models with informational rigidities, we propose a novel methodology to test the null of full-information rational expectations in a way that sheds new light on possible departures from the null. Our baseline specification relates ex-post forecast errors to the ex-ante revision of the average forecast across agents. While this is just a special case of the traditional test of full-information rational expectations (FIRE) in which one assesses whether previously available information can predict ex-post forecast errors, our specification possesses multiple advantages over this traditional approach.\(^2\) First, we rely on the predictions of theoretical models of informational rigidities to guide our choice of the relevant right-hand side variable. This mitigates the data-mining concern associated with the traditional approach in which, after trying enough right-hand side variables, one is bound to reject the null hypothesis. Second, models of informational rigidities make specific predictions about the sign of the coefficient on forecast revisions, so that our specification provides guidance not only about the null of full-information rational expectations but also about alternative models. Third, we show that the coefficient on forecast revisions maps one-to-one into the underlying degree of informational rigidity. Our methodology can therefore not only test the null of FIRE against well-specified alternatives but also provide a metric by which to assess the economic significance of departures from the null.

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\(^1\) For example, Ball, Mankiw and Reis (2005) show that price-level targeting is optimal in sticky-information model whereas inflation targeting is optimal in a sticky-price model.

\(^2\) See Taylor (1999) and Pesaran and Weale (2006) for surveys of this literature.
Two theoretical rational expectations models of informational frictions motivate our empirical specification. In the sticky-information model of Mankiw and Reis (2002), agents update their information sets infrequently as a result of fixed costs to the acquisition of information. When they do update their information sets, they acquire full-information rational expectations. The degree of information rigidity in this model is then the probability of not acquiring new information each period. The second class of models we consider consists of imperfect information models such as Woodford (2001) and Sims (2003). Here, agents continuously update their information sets but, because they can never fully observe the true state, they form and update beliefs about the underlying fundamentals via a signal extraction problem. Strikingly, both models predict the same relationship between ex-post mean forecast errors and the ex-ante mean forecast revision such that the coefficient on forecast revisions depends only on the degree of information rigidity in each model.

The resulting empirical specification can be applied to study informational rigidities for a variety of economic agents such as consumers, central banks and financial market participants, among others, as long as forecast data are available at multiple forecasting horizons, so that forecast revisions can be measured. As a first step, we focus on inflation forecasts from the U.S. Survey of Professional Forecasters (SPF) run by the Philadelphia Federal Reserve, since inflation forecasts have received the most attention in the literature. From 1969-2010, we can strongly reject the null of FIRE and find that the estimated coefficient on forecast revisions is positive, consistent with the prediction of models of informational rigidities. Furthermore, the implied degree of information rigidity is high: in the context of sticky-information models, it implies an average duration of six to seven months between information updates. Given that professional forecasters likely consist of some of the most informed economic agents, this points toward an important role for informational rigidities in macroeconomic dynamics.

In addition, we apply our specification to a much broader set of forecasted macroeconomic variables. First, the SPF includes historical forecasts for four other macroeconomic variables going back to 1968, including real GDP and unemployment, at multiple forecasting horizons. Our methodology can exploit both the multiple forecasting horizons and different macroeconomic variables, allowing us to extract much more precise estimates of informational rigidities than in previous work. Pooling across these variables and forecasting horizons leads to even stronger rejections of the null of FIRE, again in the direction predicted by models of informational rigidities. Second, starting in 1981, the SPF includes forecasts of seven additional macroeconomic variables, again at multiple forecasting horizons. Using this larger set of variables confirms the baseline finding: we can reject the null of FIRE in exactly the direction predicted by models with informational frictions and the estimates point to economically significant degrees of informational rigidities. Third, we utilize an additional survey of professional forecasters constructed by Consensus Economics which includes historical forecasts since 1989 of five
macroeconomic variables for the G-7 and five additional industrialized countries, again at multiple forecasting horizons. Pooling across these countries, variables and horizons, yields an almost identical coefficient on forecast revisions, providing further evidence that professional forecasters are subject to significant informational rigidities.

Our methodology can also shed light on the relative merit of different models of informational rigidities. For example, the sticky-information model implies a common rate of information updating for all macroeconomic variables, whereas imperfect information models imply that the degree of information rigidity associated with a macroeconomic variable should vary according to the persistence of each variable and the signal-noise ratio associated with it. Across datasets, we find robust evidence that the degree of information rigidity varies systematically across macroeconomic variables and that this cross-sectional variation is well-explained by the predicted determinants of imperfect information models: the persistence of a variable and a simple measure of the signal-noise ratio (proxied using real-time data revisions) can account for more than fifty percent of the variation in the estimated degree of information across countries and macroeconomic variables in the Consensus Economics dataset. Thus, imperfect information models appear to be a reasonable description of the underlying expectations formation process for professional forecasters.

Because our empirical specification allows us to recover estimates of the underlying degree of information rigidity, we also consider some policy determinants of the expectations formation process. For example, the monetary policy changes enacted by Volcker are likely to have played a role in the Great Moderation (Clarida et al (2000), Coibion and Gorodnichenko (2009)). The latter refers to the period of diminished macroeconomic volatility observed since the early to mid-1980s. This decline in volatility should result in a higher degree of inattention according to models with informational rigidities. We study the time variation in the estimated degree of information rigidity among U.S. professional forecasters and find evidence that accords remarkably well with this intuition: the degree of information rigidity fell consistently throughout the 1970s and early 1980s when macroeconomic volatility was high, reaching a minimum around 1983-84. Since then, the degree of information rigidity has been consistently rising as macroeconomic volatility has been subdued. One tentative interpretation of this result could be that the changes in monetary policy enacted by Volcker helped stabilize the economy in the Great Moderation, but that this economic stabilization promoted greater inattention on the part of economic agents, thereby, in the end, making the economy more susceptible to economic shocks. This suggests an additional mechanism, along with increased risk-taking on the part of financial market participants, through which the Great Moderation may have contributed to the severity of the Great Recession.

Another dimension through which policy can affect expectations is via a commitment to strict regimes, such as inflation-targeting by central banks, designed to “anchor” expectations. Such regimes
should, if credible, increase inattention on the part of economic agents leading to lower volatility in expectations of future outcomes. Because our methodology allows us to assess how attentive agents are to macroeconomic developments, combined with the fact that the sample of countries in the Consensus Economics dataset includes both official inflation-targeting countries such as the UK and unofficial inflation-targeting countries such as the U.S., we can quantify the effect of the adoption of an inflation-targeting regime on information rigidities in inflationary expectations. In short, we find that the effects of adopting an inflation-targeting regime on the degree of inattention in inflationary expectations of professional forecasters is small and not statistically significant, casting doubt on the efficacy of this policy, at least among the already-stable set of countries in our sample. This approach could readily be extended to a larger set of countries and other policy issues such as exchange rate regimes which are predicted to have important effects on expectations. Thus, an additional contribution of the paper is to provide a framework for analyzing the effects of different policy regimes on the expectations formation process of economic agents.

While research on sticky-information and imperfect information typically expresses these models in a time-dependent setting, one might naturally expect large and visible shocks to affect the rate of information-acquisition and processing by economic agents, i.e. state-dependence should be characteristic in the face of large and visible shocks. We consider this possibility by studying the time-variation in the degree of informational rigidities in two cases. First, we estimate the average effect of recessions on the degree of information rigidity in the U.S. since 1969. We find that the degree of information rigidity declines substantially after a few quarters of being in a recession and gradually recovers over time. As recessions become apparent in real time, the degree of inattention by economic agents declines. Second, we consider the natural experiment provided by the attack of September 11th, 2001, which was an immediately recognizable and significant economic shock leading to large forecast revisions by professional forecasters immediately thereafter. Because of the visibility of this shock, one might expect that these forecast revisions would not have been subject to the same degree of informational rigidities as normal business cycle conditions. Consistent with this, we find that the large subsequent forecast revisions in both the U.S. and other countries were not subject to important informational rigidities. In short, we document clear evidence of state-dependence in the expectations formation process in the presence of large economic shocks, a feature of the data which is not commonly incorporated into models of information rigidities.

This paper is closely related to recent empirical work trying to ascertain the nature of the expectations formation process. For example, Mankiw, Reis and Wolfers (2004) test the predictability of forecast errors by professional forecasters and assess whether a sticky-information model can replicate some stylized facts about the predictability of forecast errors while Khan and Zhu (2006), and Kiley
(2007), and Coibion (2010) provide empirical evidence on the sticky-information Phillips curve. One advantage of our methodology is that we can directly recover an estimate of the degree of information rigidity without having to make auxiliary assumptions about the model, such as the nature of price-setting decisions. Furthermore, our approach allows us to differentiate between sticky-information and imperfect information models. Coibion and Gorodnichenko (2008) similarly study the evidence for sticky-information and imperfect information models but do so by estimating the response of forecast errors and disagreement to structural shocks whereas our approach does not require the identification of any shock. In the same spirit, Branch (2004) compares the fit of sticky-information and model-switching characterizations of the expectations formation process while Carroll (2004) tests an epidemiological model of expectations in which information diffuses over time from professional forecasters to consumers. However, these papers focus almost exclusively on inflationary expectations whereas we utilize forecasts for a wide variety of macroeconomic variables as well as cross-country data.

