

Intrinsic Expectations Persistence

Evidence from professional and household survey expectations

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Abstract

This paper examines the expectations behavior of individual responses in the Survey of Professional Forecasters, the University of Michigan's Survey Research Center survey of consumers, and the ECB Survey of Professional Forecasters. The paper finds that the most robust feature of all of these expectations measures is that respondents inefficiently revise their forecasts, significantly under-reacting to new information. As a consequence, revisions smooth through arriving information, expectations forget past information at a rapid rate, and appear inefficiently to anchor to past forecasts. This result holds for all of the surveys at all forecast horizons for inflation, unemployment, short-term and long-term interest rates, real growth, employment growth, and key GDP components, and is quantitatively and statistically significant. It is robust to the inclusion of all of the real-time information available in these surveys. The paper then tests the micro-implications of the sticky information model of Mankiw and Reis (2002) and the noisy information model of Maćkowiak and Wiederholt (2009). In contrast to Coibion and Gorodnichenko, this paper decisively rejects these models at the micro level—indeed the evidence is inconsistent with any model in which agents efficiently filter information available to them. The paper reconciles its results regarding under-reaction to the results of over-reaction in Bordalo, Gennaioli, Ma, and Shleifer (2018). The paper also provides evidence that distinguishes this behavior from learning, suggesting that the inefficient incorporation of information is much more important quantitatively than least-squares learning in these expectations measures. Finally, this empirical regularity may bear important implications for macroeconomic dynamics, as it provides a micro-based foundation for an earlier paper's finding that intrinsic persistence in expectations may be a key source of macroeconomic persistence (Fuhrer 2017).

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Expectations lie at the heart of all current macroeconomic models. Decisions about prices that will be in effect for multiple periods, about long-lived capital goods, consumer durable goods, and housing, about life-cycle savings choices and about monetary policy inherently depend on expectations about future economic conditions. The idea that economic actors “look forward” or think about the future in making economic decisions seems relatively uncontroversial. Exactly how they peer into the future is much less clear.

The rational expectations paradigm has been used widely in macroeconomic models for decades, and has served the discipline well due to its elegance and computational simplicity. However, few believe that the theory of rational expectations is to be taken literally. Whether it serves as a reasonable approximation to the expectations-formation behavior of firms and households is an empirical matter, and likely depends on the economic question at hand, on the agents studied, and on the economic circumstances. In tranquil times, many financial market participants likely use information quite efficiently. In their own domains, successful firms likely know enough about their environment to make near-rational decisions about inputs, pricing, and market strategy. In these instances, rational expectations could work fairly well as a description of forward-looking behavior (although this too remains an empirical question).

But evidence is mounting that suggests that rational expectations may not be the best assumption to embed in macroeconomic models (see, for example, Fuhrer (2017), Trehan (2015), Fuster, Hebert and Laibson (2012), Adam and Padula (2011), and Roberts (1997)). The addition of many “bells and whistles” to DSGE models (habits, price indexation, complicated adjustment costs) as well as the ubiquity of highly autocorrelated structural shocks, may be construed as evidence that these models are misspecified, perhaps due to the restrictions imposed by the rational expectations assumption. In addition, a number of papers have shown that the rational expectations implied by such models deviate significantly from measured expectations (Del Negro and Eusepi (2010) is one notable example). This finding could mean that the models are misspecified, even though rational expectations remains the valid assumption. Or it could be that the basic model structures are reasonable, but the expectations assumption causes the models to make strongly counterfactual predictions.

A number of papers have explored alternative expectations assumptions and their implications for economic outcomes, in both theoretical and empirical settings. A leading example is learning: see Adam (2005), the many papers of Evans and Honkapohja and their 2001 book, Milani (2007), Orphanides and Williams (2005), and Slobodyan and Wouters (2012). Milani (2007) shows

that the introduction of adaptive learning significantly reduces the dependence of a particular DSGE model on habit formation and price indexation to explain the persistence of macroeconomic time series. Slobodyan and Wouters (2012) find a notable reduction in the persistence of the estimated shocks that drive wages and prices; they also note that the expectations based on the “small forecasting models” in their paper bear a close resemblance to survey expectations. Others have posited models of information frictions to better explain macroeconomic dynamics, including the “sticky information” model of Mankiw and Reis (2002), and the “noisy information” models motivated by Sims’ (2003, 2006) work on rational inattention, and implemented in Maćkowiak and Wiederholt (2009), and Bordalo, Gennaioli, Ma, and Shleifer (2018a,b), for example.