The paper is structured as follows. Section 2 presents the predicted relationship between ex-post forecast errors and ex-ante forecast revisions in sticky-information and imperfect information models. Section 3 describes the empirical methodology and provides results for inflation forecasts of professional forecasters, as well as broader evidence from forecasts of other macroeconomic variables. Section 4 presents evidence on the underlying macroeconomic and policy determinants of informational rigidities and documents a likely role for state-dependence in the expectations formation process. Section 5 concludes.

II Forecast Errors, Forecast Revisions and Informational Rigidities

In this section, we present two models of informational rigidities and derive their respective predictions for the relationship between ex-post forecast errors and ex-ante forecast revisions.

2.1 Sticky Information

Mankiw and Reis (2002) proposed a model of inattentive agents who update their information sets each period with a probability of $1-\lambda$ but acquire no new information with a probability of $\lambda$, so that $\lambda$ can be interpreted as the degree of information rigidity and $1/(1-\lambda)$ is the average duration between information updates. When agents update their information sets, they acquire full information and have rational expectations. Reis (2006) shows how this time-dependent updating of information sets obtains when firms face a fixed cost to updating their information. In such a setting, the average forecast across agents ($F_t$) of a variable at time $t+h$ ($x_{t+h}$) is a weighted average of current and past rational expectations forecasts ($E_{t+j}$) of the variable such that

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

(1)
The average forecast at time $t-1$ can similarly be written as
\[ F_{t-1}x_{t+h} = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-1-j}x_{t+h} \]  
(2)
which implies that the current average forecast is just a weighted average of the previous period’s forecast and the current rational expectation of variable $x$ at time $t+h$
\[ F_t x_{t+h} = (1 - \lambda)E_t x_{t+h} + \lambda F_{t-1} x_{t+h}. \]  
(3)
The full-information rational expectations are such that
\[ E_t x_{t+h} = x_{t+h} + v_{t+h,t}, \]  
(4)
where $v_{t+h,t}$ is the rational expectations error and is therefore uncorrelated with information dated $t$ or earlier.

Combining (3) and (4) yields the predicted relationship between the ex-post mean forecast error across agents and the forecast revision
\[ x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1 - \lambda} \Delta F_t x_{t+h} + v_{t+h,t}, \]  
(5)
where $\Delta F_t x_{t+h} = F_t x_{t+h} - F_{t-1} x_{t+h}$. Importantly, the coefficient on the forecast revision depends only the degree of information rigidity $\lambda$. In the special case of no informational frictions, $\lambda=0$ and the specification collapses to equation (4), i.e. the average forecast error is unpredictable using information dated $t$ or earlier. Because the sticky-information model implies a single rate of information acquisition, equation (5) holds for any macroeconomic variable and any forecasting horizon. In addition, this specification will hold regardless of the structure of the rest of the model.

### 2.2 Imperfect Information

Following Sims (2003) and Woodford (2003), we consider models in which agents continuously update their information sets but never observe the true values. Suppose that a macroeconomic variable follows an AR(1) process
\[ x_t = \rho x_{t-1} + v_t \]  
(6)
where $0 \leq \rho \leq 1$. Agents cannot directly observe $x$ but instead receive a signal $x^i_t$ such that
\[ x^i_t = x_t + \omega^i_t \]  
(7)
where $\omega^i_t$ represents noise which may be correlated across agents. Each agent $i$ then generates optimal forecasts given their information sets ($F^i_t x_{t+h}$) via the Kalman filter
\[ F^i_t x_t = F^i_{t-1} x_t + G [x^i_t - F^i_{t-1} x_t]. \]  
(8)
$G$ is the Kalman gain which represents the relative weight placed on new information relative to previous forecasts. When the signal is perfectly revealing about the true state, $G=1$ while the presence of noise induces $G < 1.$ Thus, $1-G$ can be interpreted as the degree of information rigidity in this model.
Averaging across agents and rearranging, one can show that the following relationship between ex-post average forecast errors and ex-ante forecast revisions holds

$$x_{t+h} - F_t x_{t+h} = \frac{1-G}{G} \Delta F_t x_{t+h} + \varepsilon_{t+h,t}$$  \hspace{1cm} (9)

where $\varepsilon_{t+h,t} = \sum_{i=1}^{h} \rho_i v_{t+i}$ is the rational expectations error and $F$ denotes the average forecast across agents. This specification is identical to that obtained under sticky-information, when $1-G$ is interpreted as the degree of information rigidity. Unlike under sticky information, the coefficient on forecast revisions need not be the same for different macroeconomic variables in imperfect information models. Instead, the coefficient will vary with the determinants of the Kalman gain, e.g. the persistence of the series and the signal-noise ratio.

III Tests of FIRE and New Evidence on Information Rigidities

This section a) describes our empirical methodology and relates it to previous literature, b) applies our methodology to inflation forecasts of U.S. professional forecasters and c) considers broader evidence of informational rigidities pooled across macroeconomic variables as well as d) cross-country evidence on informational rigidities.

3.1 A New Approach for Assessing the Nature of the Expectations Formation Process

The sticky information and imperfect information models both point to the same relationship between ex-post forecast errors and ex-ante forecast revisions such that the coefficient on forecast revisions maps one to one into the structural degree of informational rigidities. This relationship can be readily estimated for a given macroeconomic variable $x$, mean forecasts across agents $F x$ and forecasting horizon $h$ using the following empirical specification:

$$x_{t+h} - F_t x_{t+h} = c + \beta \Delta F_t x_{t+h} + \varepsilon_t$$  \hspace{1cm} (10)

This is just a special case of the more general test of full-information rational expectations commonly employed in the literature in which the forecast error is regressed on a subset of the information available to agents at the time the forecast was made, i.e

$$x_{t+h} - F_t x_{t+h} = c + \beta z_t + \varepsilon_t.$$  \hspace{1cm} (11)

Under the null of full-information rational expectations, forecast errors (the LHS) should be uncorrelated with all past information (any variable $z$ dated $t$ or earlier) and should have a constant of zero. Our empirical specification in contrast imposes that the RHS variable be the revision in forecasts of the relevant time horizon. Despite the fact that our specification appears to just be a special case of the more general test, it addresses several important shortcomings of traditional tests.
The first limitation comes from the absence of any theoretical guidance as to which variables should be included on the RHS. This leads to important data-mining concerns: if a researcher tries enough macroeconomic variables and lags thereof, the null hypothesis of a zero coefficient is bound to be rejected. Consider a typical exercise applying (11) to inflation forecasts. Following much of the literature, we focus on mean inflation forecasts for the current and next three quarters from the Survey of Professional Forecasters from 1969 to 2010. A common first step in the literature is to include the contemporaneous forecast of future inflation to verify that the coefficient is zero, i.e. that forecasts are unbiased. For our time sample, this yields estimates of the constant and $\beta$ that are insignificantly different from zero, a finding which is consistent with the null of FIRE. As a reasonable alternative right-hand side variable, one might include the lagged forecast error as an indicator that forecast errors are serially correlated. In this case, we get an estimate of the constant that is again not statistically different from zero but $\hat{\beta} = 0.43 \ (0.16)$, so we can reject the null of FIRE at the 5% significance level. As documented in Pesaran and Weale (2006), such sensitivity to the RHS is characteristic of this methodology and calls for caution in interpreting apparent rejections of the null hypothesis.

Secondly, even if we observe a rejection of the null hypothesis that is not driven by data-mining, such a rejection is not directly informative about alternative models of the expectations formation process. Does the finding of serially correlated forecast errors point to adaptive expectations, sticky information, imperfect information, or strategic behavior on the part of forecasters? In the absence of clear theoretical predictions from these models about the estimated coefficients in these empirical specifications, little insight about the expectations formation process is gained from statistical rejections of the null hypothesis.

Third, and most fundamentally, these tests are uninformative about the economic significance of the results. The assumption of full-information rational expectations is easy to disprove: as emphasized by Mankiw, Reis and Wolfers (2003), the fact that economic agents systematically disagree about expected outcomes is inherently inconsistent with all agents knowing the true structure of the model and observing all economic variables and shocks perfectly in real-time. What matters of course for economists is not whether the assumption is literally true, since it clearly is not, but rather whether the deviations from FIRE are significant enough to have important economic implications. The statistical rejection of the null of FIRE arising from the predictability of forecast errors by certain macroeconomic variables over different time periods does not directly shed light as to whether these rejections are economically significant.

Our approach can address most of these concerns. First, because we derive predictions from models of informational rigidities that nest the full-information assumption, we have guidance from the theory as to what the relevant RHS variable should be, namely the revision in forecasts for the relevant
time horizon. Thus, the incentive for data-mining is reduced since the relevant RHS variable is motivated by theoretical considerations. Second, there is a well-defined alternative hypothesis from models of informational rigidities, given by the prediction that $\beta > 0$. One can even consider an additional restriction implied by models of informational rigidities by decomposing the forecast revision term into two components (the current forecast and the previous period’s forecast) and testing if the coefficient on the current forecast is positive, the coefficient on the lagged forecast is negative, and that the sum of the two coefficients is zero. Third, because both theoretical models of informational rigidities imply that the estimated coefficient on forecast revisions maps directly into the underlying structural parameters governing the degree of information rigidity, our methodology can recover direct estimates of informational frictions. This can help assess the economic significance of any rejections of the null hypothesis of FIRE.

Our methodology has one important practical limitation: because the RHS variable is the revision in forecasts for a specific time period, the dataset must include a time series of forecasts of macroeconomic variables with overlapping forecasting time horizons. Unfortunately, many surveys are not done in such a fashion. The Michigan Survey of Consumers surveys a cross-section of consumers each month about their expectations of future macroeconomic variables, but does so over fixed time horizons such as the next twelve months. Forecasts from adjacent time periods therefore do not perfectly overlap in their forecasting horizons so that forecast revisions cannot be constructed in a manner consistent with the predictions of the models with informational rigidities. On the other hand, financial market forecasts, such as those extracted from the term structure of interest rates or forward and futures contracts are well-suited to our methodology, as are the Greenbook forecasts of the Federal Reserve and surveys of professional forecasters such as the U.S. Survey of Professional Forecasters from the Philadelphia Fed or the cross-country surveys done by Consensus Economics. While we focus exclusively on professional forecasters in this paper, the methodology can nonetheless be applied to other types of economic agents as long as forecast data include time variation in forecasts over specific time periods.

3.2 Evidence from U.S. Inflation Forecasts of Professional Forecasters

As a first step to applying our methodology, we again follow most of literature on survey measures of expectations and focus on historical inflation forecasts by U.S. professional forecasters. Both sticky-information and imperfect information models predict a relationship between the mean ex-post inflation forecast errors and the mean inflation forecast revisions such that

$$\pi_{t+h} - F_t \pi_{t+h} = c + \beta(F_t \pi_{t+h} - F_{t-1} \pi_{t+h}) + \epsilon_t.$$  \hfill (12)
where $\beta > 0$ if informational rigidities are present. From 1969-2010, we find $\hat{\beta} = 1.23 (0.50)$ with Newey-West standard errors. As a result, we can reject the null of FIRE at the 5% level of statistical significance, as when we used the lagged forecast errors on the RHS. However, this result tells us much more about the expectations formation process. First, the rejection of the null goes exactly in the direction predicted by models of informational rigidities, so that this presents direct evidence in favor of these models. In other words, the coefficient estimate is informative not just about the null hypothesis of FIRE but also about alternative models. Second, because $\beta$ maps into the degree of information rigidity from each model, we can extract an estimate of informational frictions: $\hat{\lambda} = \frac{\hat{\beta}}{1+\hat{\beta}} \approx 0.55$. In the context of sticky-information models, this would imply that agents update their information sets every six to seven months on average. As documented in theoretical work, this magnitude of informational frictions should have important quantitative implications for macroeconomic dynamics. Thus, our approach implies that informational frictions are economically as well as statistically significant. To provide additional evidence that this result is driven by informational rigidities, we can also test the restriction implied by these models, namely that the coefficient on the contemporary forecast and that on the lagged forecast are equal in absolute value. To implement this additional test, we decompose the forecast revision into two terms as follows

$$\pi_{t+h} - F_t \pi_{t+h} = c + \beta_1 F_t \pi_{t+h} + \beta_2 F_{t-1} \pi_{t+h} + \epsilon_t.$$  

(13)

Under models of informational rigidities, we expect $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_1 + \beta_2 = 0$. Estimating equation (13) from 1969-2010, we find $\hat{\beta}_1 = 1.24 (0.51)$ and $\hat{\beta}_2 = -1.27 (0.51)$. The signs on both coefficients conform to the theoretical predictions of models of informational rigidities, and we cannot reject the null that the sum of the two coefficients is equal to zero. The results therefore provide additional evidence consistent with the notion that the expectations formation process of professional forecasters is subject to information constraints.

Further evidence on the importance of informational rigidities comes from considering alternative explanations for the rejection of the null hypothesis. One prominent view is that bias the reported forecasts of professionals may be driven in part by strategic behavior. Laster et al. (1999) formalize this notion and find that forecasters whose wages depend most on publicity should produce forecasts that differ most from the consensus (i.e. the “Roubini effect”). Their empirical results confirm that forecasters affiliated with financial services providers have particularly large biases on average. This type of strategic behavior, if quantitatively important, could lead to the appearance of informational rigidities where none in fact is present. To assess this possibility, we decompose the inflation forecasts of the SPF into the mean forecasts of financial services firms and those not affiliated with financial services.
firms, then re-estimate equation (12) for each type of forecaster. The point estimates of $\beta$ are nearly identical across industry affiliations, and we cannot reject the null that the point estimates are equal for these two types of forecasters. Thus, our results are unlikely to be driven by strategic behavior among professional forecasters.

3.3 Pooled U.S. Evidence on Information Rigidities among Professional Forecasters

While much of the empirical literature on the expectations formation process has focused on inflation forecasts, our methodology is readily applicable to different macroeconomic variables. Furthermore, we can also exploit the multiple forecasting horizons available in the data to further expand the power of our tests. In this section, we apply our methodology to professional forecasts for a multitude of macroeconomic variables and forecasting horizons.

As a first step, we exploit the fact that the Survey of Professional Forecasters contains quarterly forecasts for 4 additional macroeconomic variables going back to 1968Q4: besides the GDP price deflator, these include real output, industrial production, housing starts, and the unemployment rate. Furthermore, each of these variables is forecasted at multiple forecasting horizons, ranging from forecasts of the current quarter to 4 quarters ahead. To take advantage of this additional dimension, we utilize each of the individual quarterly forecasting horizons in our estimation. Thus, we estimate a pooled regression

$$x_{i,t+h} - F_t x_{i,t+h} = \epsilon_{i,h,t}$$

where $x_i$ indicates which macroeconomic variable is included and $h$ denotes the specific forecasting horizon ranging from 0 (forecasts of the current quarter) to 3 (forecasts for 3 quarters ahead). While the SPF includes forecasts up to 4 quarters ahead, the horizon is limited to 3 quarters in the empirical specification because forecast revisions call for an additional forecasting horizon, e.g. when $h=3$, the forecast revision is $F_t x_{i,t+3} - F_{t-1} x_{i,t+4}$. To construct forecast errors, we use real-time values available one year after the relevant time horizon. For the first three series, forecasts of annualized quarterly percent changes are constructed from the underlying mean forecasts of the levels. Table 1 presents the results of this pooled regression over 3,240 observations as well as when we include fixed effects for the forecasting horizon and macroeconomic variable. Our estimate of $\beta$ is positive and statistically significant in both cases so that we can reject the null of full-information rational expectations in exactly the direction predicted by models of informational rigidities. The point estimate of $\beta$ implies an average duration between information updates of four months. The standard errors are now much smaller than

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3 The Survey of Professional Forecasters provides an identifier for the industry with which each forecaster is affiliated: financial services, non-financial services, and unknown. This industry identifier is available since 1990.

4 Output is measured by GNP prior to 1992 and GDP thereafter. The price deflator is the implicit GNP deflator before 1992, implicit GDP deflator from 1992 to 1996, and the chained GDP deflator thereafter.

5 For each pooled dataset, we identify and remove outliers using jackknife and Cook’s distance.
when the degree of information rigidity was based only on forecasts of one-year ahead inflation rates, which reflects the increased precision arising from pooling across multiple macroeconomic variables and forecasting horizons. Furthermore, when we decompose the forecast revision into two components, the contemporaneous forecast and the lagged forecast, as in equation (13), each coefficient is of the sign predicted by theoretical models of informational rigidities and we cannot reject the null hypothesis from these models that the sum of the two coefficients is equal to zero at the five percent level of statistical significance.

Starting in 1981, the SPF includes forecasts of 8 additional macroeconomic variables: the 3-month Treasury bill (Tbill) rate, the AAA interest rate, real consumption expenditures, real residential investment, real non-residential investment, real federal government expenditures, real state/local government expenditures, and the overall CPI. For each NIPA series and CPI inflation, we construct forecasts of annualized quarterly percent changes and use real-time data to construct forecast errors, while the two interest rates are measured in levels. The forecast horizons again run from $h=0$ to $h=3$. Thus, pooling across all of the variables available in the SPF since 1981 and all forecasting horizons yields 5,793 observations. The results from estimating equation (14), presented in Table 1, again point to an estimate of $\beta$ which is positive and statistically different from zero, whether or not fixed effects are included. The point estimate is somewhat larger than in the previous case, pointing to average durations between information updates of approximately five months. Given that the forecasts come from professional forecasters, for whom informational rigidities should likely be smaller than those faced by most other economic agents such as consumers and firms, this points to informational rigidities likely playing an important role in macroeconomic dynamics. Furthermore, a decomposition of the forecast revision into current versus lagged forecasts again yields the result predicted by models of informational rigidities that we cannot reject the sum of the two coefficients being equal to zero nor can we reject the sign restrictions implied by these models.