It is striking that relatively few authors have examined in detail the expectations behavior of individual economic agents. Most of the empirical papers cited above use aggregated measures of expectations from available surveys and (in fewer cases) from financial asset prices. Exceptions include empirical work by Crowe (2010), Andrade and Le Bihan (2013), Paloviita and Viren (2013) and a vast theoretical literature that emphasizes the role of higher-order expectations (see especially Frydman and Phelps (2013) and the papers contained and cited therein). Gennaioli, Ma and Shleifer (2016) document the characteristics of surveys of CFO’s expectations of earnings growth. They find that they are not well proxied by Tobin’s Q or discount rates, that they are not rational (in the sense that they make errors that are predictable using information available to the CFOs at the time of prediction), and that they do well in explaining both investment plans and realized investment. But few have attempted to characterize the underlying behaviors in the micro-data from the oft-cited aggregate surveys from the Survey of Professional Forecasters (SPF) and the University of Michigan’s Survey Research Center survey of consumers. Bordalo, Gennaioli, Ma, and Shleifer (2018a) examines a wide array of forecasts for macroeconomic variables, much like this paper, but in contrast, they typically find over-reaction to news. We will turn to their results in section 6 below.

This paper examines a rich set of micro-data evidence on the expectations behavior of firms and households, both in the U.S. and in the Euro Area. The paper is motivated by the observation that aggregated expectations from the SPF appear to improve significantly the performance of standard dynamic macroeconomic models (Fuhrer 2017). While that paper provides an internally consistent way of describing expectations behavior, it does not answer the fundamental question of why survey expectations appear to account for a significant portion of the persistence found in macroeconomic data. That is, apart from the theoretical mechanisms that commonly generate persistence in macroeconomic models (for example, persistence in marginal costs, habit formation,

price indexation, or costs of adjustment), expectations appear to add intrinsic persistence above and beyond (or perhaps, instead of) these mechanisms, and in so doing, account for a large fraction of the persistence observed in macroeconomic time series.

To be a bit more precise about the macroeconomic observation, consider an inflation Euler equation that is widely used in many DSGE models:

$$\pi_t = (\beta - \omega)E_t\pi_{t+1} + \omega\pi_{t-1} + \gamma s_t + \varepsilon_t; \varepsilon_t = \frac{\eta_t}{1 - \rho L},$$

where π is inflation, s is marginal cost, β is the discount rate, ε_t is the serially correlated shock to the equation with autocorrelation parameter ρ and *iid* innovation η_t , and $E_t\pi_{t+1}$ is the rational or model-consistent expectation of the next period's inflation rate. A number of authors have found fairly sizable and significant estimates of ω in estimated versions of this equation (Christiano, Eichenbaum, and Evans (2005), Smets and Wouters (2007)). In addition, it is quite common to estimate sizable values for ρ , the parameter indexing the degree of autocorrelation in the structural shock ε_t .

However, if one instead uses survey measures of expectations in this equation—for example, the median forecast of inflation for period $t+1$ from the Survey of Professional Forecasters—one finds that the data prefer an estimated value for ω that is much smaller and typically not statistically significantly different from zero. In addition, the estimated autocorrelations of the error term ε_t , while sizable in rational expectations implementations of the equation, are much smaller and not significantly different from zero. The same is true for other key equations in standard DSGE models: Structural add-ons that induce lagged dependent variables (habits in consumption, for example) diminish greatly in importance, and structural shocks become much less, if at all, autocorrelated.

What is happening in the estimates of these models with survey expectations? The expectations themselves have induced some inertia that was previously proxied by indexation, habits, and/or autocorrelated shock processes. For inflation, the expectations add persistence above and beyond the persistence that inflation inherits from the marginal cost process. For habits, the expectations capture much of the sluggish adjustment of consumption growth to shocks that were

previously proxied by lagged consumption.¹ While Fuhrer (2017) documents this finding with aggregate data, this paper aims to understand the underlying expectation behaviors that give rise to this kind of persistence in measures of expectations.