### 3.4 Cross-Country Evidence on Information Rigidities among Professional Forecasters

In addition to the U.S. Survey of Professional Forecasters, we have constructed a dataset of quarterly forecasts from the international survey of professional forecasters done by Consensus Economics. This dataset covers twelve countries: the G-7 countries of U.S., U.K., France, Germany, Italy, Japan and Canada as well as Spain, Norway, the Netherlands, Sweden and Switzerland. Data for the G-7 countries are constructed from monthly forecasts, while the other countries are based on quarterly estimates. This dataset includes forecasts for inflation, real GDP, real consumption, real investment, real federal government expenditures, real state/local government expenditures, and the overall CPI. The forecast horizons again run from $h=0$ to $h=3$. Thus, pooling across all of the variables available in the SPF since 1981 and all forecasting horizons yields 5,793 observations. The results from estimating equation (14), presented in Table 1, again point to an estimate of $\beta$ which is positive and statistically different from zero, whether or not fixed effects are included. The point estimate is somewhat larger than in the previous case, pointing to average durations between information updates of approximately five months. Given that the forecasts come from professional forecasters, for whom informational rigidities should likely be smaller than those faced by most other economic agents such as consumers and firms, this points to informational rigidities likely playing an important role in macroeconomic dynamics. Furthermore, a decomposition of the forecast revision into current versus lagged forecasts again yields the result predicted by models of informational rigidities that we cannot reject the sum of the two coefficients being equal to zero nor can we reject the sign restrictions implied by these models.

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6 Because the errors are likely to be correlated over time as well as across macroeconomic variables and forecasting horizons, we use Driscoll-Kraay (1998) standard errors which are robust to both time and cross-sectional correlation of the error terms.

7 Consensus Economics provides forecasts for many more countries than the twelve included in our sample, often at the monthly frequency, but these forecasts are restricted to the calendar year time horizon. While our methodology
spans 1989 to 2010 while data for other countries begin primarily in 1994. For each country, forecasts for five macroeconomic variables are available: consumer price inflation, real GDP growth, interest rates, industrial production growth and real consumption growth. Forecasts are available for the current quarter and for the subsequent 5-6 quarters. As a first step, we estimate the average degree of information rigidity pooled across all macroeconomic variables, countries and forecast horizons, i.e.

$$ x_{i,j,t+h} - F_{i} x_{i,j,t+h} = c + \beta \Delta F_{i} x_{i,j,t+h} + \varepsilon_{i,j,h,t} $$

(15)

where $i$ denotes the macroeconomic variable, $j$ the country and $h$ the forecasting horizon. Based on 22,347 observations, the results again point to an estimate of $\beta$, presented in Table 1, that is positive and statistically significant, confirming our finding from U.S. professional forecasters. This occurs when equation (15) is estimated by OLS or including fixed effects for different countries, variables, and forecasting horizons. The implied degree of information rigidity points to information sets being updated every four to five months on average, which is very close to the estimates for the U.S. using a much wider set of variables. When we decompose the forecast revision (Panel B), each coefficient has the same sign as predicted by models of informational rigidities and we again cannot reject the null hypothesis that the sum of the two coefficients is equal to zero at the five percent level of statistical significance.

In addition, we consider country-specific estimates of the degree of information rigidity, pooled over macroeconomic variables and forecasting horizons. Figure 1 plots the resulting estimates of $\beta$ for each country. The countries with the highest degrees of informational rigidities are Spain and Sweden, while the lowest are Canada and Norway. Note that all of the estimates are statistically significantly positive so we can reject the null of full-information rational expectations for every country and this rejection of the null goes exactly in the direction predicted by models of informational rigidities. The substantial cross-country heterogeneity in information rigidity, ranging from estimates of 0.3 for Canada to almost one for Spain, point to a likely role for policy and institutions in determining country levels of information rigidity, an issue to which we return in section 4.2.

IV Determinants of Informational Rigidities

The empirical results pooled across macroeconomic variables and forecasting horizons are strongly supportive of models with informational frictions: the estimated coefficients on forecast revisions are consistently positive as predicted by these theories and large enough to affect macroeconomic dynamics. Given these findings, we turn to the question of differentiating between sticky information and imperfect

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is well-suited to these fixed forecasting horizons, we focus on this restricted set of countries because of the larger set of forecasting horizons available.

\(^8\) Forecasts for Norway and Switzerland only become available in 1998.
information models of the expectations formation process, as well as evaluating the underlying macroeconomic and policy determinants of informational rigidities.

4.1 Differentiating by Forecast Horizon and Forecasted Variable

In the sticky-information model of Mankiw and Reis (2002) and Reis (2006), firms update their information sets infrequently, but when they do so, they acquire full-information rational expectations. As a result, there is a single parameter governing the frequency of updating information which is common across macroeconomic variables and forecasting horizons. Thus, a testable implication of the sticky-information model is that the estimated degree of information rigidity is invariant to the forecasting horizon and the variable being forecasted. In imperfect information models, on the other hand, the coefficient on forecast revisions for a given macroeconomic variable will be governed by the Kalman gain associated with that variable, which will depend on factors such as the persistence of the series and the strength of the signal observed with respect to that macroeconomic variable. While signals should generally be correlated across variables, they need not be identical. For example, the magnitude of data revisions varies across variables, as does the frequency of data releases. Both factors would affect the strength of the signal observed for a macroeconomic variable when forecasts are done at the quarterly frequency. One way to try and assess the relative merits of these two models in accounting for the expectations formation process of professional forecasters is to compare the estimated degrees of information rigidity across macroeconomic variables being forecasted as well as along the forecasting horizon.

To do so, we provide two decompositions of our pooled estimates from each dataset: one by forecasting horizon (left column of Figure 2) and one by macroeconomic variable (right column of Figure 2). For the U.S. SPF, we cannot reject the null hypothesis of equal coefficients across forecasting horizons, as predicted by both models of informational rigidities for quarterly forecasts ($p$-values of 0.15 and 0.23 for 1968 variables and 1981 variables respectively), but we can strongly reject ($p$-value < 0.001) the null of equality across macroeconomic variables for the thirteen variables available since 1981 and weakly so for the five variables available since 1968 ($p$-value = 0.06). With the cross-country Consensus Economics data, we can again strongly reject the null of equality across macroeconomic variables ($p$-value < 0.001) and, unlike with the U.S. SPF data, we can also strongly reject the null of equality across forecast horizons ($p$-value < 0.001).

One clear result is that the degree of information rigidity is not equal across macroeconomic variables: an implication at odds with sticky-information models. On the other hand, the fact that heterogeneity in information rigidity exists across macroeconomic variables does not imply that imperfect information models can account for this cross-sectional variation. In the simple imperfect information
model of section 2.2, the degree of information rigidity depends on the Kalman gain, which is a function of the persistence of the underlying macroeconomic process as well as the precision of the signal received by economic agents. More persistent processes imply, holding all else constant, that agents should pay less attention to current signals since past values are relatively more informative than when the underlying process is less persistent. A more precise signal naturally implies that agents should place relatively more weight on the current signal than on past forecasts. Thus, imperfect information models imply that the degree of information rigidity should be increasing in the persistence of the series being forecasted as well as the amount of noise in the signal.

To assess these predictions, we construct measures of each as follows. First, for each country \( j \) and macroeconomic variable \( i \) in the Consensus Economics survey of professional forecasters, we fit an AR(1) process which yields an estimate of both the persistence of the variable (\( \rho_{i,j} \)) and the volatility of its innovations (\( \sigma_{i,j} \)). Second, we generate a measure of the noise associated with each series from the average size of revisions to this variable.\(^9\) Third, we construct a measure of the noise-signal ratio (\( \kappa_{i,j} \)) by taking the ratio of the standard deviation of revisions to the standard deviation of the innovations to the variable from the first step. Given these measures of the predicted determinants of information rigidity, we assess their importance by regressing our estimates of the coefficients on forecast revisions for each country-macroeconomic variable pair, pooled across forecasting horizons, in the cross-country Consensus Economics dataset set

\[
\beta_{i,j} = c + \gamma_1 \sigma_{i,j} + \gamma_2 \rho_{i,j} + \gamma_3 \kappa_{i,j} + \phi_i + \eta_j + \epsilon_t
\]  

(16)

where \( i \) denotes a specific variable, \( j \) denotes the country, \( \phi_i \) and \( \eta_j \) are variable and country fixed effects, and \( \beta_{i,j} \) is the estimated coefficient on forecast revisions for each country-variable pair in the cross-country data-set.\(^10\) With twelve countries and five variables for each, this yields a cross-section of 60 observations. The variable measuring the volatility of innovations is not expected to be different from zero in simple imperfect information models once the noise-signal ratio is controlled for. However, there are several reasons to include it. First, if strategic motivations for professional forecasters were important, one might expect these to be particularly strong for more volatile variables for which there is a greater probability of correctly calling a dramatic change. Second, in rational inattention models such as Sims (2003) or Mackowiak and Wiederholt (2008), firms may find it optimal to allocate more resources to gathering information about more volatile variables if this volatility parleys into larger effects on the

\(^9\) Specifically, for each time period, we take the difference between measures of the variable available two quarters and four quarters later, then compute the standard deviation of these revisions across the entire sample. Alternative time horizons for measuring revisions yield the same qualitative results. Real-time data, including revisions over the course of a year, are included in the Consensus Economics dataset.

\(^10\) Because the cross-section of forecasted macroeconomic variables in the U.S. Survey of Professional Forecasters is relatively small (13 variables consistently available since 1981), we only apply this analysis to the cross-country data.
objective function. Third, if the underlying source of information rigidity included a sticky-information component reflecting fixed costs to acquiring new information about a variable, then greater volatility in that variable would imply more frequent updating of information as suggested by Reis (2006). Note that all three effects would point toward a negative coefficient on volatility \((\gamma_1)\) in equation (16). On the other hand, greater volatility could also plausibly lead to fewer resources being devoted to forecasting a variable. For example, Meese and Rogoff (1983) showed that most exchange rate forecasts could not outperform a random walk forecast. For this kind of variable, there could be little to gain by devoting additional resources to forecasting.

The results are presented in Table 2. In the baseline specification without fixed effects, the coefficients on the persistence and the noise-signal ratio of each country-variable pair are positive and highly statistically significant, as predicted by models of imperfect information. The coefficient on the volatility of innovations to the variable is also positive and statistically significant. Strikingly, this simple specification can account for fifty-five percent of the heterogeneity in informational rigidities. Thus, not only are the theoretical predictions of imperfect information models qualitatively consistent with the observed heterogeneity in informational rigidities across countries and variables, but this model can also quantitatively account for much of the observed cross-sectional variation.\(^\text{11}\)

Table 2 also presents results with country and variable fixed effects. When country-specific fixed effects are added, the qualitative results are unchanged and the fraction of the heterogeneity accounted for by the empirical specification rises to nearly 60%, which implies that there are likely some country-specific factors affecting the degree of informational rigidities above and beyond what is captured by the volatility, persistence and noise-signal ratio of the underlying macroeconomic variables. This likely reflects policy and institutional factors, a point to which we return in section 4.2. When variable-specific fixed effects are added, the coefficients again remain statistically significantly different from zero, and the fraction of the heterogeneity accounted for by the empirical specification rises to over 65%. Including both variable and country fixed effects delivers the same qualitative results with a higher \(R^2\), although the noise-signal ratio now becomes statistically insignificant. This reflects a small decrease in the point estimate but a more than doubling of the standard errors relative to the baseline specification, so that this is most likely driven by a collinearity problem with the joint fixed effects. Furthermore, our measures of the noise in each series reflect only real-time measurement issues and omit a variety of other factors.

\(^{11}\) The results are robust to a number of variations. For example, we used the implied degree of information rigidity \((\lambda\text{ or }1-G)\) rather than \(\beta\) on the LHS and found nearly identical results. Similar results obtain if we control for the fact that the LHS variables are estimated with different degrees of precision, or if we drop the few observations for which \(\beta\) is estimated to be negative. Using higher-order autoregressive processes to measure the persistence of the series and volatility of the innovations also does not qualitatively affect the findings.
which could affect the inherent noise associated with each variable. For example, the transparency of central banks would likely affect the noise-signal ratio of interest rates and inflation.

The fact that we can reject the null of equality across forecast horizons using the Consensus Economics data but not for the U.S. SPF is also useful to differentiate between the models. As presented in Section 2, both models predict that the estimated coefficient on forecast revisions should be identical for different forecasting horizons \textit{when forecasts are for quarterly changes}. However, the forecasts of GDP, consumption and industrial production growth in the Consensus Economics survey are for year-on-year changes, and the inflation rate is measured by year-on-year changes in the price level. This distinction makes no difference under sticky-information, and the prediction remains that the coefficient on forecast revisions be equal across forecasting horizons, contrary to what we observe in the data. For imperfect information models, on the other hand, this distinction is important. Consider, for example, the forecast for the current quarter year-on-year GDP growth: the forecasters have observed values for at least two, and likely three, of the four quarters over which they are forecasting. Hence, they have already received very strong signals about the value of current year-on-year GDP growth. When, on the other hand, they must forecast year-on-year GDP growth in four quarters, they will not have observed any of the quarterly values over which the forecast is made and therefore the available signals will be much weaker. Thus, the strength of the signal is falling over the first four forecasting horizons (\(h = 0\) to 3) so that one would expect the estimated coefficient on forecast revisions to be rising over these horizons, which is exactly the pattern observed in Figure 2.\footnote{The drop in the estimated coefficients at longer forecasting horizons in Figure 2, which occurs in both the SPF and Consensus data, appears to be driven entirely by finite sample issues combined with some variables not being very persistent. This is because, with low persistence, forecasts of distant values will be near constant, so that contemporaneous forecast revisions will have very little explanatory power for ex-post forecast errors, pushing the estimated coefficient toward zero in small samples. This is true under both sticky-information and imperfect information models and is thus not informative about the relative merit of the two approaches. We have verified in Monte Carlo simulations that this persistence issue can reproduce the observed decline in estimated coefficients in Figure 2. Furthermore, when we reproduce the decomposition across forecasting horizons for variables measured in changes (GDP growth, consumption growth, etc) which are not very persistent versus those variables measured in levels which are much more persistent on average, we find that the decline in estimated coefficients at longer forecasting horizons is non-existent for the latter but particularly pronounced for the former. Results available upon request.}

We have verified in Monte Carlo simulations of the imperfect information model in section 2.2 that this feature of the Consensus Economics surveys can indeed account for the rising estimated coefficients across forecasting horizons (see Appendix 1). Further evidence that the large increase in estimated coefficients with the forecasting horizon is driven by this feature of the Consensus Economics forecasts is that, if we estimate the coefficient on forecast revisions at different horizons specifically for interest rate forecasts, which are not measured in year-on-year changes, the rising pattern of estimated coefficients is substantially dampened.
4.2 Policy and Institutional Determinants of Information Rigidity

The previous section presents evidence that the varying degrees of information rigidity associated with macroeconomic variables are well-explained by the persistence and noise-signal ratios of these variables. However these determinants are themselves functions of policy and institutional characteristics. In this section, we consider the possible effect of two sets of monetary policy changes on the degree of information rigidity. First, we assess whether informational rigidities in the U.S. changed with the onset of the Great Moderation, the dramatic decline in macroeconomic volatility commonly associated with the monetary policy changes enacted under Fed Chairman Paul Volcker. Second, we consider whether the official adoption of inflation targeting by central banks affects the degree of information rigidity in inflation forecasts.

4.2.1. Great Moderation

McConnell and Perez-Quirós (2000) and others have documented a substantial decrease in macroeconomic volatility both in the U.S. and other developed countries since the early to mid-1980s. Figure 3 plots the time-varying standard deviation of real GDP growth for the U.S., for example, which is rising throughout the 1970s, peaks in the very early 1980s, then exhibits a very sharp decline in the mid-1980s, declining by more than half relative to the average level during the 1970s. While the source of this phenomenon remains a point of contention, one prominent explanation emphasizes the changes in monetary policy put in place under Volcker, either in terms of stronger endogenous response to macroeconomic fluctuations as in Clarida et al (2000) or because of the Volcker disinflation as in Coibion and Gorodnichenko (2009). At the same time, there is only mixed evidence that microeconomic volatility declined over this time period. For example, Davis et al (2006) report that the volatility of employment has fallen since the 1970s for non-publicly traded firms while Comin and Mulani (2004) and Comin and Philippon (2005) show that volatility increased for publicly traded firms over the same period. Furthermore, volatility at the household level appears to have been trending up over time (see Davis and Kahn (2008) for a review). As a result of the reduction in the volatility of macroeconomic variables relative to microeconomic variables, one might expect that economic agents would choose to allocate relatively more resources to tracking micro rather than macro-level shocks since these shocks become quantitatively more important for profits and utility. Thus informational rigidity should have increased with the arrival of the Great Moderation.

To explore this hypothesis, we estimate equation (10) for each quarter separately using SPF data and then compute non-parametrically a local average of the estimated $\beta$’s for each period. Figure 3 plots the dynamics of the local averages of $\beta$ as well as associated standard errors. The figure shows that informational rigidities were falling from the late 1960s to the early 1980s as the volatility of...
macroeconomic variables was rising.\textsuperscript{13} The minimum level of information rigidity is reached in 1983-84, which closely matches the start of the Great Moderation identified in McConnell and Perez--Quirós (2000). Since then, the estimated degree of information rigidity has consistently been increasing and reaches its maximum level over the entire sample in 2009. The changes in the level of informational rigidities over time are statistically and economically significant, especially when one compares mid-1980s and in late 2000s. For example, in the context of the sticky information model, the frequency of information updates rose from about once per quarter in the mid-1980s to about once every 2½ quarters in the late 2000s.