The paper uses the individual responses in the SPF, the European SPF (ESPF) and the Michigan Survey of Consumers to better understand the sources of inertia in expectations data. The SPF comprises a few thousand observations on a few hundred firms over the past 30 to 45 years (depending on the variable studied), while the Michigan survey contains over 500,000 observations on tens of thousands of households since 1978. The ESPF begins in 1999, surveys about 100 firms and like the SPF contains several thousand observations per expectations variable. The structures of the datasets differ: Whereas many firms in the SPF and ESPF participate in the survey for many years, if not decades, the Michigan survey samples a household once and then, for a subset of respondents, once again, six months later. The ability to observe the revisions in individual respondents' forecasts is essential to the questions this paper aims to investigate. While all the surveys allow one to compute revisions in expectations, the SPF and the ESPF are much richer in this dimension.

While firms' and households' expectations differ in some respects, this paper finds that they share one key feature. The forecast revisions exhibit what appears to be a significant inefficiency that bears important implications for macroeconomic dynamics: While forecasters revise forecasts in response to new information, such as that revealed in the lagged central tendency of forecasts (and other variables), they appear to inefficiently incorporate new information by tying forecast revisions to their own forecasts for the same variable made in the previous period. As the paper will show, this dependence of revisions on past forecasts implies that forecasters down-weight the impact of new information on their forecasts, smoothing through the information in news rather than incorporating it efficiently.² It also implies that they “forget” information at a fairly rapid rate, rather than accumulating news random walk-style into their forecasts.

Two possible rationales for this observation derive from the models of sticky or noisy information mentioned above. In these frameworks, forecast revisions could be linked to past forecasts, either because forecasters have not yet updated their information sets, or because they reduce the weight on news received, because the signal in the new information is confounded by

¹ Fuhrer (2000) is one of the earliest papers to document the strong empirical significance of habit formation in monetary policy models.

² Earlier papers that examined the properties of forecast revisions for limited sets of forecasters include Berger and Krane (1985) and Nordhaus (1987).

noise, which they efficiently filter out. Coibion and Gorodnichenko (2015) provide tests of aggregate expectations that appear generally to conform with these models. We will examine implications of these models below, and conclude that micro data strongly contradict the aggregate results in Coibion and Gorodnichenko.³

In particular, our evidence suggests that it is uncommon for professional forecasters not to update their information sets from quarter to quarter. However, when they do update, they update inefficiently, making forecast errors that are strongly predictable using information that was available to them at the time of prediction. Households may well update infrequently, but they are similarly shown to update quite inefficiently when they do update. The noisy information model implies that although forecasters filter the information contained in news, they do so efficiently, so their forecast errors should also be efficient with respect to information known at the time of the forecast. This implication is strongly rejected in the micro data.

Bordalo *et al* (2018a) examine micro data from the SPF and the Blue Chip forecasters' surveys, and find that forecasters generally *over-react* to news. Forecasts at the individual level are also found to be predictable (by forecasters' revisions), in violation of the sticky information and noisy information models. They propose a model of “diagnostic expectations” that is consistent with under-reaction at the aggregate level and over-reaction at the individual level. However, as we show in section 6, their test of over- and under-reaction, while informative about the predictability of forecast errors, turns out to be a weak test of over- or under-reaction. The tests in this paper in contrast develop more uniform and strongly significant evidence of under-reaction at the individual forecaster level, the opposite of the implications of the diagnostic expectations model.

One variable that all forecasters appear to incorporate in their revisions is the lagged median of individual forecasts. This information is not available to forecasters at time $t-1$, so using it to update time t forecasts is entirely reasonable, as it serves as a handy aggregator of diverse views on the variables of interest. This result is related to but quite distinct from the “epidemiological” phenomenon found in Carroll (2003), whereby in the aggregate, household forecasts are found to converge over time to the forecasts of professionals. Here, the individual forecasters within the cross-section of household or professional forecasts link their forecasts to previously observed aggregate forecasts from the same sector. While it is rational for forecasters to incorporate this news

³ Coibion and Gorodnichenko (2015) are careful to point out that their key test—that forecast errors should be related only to forecast revisions—holds only on average across forecasters.

into their forecast revisions, forecasters consistently and significantly under-react to the news in the lagged median forecast, as they do to all incoming news.

Another obvious rationale for sluggish expectations adjustment is that agents must learn about the economic environment. Inefficient adjustment to new information will be shown to be a much stronger feature of the data than classic adaptive least-squares learning. The paper provides formal evidence comparing least-squares learning and intrinsic expectations persistence, and finds the latter to be both quantitatively and statistically much more important in determining expectations behavior.

The inefficient response of individual forecasts to news can impart additional persistence to key macro variables when such expectations behavior is embedded in standard models. Importantly, this behavior can induce persistence beyond the persistence that expectations would normally inherit from the variables they wish to forecast. Thus, the pervasiveness of this kind of expectations behavior may bear important implications for explaining the persistence of aggregate macro time series. The rational expectations assumption constrains expectations to embody only those characteristics that the model implies for its variables. The empirical results in this paper suggest that actual expectations add significant persistence of their own to the system. The final section of the paper provides a simple illustration of this effect in a stylized DSGE model.

While much work remains to be done in characterizing such expectations behavior from a theoretical perspective, the implications of these findings for macroeconomic modeling are significant. If expectations at the micro level induce “intrinsic persistence” in the sense articulated in the context of standard inflation models in Fuhrer (2006, 2011), then this persistence may account for a significant portion of the persistence observed in key macroeconomic time series, consistent with the macro-survey findings referenced above. This suggests that other sources of persistence that are common in DSGE models and the like may be (at least in part) an artifact of the misspecification of expectations in those models.

1. Evidence from professional forecasters

We begin by examining the expectations formed by the (presumably) more-sophisticated actors in the economy, namely those who make their living forecasting macroeconomic aggregates such as unemployment, inflation, interest rates and growth. To be sure, not all of the firms surveyed in the SPF or the ESPF are large firms with extensive staff and a long track record of forecasting and forecast model-building. However, as compared to the expertise that is likely embodied in the

average household, it seems reasonable to assume that this group of forecasters is relatively sophisticated.

Tables 1a and 1b provide some summary statistics describing key features of the SPF and ESPF samples. Figure 1 shows the duration and timing of each forecaster’s participation in the SPF survey from 1981:Q3 to the most recent survey in the sample.⁴ A few forecasters are in the survey for two decades or more; quite a few participate for only a few years. The mean and median forecasts for selected years suggest that, on average, forecasts are not strongly skewed in one direction or the other. The sample is roughly evenly split between financial and nonfinancial firms. Others have written about the forecasting accuracy of the SPF and other forecasts (see, for example, Batchelor (1986), Bryan and Gavin (1986), Mehra (2002), and Thomas (1999)). For more details on the SPF, Michigan and ESPF data, see the links to the sources in Appendix A.⁵ As we will see below (Table 15), it is generally not difficult to reject the null of efficiency. However, we will examine in more detail a particularly striking form of inefficiency in what follows.

To help with interpretation of the results that follow, it is useful to consider a simple framework for efficient forecasts and forecast revisions.⁶ An efficient forecast of a variable x made at time t for forecast period $t+1$ should equal the forecast for the same variable and period made at period $t-1$, plus news about the variable that is received in period t :

$$x_{t+1,t} = x_{t+1,t-1} + News_t \quad (1.1)$$

Many of the regressors in equation (1.10) below may be interpreted as news that becomes available in period t and is relevant to the forecast for x in period $t+1$ —the estimates of lagged actual inflation and other macro variables, and the lagged median of forecasts made in $t-1$.⁷ Equivalently, (1.1) implies that the forecast revision from period $t-1$ to period t will reflect only news:

$$R_{t+1,t} \equiv x_{t+1,t} - x_{t+1,t-1} = News_t \quad (1.2)$$

Equation (1.1) can be modified for use as an efficiency test regression:

$$x_{t+1,t} = ax_{t+1,t-1} + News_t \quad (1.3)$$

⁴ We focus on this sample as it represents the period over which the consumer price index (CPI) is collected for the survey. This variable has the advantage that the survey collects both its lagged values and long-term forecasts of it.