This significant time-variation in the estimated coefficient on forecast revisions suggests that one should be wary of treating informational rigidities at the macroeconomic level as a structural parameter since these rigidities can vary over time in response to changes in macroeconomic conditions. Specifically, more tranquil times should be ceteris paribus associated with greater informational rigidities. Interestingly, if the Great Moderation was caused by changes in monetary policy, then these policy changes not only reduced macroeconomic volatility but they also increased the potency of monetary policy as greater informational rigidities tend to amplify the effects of nominal shocks. On the other hand, the rising degree of inattention in the late 2000s relative to the mid-to-late 1980s implies that the same sized shock would have larger real effects in the latter period because informational rigidities, like nominal rigidities, amplify the response of the economy to a given set of shocks. Thus, this suggests an additional mechanism, along with increased risk-taking on the part of financial market participants, through which the Great Moderation may have contributed to the severity of the Great Recession.

### 4.2.2 Inflation targeting

Another frequently cited contribution of modern central banking is the notion that it has contributed to “anchoring” expectations. One policy used to achieve this goal which has received particular attention is inflation targeting, or the official commitment by a central bank to achieving a numerical target for the inflation rate over some time horizon.\textsuperscript{14} This mechanism, if credible, should lead to a reduction in both the level and the volatility of inflation. The latter implies that, with increased stability, economic agents should devote fewer resources to forecasting inflation. As a result, an implication of credible inflation-targeting regimes should be increased inattention to inflation on the part of forecasters, thereby generating the “anchoring” of expectations. For example, in an extreme case of perfect targeting, all volatility in the

\textsuperscript{13} Although we do not have SPF forecast data before 1968, we conjecture that the relatively high informational rigidities in the late 1960s can be explained by the relatively tranquil period experienced by the U.S. economy in 1960s.

\textsuperscript{14} See Bernanke and Mishkin (1997) for an overview.
inflation rate would be eliminated and therefore economic agents should not allocate any attention to this variable.

However, previous work has had to rely on indirect methods to assess the anchoring of expectations. For example, Levin et al (2004) find that in countries without an explicit inflation target, private sector inflation forecasts at horizons up to 10 years are significantly correlated with a three-year moving average of lagged inflation, but this correlation is largely absent from the five IT countries in their sample. Similarly, Gürkaynak, Levin, and Swanson (2006) find that long-horizon market-based inflation forecasts were invariant to domestic economic news in the UK and Sweden after the adoption of inflation-targeting, but that this was not the case in the UK prior to adopting inflation-targeting or in the U.S. While indicative of a qualitative effect of inflation-targeting, these methods cannot directly assess the quantitative implications of inflation-targeting on the expectations formation process. Our methodology, on the other hand, can readily be applied to study the effect of this type of policy on the expectations formation process with a firm theoretical footing. To do so, we can relate ex-post inflation forecast errors to ex-ante forecast revisions augmented with a time-dummy for inflation-targeting and an interaction term

\[
\pi_{i,t+h} - F_t \pi_{i,t+h} = c + \beta \Delta F_t \pi_{j,t+h} + \gamma (\Delta F_t \pi_{j,t+h} \times IT_{j,t}) + \alpha IT_{j,t} + error_{jt},
\]

where \(j\) and \(t\) index countries and time, \(\pi\) is the inflation rate, \(IT\) is a dummy variable equal to one if a country targets inflation and zero otherwise, and \(\gamma\), the coefficient on the interaction term, will measure the change in information rigidity associated with inflation targeting, if any. This specification thus allows one to assess not just the possibility that inflation-targeting affects the expectations formation process but also quantify the effect of the policy in terms of its effects on the degree of information rigidity.

Within our cross-country sample, there is a set of countries who became unambiguous inflation targeters over the course of time sample: the Bank of Canada officially adopted inflation-targeting in February of 1991, the Bank of England in October of 1992, the Swedish Riksbank in January of 1993, the Spanish Banco de Espana in January of 1995 and the Norwegian Norges Bank in March of 2001. However, other countries in the dataset are close to being inflation-targeting regimes. For example, the European Central Bank (ECB) has an official inflation target of less than, but close to, 2% a year but, because it also has other objectives, is not as clear a case of an inflation-targeting regime as the first group. If the ECB is included as an inflation-targeting regime, then all of the countries joining the Euro-area in 1999 can be viewed as adopting an inflation target. Other countries are also sometime considered de facto inflation targeters. Germany, prior to the Euro, and Switzerland have been officially targeting monetary aggregates since the late 1970s, but Bernanke and Mishkin (1997) argue that they should best be thought of as hybrid inflation-targeting regimes. Similarly, while the Federal Reserve is legally

\[\text{See Little and Romano (2008) and Roger (2010) for detailed lists of inflation-targeting countries.}\]
subject to the dual mandate and has never officially acknowledged an official inflation target, it is frequently viewed as a de facto inflation-targeting regime. In light of the de jure versus de facto distinction, we consider three definitions of a country targeting inflation: i) narrow which covers only countries officially declaring inflation targeting; ii) broad which includes countries in the narrow definition and countries implementing inflation targeting de facto (i.e., Euro area, USA, Germany and Switzerland); iii) intermediate which consists of countries in the narrow definition and countries in the Euro area.16

Results reported in Table 3 suggest that there is no robust evidence that inflation targeting leads to greater information rigidity with respect to the inflation rate, regardless of whether we apply a narrow or broad definition of inflation-targeting. While the point estimates of $\gamma$ are consistently positive, such that inflation-targeting leads to higher degrees of inattention, none are statistically different from zero at the five percent level. Only in the case of the intermediate definition, i.e. including official inflation-targeting regimes and the ECB, is the estimate significant at the ten percent level. Importantly, the point estimates of $\gamma$ are all small, on the order of 0.1. This implies that, even if these coefficients were statistically significant, the implied effect on informational rigidities would not be economically large. As a result, there is little evidence that inflation-targeting has had important effects on the expectations formation process among these countries.

4.3 State-Dependence informational rigidities

Figure 3 documents important time variation in the degree of information rigidity for the U.S. consistent with the large changes in macroeconomic volatility observed over this time period. This finding points to the possibility that the acquisition of processing of information may be more state-dependent than commonly assumed. In this section, we investigate whether information rigidities exhibit state dependence over the course of the business cycle as well as in response to a large, visible shock at the aggregate level.

4.3.1. Informational rigidity over the business cycle

Our results in the previous section indicate that calm times are associated with stronger informational rigidities. In light of this evidence, one may expect that recessions, as periods of increased volatility, should be times when economic agents update and process information faster than in expansions since the

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16 The only country which does not qualify as inflation-targeting at some point in time under the broad definition is Japan. However, even this case is ambiguous: Little and Romano (2008) classify Japan as a hybrid inflation-targeter as of March 2006.
(relative) cost of ignoring macroeconomic shocks in recession rises. Using estimates of $\beta$ computed for each quarter separately as in the previous section, we consider the following econometric specification

$$\beta_t = \alpha + \sum_j \phi_j NBER_{t-j} + \text{error}_t,$$

where $NBER$ is a dummy variable equal to one when the NBER declares the start of a recession in the economy and zero otherwise. By varying index $j$, we construct a sequence of estimated $\phi_j$ which may be interpreted as an impulse response of informational rigidities to a recession. To smooth the path of coefficients $\phi_j$, we fit a polynomial distributed lag model with the polynomial order equal to 4 and $J = 20$.

Figure 4 shows the path of the estimated $\phi_j$ over four years after the economy slides into a recession. We assume that the economy starts at an average level of informational rigidity which is equal to $\bar{\alpha}$. At the time the start of a recession is declared and shortly thereafter, informational rigidities are and remain relatively high. However, as time passes, informational rigidities become less severe to the point where information is updated very frequently (practically every period) one to two years after the start of the recession. Note that the estimated $\phi_j$ turns negative after three-four quarters which is consistent with the time it takes the NBER to declare the start of a recession. In other words, it may take three to four quarters for economic agents to reach the conclusion that the economy is in a recession. The degree of informational rigidity stays low about two years and then it starts to recover to the level observed before the start of a recession.

These dynamics of informational rigidity pose a challenge for popular models of informational frictions such as the sticky information and imperfect information models. In both types of models the choice of frequency of updates or allocation of attention is made given the “average” behavior of the economy rather than a specific contingency. Consequently, agents in these models do not reoptimize every period how much attention should be allocated to tracking macroeconomic conditions and the degree of informational rigidity does not vary over the business cycle. An alternative class of models with state-dependent acquisition of information (e.g., Gorodnichenko (2008)) can qualitatively generate variation of informational rigidities over the business cycle and, more generally, in response to aggregate shocks. For example, Gorodnichenko (2008) shows in a theoretical model that the acquisition of information endogenously increases shortly after the occurrence of an aggregate shock as economic agents face increased uncertainty about the current state of the economy and consequently find it beneficial to devote more resources to learning about current macroeconomic conditions.
4.3.2. The 9/11 Attacks

Both models of informational rigidities considered in section 2 imply that the average current forecast is a weighted average of the previous forecast and the current full-information rational expectation forecast. This accounts for the gradual adjustment of forecasts over time and the positive relationship between forecast errors and forecast revisions. However, like time-dependent pricing, it should be clear that if a large shock occurs, state-dependency will come into play and affect the expectations formation process. For example, under the sticky-information model of Reis (2006), if firms face a fixed cost to acquiring new information, then information updates will be infrequent and time-dependent if no new information can acquired without paying the fixed cost. But if a large shock occurs which is visible to economic agents, this would induce a state-dependent response and synchronized updating of information as in the state-dependent sticky-information model of Gorodnichenko (2008). As a result, the degree of information rigidity should be much lower after a large and visible shock than during normal periods. A similar prediction should obtain under imperfect information models augmented to allow for state-dependence. For example, in Sims (2003), firms are assumed to face a fixed shadow value of information, then choose how to allocate their information-acquisition capacity to maximize profits. However, in the presence of a large and visible shock, agents should perceive an increase in the shadow value and would optimally raise the total amount of resources devoted to processing information, leading to a lower level of information rigidity in the periods following the shock. Thus, in both models, allowing for state-dependence would imply differential rates of informational rigidities in the case of large and highly visible shocks than in the case of normal fluctuations.

The time period of our analysis includes one such unambiguously visible and economically potent shock: the attacks of September 11th, 2001. As shown in Figure 5, the 9/11 attacks were followed by very large downward revisions to U.S. macroeconomic forecasts. For example, in the survey done in August 2001, the consensus forecast for the growth rate of the year-on-year real GDP for 2002Q1 was approximately 2%. In the special October forecasts of professional forecasters organized by Consensus Economics in response to the September 11th attacks, the consensus forecast for the same time period was revised down to -0.5%. Forecasts of industrial production were similarly substantially lowered as a result of the attacks. However, by February 2002, forecasters had raised their projected growth rates of real GDP back up substantially whereas forecasts of industrial projection growth remained very similar to the initial post-9/11 forecasts. The latter points to a rapid adjustment of expectations in line with the full-information rational expectations assumption, whereas the former actually points to overshooting expectations.
To quantitatively assess whether the degree of information rigidity varied during the periods immediately following the 9/11 attacks, we create a dummy variable \( I_{9/11} \) equal to one in the fourth quarter of 2001 and the first two quarters of 2002. We then consider the following specification

\[
x_{j,t+h} - F_t x_{j,t+h} = c + \beta \Delta F_t x_{j,t+h} + \gamma \left( \Delta F_t x_{j,t+h} \times I_{9/11} \right) + \alpha I_{9/11} + \text{error}_j.
\]  

(18)

The coefficient \( \gamma \) on the interaction term of forecast revisions and the 9/11 dummy indicates the difference in the degree of information rigidity associated with the forecast revisions during these three quarters. Results from applying this methodology to U.S. professional forecasters for those macroeconomic variables available since 1968 as well as the estimates using the larger set of variables from 1981 are presented in Table 4 (columns (1)-(4)) as well as results from applying this test to the cross-country dataset, pooled across all countries, variables, and forecasting horizons (columns (5) and (6)). In each case, the coefficient \( \gamma \) is negative and statistically significant, indicating that the degree of information rigidity was lower during the forecast revisions following the 9/11 attacks, as expected in the face of a large and visible shock. In fact, point estimates of \( \gamma \) are, if anything, larger in absolute value than the point estimates of \( \beta \), so that the forecast revisions can be characterized as either full-information rational expectations or even overshooting expectations in the case of the U.S.\(^{17}\) Thus, consistent with the predictions of state-dependent models of informational rigidities, large and highly visible economic shocks will lead to much more rapid adjustment of expectations than during run-of-the-mill periods. The fact that our empirical methodology can identify and differentiate between these types of forecast revisions lends further credence to the notion that informational frictions are the source of the underlying rigidity in the expectations formation process.

V Conclusion

Building from the predictions of models of informational rigidities, we provide a new test of the null of full-information rational expectations which is informative about the economic significance of departures from the null as well as the models that can account for these departures. Applying this methodology to professional forecasters, we document widespread rejections of full-information rational expectations in exactly the direction predicted by models of informational rigidities for the U.S. and other industrialized countries. The estimates also point to economically significant estimates of informational rigidities, thereby providing support for the recent body of work studying the integration of informational frictions into modern macroeconomic models. In addition, our approach can shed light on how best to model the expectations formation process: we document a variety of evidence indicating that professional forecasters can adequately be modeled via imperfect information models.

\(^{17}\) Similar results obtain if we focus on U.S. forecasts in the Consensus Economics data.
While we have focused exclusively on professional forecasters, this methodology can be applied to other economic agents, as long as forecast data is available at multiple forecasting horizons. Thus, one could readily apply this framework to financial market forecasts, such as those implied by the term structure of interest rates or futures/forward contracts for exchange rates and commodity prices, to quantify the implications of informational frictions for financial markets. Similarly, the Greenbook forecasts of the Federal Reserve are well-suited to study the nature and degree of informational frictions faced by the U.S. central bank, which could shed light on the historical experience and have implications for optimal policy. Our methodology could also be applied to quantify informational rigidities for consumers and firms, with obvious implications for macroeconomic dynamics. In short, this approach can shed new light on the nature of the expectations formation process for different economic agents, as well as quantify the importance of these informational rigidities.

In addition, one can apply this methodology to study the implications of different policies on the expectations formation process. For example, we document that the Great Moderation, frequently attributed to the monetary policy changes enacted by Volcker, was associated with a pronounced and persistent increase in the degree of information rigidity for professional forecasters. This provides a new mechanism through which, along with increased risk-taking behavior on the part of financial market participants, the Great Moderation may have played a role in generating the Great Recession. Similarly, our empirical specification can help quantify the effect of policy changes on the expectations formation process, thereby providing a more theoretically grounded notion of otherwise ill-defined concepts such as “anchored” expectations. For example, we provide evidence that the adoption of inflation-targeting regimes among industrialized countries had little to no effect on the estimated degree of information rigidity among professional forecasters, thereby casting doubt on the quantitative importance of this policy for expectations. Importantly, this approach can be applied to study a wide variety of policies such as exchange rate regimes or central bank independence and thereby shed new light on one of the key mechanisms via which these policies are supposed to affect dynamics, namely through the expectations formation process.
References


Table 1. Pooled Estimates of the Expectations Formation Process

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>5 Variables</td>
<td>13 Variables</td>
<td>5 Variables 12 countries</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>FE (2)</th>
<th>OLS (3)</th>
<th>FE (4)</th>
<th>OLS (5)</th>
<th>FE (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast revision</td>
<td>0.387**</td>
<td>0.382**</td>
<td>0.653***</td>
<td>0.653***</td>
<td>0.690***</td>
<td>0.635***</td>
</tr>
<tr>
<td>$\Delta F_t x_{t+h}$</td>
<td>(0.178)</td>
<td>(0.177)</td>
<td>(0.188)</td>
<td>(0.188)</td>
<td>(0.143)</td>
<td>(0.139)</td>
</tr>
<tr>
<td>Observations</td>
<td>3,240</td>
<td>3,240</td>
<td>5,793</td>
<td>5,793</td>
<td>22,341</td>
<td>22,341</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.019</td>
<td>0.018</td>
<td>0.030</td>
<td>0.032</td>
<td>0.047</td>
<td>0.043</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
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<th>OLS (3)</th>
<th>FE (4)</th>
<th>OLS (5)</th>
<th>FE (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F_t x_{t+h}$</td>
<td>0.421**</td>
<td>0.429**</td>
<td>0.651***</td>
<td>0.670***</td>
<td>0.721***</td>
<td>0.663***</td>
</tr>
<tr>
<td>$F_{t-1} x_{t+h}$</td>
<td>(0.173)</td>
<td>(0.174)</td>
<td>(0.179)</td>
<td>(0.179)</td>
<td>(0.140)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>$F_{t-1} x_{t+h}$</td>
<td>-0.481**</td>
<td>-0.530***</td>
<td>-0.576***</td>
<td>-0.506**</td>
<td>-0.782***</td>
<td>-0.736***</td>
</tr>
<tr>
<td>p-value ($\beta + \gamma = 0$)</td>
<td>0.135</td>
<td>0.234</td>
<td>0.258</td>
<td>0.104</td>
<td>0.073</td>
<td>0.233</td>
</tr>
<tr>
<td>Observations</td>
<td>3,240</td>
<td>3,240</td>
<td>5,793</td>
<td>5,793</td>
<td>22,341</td>
<td>22,341</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.022</td>
<td>0.023</td>
<td>0.032</td>
<td>0.039</td>
<td>0.0731</td>
<td>0.233</td>
</tr>
</tbody>
</table>

Notes: The table reports estimated specifications (10) and (12) in Panels A and B respectively. Driscoll-Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.
<table>
<thead>
<tr>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td>estimated coefficient on forecast revisions for country-variable pairs</td>
<td><strong>Dependent variable:</strong></td>
<td>estimated coefficient on forecast revisions for country-variable pairs</td>
<td><strong>Dependent variable:</strong></td>
</tr>
<tr>
<td>Volatility of Innovations, $\sigma_{i,j}$</td>
<td>0.396***</td>
<td>0.408***</td>
<td>0.374***</td>
<td>0.430***</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.061)</td>
<td>(0.101)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Persistence of Series, $\rho_{i,j}$</td>
<td>2.018***</td>
<td>2.040***</td>
<td>1.603***</td>
<td>1.638***</td>
</tr>
<tr>
<td></td>
<td>(0.319)</td>
<td>(0.371)</td>
<td>(0.415)</td>
<td>(0.442)</td>
</tr>
<tr>
<td>Noise-Signal Ratio, $\kappa_{i,j}$</td>
<td>0.418***</td>
<td>0.393***</td>
<td>0.428**</td>
<td>0.336</td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>(0.140)</td>
<td>(0.204)</td>
<td>(0.247)</td>
</tr>
<tr>
<td>Country-Fixed Effects</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Variable-Fixed Effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
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<td>60</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.547</td>
<td>0.591</td>
<td>0.659</td>
<td>0.706</td>
</tr>
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</table>

Note: The table reports estimated specification (16). Robust standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.
Table 3. Informational rigidities and inflation targeting.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Forecast error $\pi_{jt+h} - F_t\pi_{jt+h}$</th>
<th>Canada, 1991-present</th>
<th>Canada, 1991-present</th>
<th>Canada, 1991-present</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Norway, 2001-present</td>
<td>Norway, 2001-present</td>
<td>Norway, 2001-present</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Euro area, 1999-present</td>
<td>Euro area, 1999-present</td>
<td>Euro area, 1999-present</td>
</tr>
<tr>
<td></td>
<td></td>
<td>USA, 1989-present</td>
<td>Germany, 1989-present</td>
<td>Switzerland, 1989-present</td>
</tr>
<tr>
<td>OLS</td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>$\Delta F_t\pi_{jt+h}$</td>
<td></td>
<td>0.200*</td>
<td>0.168</td>
<td>0.121</td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>0.168</td>
<td>0.109</td>
<td>0.109</td>
</tr>
<tr>
<td>$\Delta F_t\pi_{jt+h} \times IT_{jt}$</td>
<td></td>
<td>0.062</td>
<td>0.057</td>
<td>0.177*</td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td>0.057</td>
<td>0.105</td>
<td>0.105</td>
</tr>
<tr>
<td>Observations</td>
<td></td>
<td>4,541</td>
<td>4,541</td>
<td>4,541</td>
</tr>
<tr>
<td>R-squared</td>
<td></td>
<td>0.019</td>
<td>0.015</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Notes: The table reports estimated specification (17). $IT_{jt}$ is the dummy variable equal to one if a country targets inflation in a given time period and zero others. In columns (1) and (2) the set of inflation targeting countries includes only countries with explicit mandate to target inflation. In columns (3) and (4), the set of inflation countries is augmented with countries in the Euro area since the European Central Bank admits an inflation target. In columns (5) and (6), the set of inflation countries is further augmented with the USA since the Federal Reserve Board implicitly admitted an inflation target. Note that the start of inflation targeting is determined by the beginning of the sample. Driscoll-Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.
### Table 4. 9/11.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast error</td>
<td>OLS FE</td>
<td>OLS FE</td>
<td>OLS FE</td>
</tr>
<tr>
<td>( x_{t+h} = F_t x_{t+h} )</td>
<td>(1) (2) (3) (4) (5) (6) (1) (2) (3) (4) (5) (6)</td>
<td>(1) (2) (3) (4) (5) (6) (1) (2) (3) (4) (5) (6)</td>
<td>(1) (2) (3) (4) (5) (6) (1) (2) (3) (4) (5) (6)</td>
</tr>
<tr>
<td>( \Delta F_t x_{t+h} )</td>
<td>0.414*** (0.049) 0.407*** (0.045)</td>
<td>0.713*** (0.139) 0.732*** (0.148)</td>
<td>0.736*** (0.060) 0.681*** (0.058)</td>
</tr>
<tr>
<td>( \Delta F_t x_{t+h} \times I_t^{9/11} )</td>
<td>-0.894** (0.222) -0.851** (0.219)</td>
<td>-1.041*** (0.274) -1.011*** (0.267)</td>
<td>-0.826*** (0.129) -0.828*** (0.117)</td>
</tr>
<tr>
<td>p-value (( \beta + \gamma )) = 0</td>
<td>&lt; 0.01 &lt; 0.01</td>
<td>&lt; 0.01 &lt; 0.01</td>
<td>0.467 0.209</td>
</tr>
<tr>
<td>Observations</td>
<td>3,240 3,240</td>
<td>5,793 5,793</td>
<td>22,341 22,341</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.022 0.021</td>
<td>0.035 0.036</td>
<td>0.051 0.047</td>
</tr>
</tbody>
</table>

Notes: The table reports estimated specification (18). \( I_t^{9/11} \) is the dummy variable equal to one in 2001Q4, 2002Q1, and 2002Q2 and zero otherwise. \( p\text{-value} (\beta + \gamma) = 0 \) shows the probability value for the null that the coefficients on \( \Delta F_t \pi_{t+h} \) and \( \Delta F_t x_{t+h} \times I_t^{9/11} \) sum up to zero. Driscoll-Kraay (1998) standard errors are in parentheses. ***, **, * denote significance at 0.01, 0.05, and 0.10 levels.
Figure 1: Country-Specific Estimates of Informational Rigidities

Notes: The figure plots estimated coefficient $\beta$ on forecast revisions in specification (10) for each country separately. Each circle presents a point estimate for a given country and whiskers show the 95% confidence interval. The solid red line is the point estimate of the coefficient on forecast revisions in specification (10) on pooled (across countries) sample with the shaded region showing the associated 95% confidence interval. All standard errors are Driscoll and Kraay (1998). CA = Canada, CH = Switzerland, DE = Germany, FR = France, IT = Italy, JP = Japan, ND = Netherlands, NW = Norway, SP = Spain, SW = Sweden, UK = United Kingdom, US = USA.
Figure 2: Estimates of Information Rigidity by Macroeconomic Variable

Panel A: U.S. SPF Variables Available 1968-2010

Panel B: U.S. SPF Variables Available 1982-2010

Panel C: Variables Available in Cross-Country Panel Data

Notes: The figure plots estimated coefficient $\beta$ on forecast revisions (left column) and macroeconomic variables (right column) in specification (10) for each variable separately. Each circle presents a point estimate for a given country and whiskers show the 95% confidence interval. The solid red line is the point estimate of the coefficient on forecast revisions in specification (10) on pooled (across variables) sample with the shaded region showing the associated 95% confidence interval. All standard errors are Driscoll and Kraay (1998). GY = real GDP growth rate, HS = Housing starts, IP = Growth rate of industrial production index, DEFL = Inflation rate for GDP deflator, UE = Unemployment rate, 3TB = 3 month treasury bill interest rate, AAA = Interest rate on AAA debt, CPI = Inflation rate for the consumer price index, C = Consumption growth rate, GF = growth rate of federal government consumption expenditures, GS = Growth rate of state government consumption expenditures, NRI = Growth rate of non-residential investment; RI = growth rate of residential investment.
Notes: the figure plots the time series of two variables. The first is the standard deviation of the U.S. real GDP growth rate (annualized) over a five year moving window (red dash line; right axis). The second is the smoothed coefficient $\beta_t$ on forecast revisions in specification (10) estimated for each quarter separately on the SPF data (black thick solid line; left axis). The shaded region is the 95% confidence interval. The smoother is a local average which uses Epanechnikov kernel with bandwidth equal to five.
Notes: the figure plots the response of the coefficient $\beta_t$ on forecast revisions in specification (10) estimated for each quarter separately on the SPF data. The response is estimated as in specification (17). The response is normalized to be at the average value of the coefficient $\beta_t$ one period before a recession starts. The shaded region is the 95% confidence interval. The horizontal, thin, dashed line shows the average value of the coefficient $\beta_t$. The vertical, thin, dashed line shows the time when economy moves into a recession.
Figure 5: Forecasts of U.S. Production Before and After the September 11th, 2001 Attacks:

Panel A: Real GDP Growth Rate

Panel B: Industrial Production Growth Rate

Note: The figure plots consensus forecasts of real GDP growth rates (top panel) and industrial production growth rates (bottom panel) from three different surveys of professional forecasters by Consensus Economics.