⁵ For many applications, including price-setting and investment behavior, it would be more appropriate to investigate the properties of firms’ expectations. However, a consistent dataset that includes firms’ numerical expectations of key macroeconomic variables does not exist for the United States. See Coibion, Gorodnichenko, and Kumar (2015) for an analysis of a set of New Zealand firms’ expectations.

⁶ See Nordhaus (1987) for an exposition of the relationship between forecast revisions and efficiency.

⁷ Here the “*News*” term subsumes the coefficient on the variables that constitute information, which would reflect the information content of those variables for forecasting x , although we do not assume that all of the information is incorporated efficiently, given the other results in the paper.

when the coefficient a differs significantly from one (typically in these data $a < 1$), then the revision from period $t-1$ to period t responds inefficiently to the news received in period t :

$$R_{t+1,t} \equiv x_{t+1,t} - x_{t+1,t-1} = (a-1)x_{t+1,t-1} + News_t \quad (1.4)$$

This particular inefficiency implies a muted or smoothed response to news.⁸ To see this, first allow for an intercept in the regression in equation (1.3), where the intercept could reflect an expectations anchor for the series, perhaps an initial forecast prior to the accumulation of news:

$$x_{t+1,t} = ax_{t+1,t-1} + News_{t+1,t} + (1-a)\mu \quad (1.5)$$

An efficient forecast would entail $a = 1, \mu = 0$. Note that the “news” term has been made more specific to denote the news about x_{t+1} that is observed in period t . We can solve equation (1.5) in terms of the history of news:

$$x_{t+1,t} = \sum_{i=0}^{\infty} a^i N_{t+1,t-i} + \mu \quad (1.6)$$

When $a = 1, \mu = 0$, equation (1.6) implies that the forecast equals the cumulative sum of the news received about x .

$$x_{t+1,t} = \sum_{i=0}^{\infty} N_{t+1,t-i} \quad (1.7)$$

When $a < 1$ and $\mu \neq 0$, the equation implies that news is down-weighted for all horizons, with geometrically declining weights a^i going back in time. One can think of equation (1.6) with $a < 1$ and $\mu \neq 0$ as reflecting a muted response of forecasts to news, with forecasts that are biased towards the anchor μ , whatever that may represent.

One can similarly see the implications for smoothing by considering a sequence of forecasts for a fixed terminal date $t+k$ made at viewpoints dates $j=1, \dots, t$. Define the expectation at viewpoint date t as the cumulative sum of the revisions $R_{t+k,j}$ up to that point, given an initial forecast $x_{t+k,0}$:

$$x_{t+k,t} = x_{t+k,0} + \sum_{j=1}^t R_{t+k,j} \quad (1.8)$$

⁸ Note that for values of $a > 1$, the equation would imply an over-reaction to news, as is the case for some variables in some surveys of financial market participants.

For efficient forecasts, the revisions are just the sum of the news shocks received in each period, since $R_{t+k,j} = N_j$, as noted above. A simple way of contrasting the processes for revisions under the assumptions of efficient versus inefficient incorporation of news is⁹:

$$\begin{aligned} R_{t+k,j}^E &= N_j \\ R_{t+k,j}^I &= \rho R_{t+k,j-1}^I + (1-\rho)N_j \end{aligned} \tag{1.9}$$

Where the superscripts [E,I] represent “efficient” and “inefficient.” Accumulating the revisions in the top equation of (1.9) yields a Martingale process; accumulating the revisions in the bottom equation of (1.9) yields a smoother expectations process. For illustrative purposes, using an arbitrary sequence of news shocks and setting ρ to the values [0.9,.75,.6] yields the simulated expectations series in Figure 2.¹⁰

It is clear from Figure 2 that expectations that inefficiently incorporate news in this way will tend to smooth the response to news. Note that the first autocorrelation for the inefficient expectations series (a rough proxy for the “persistence” of the series) increases from 0.77 to 0.87 as ρ rises from 0.6 to 0.9, while the first autocorrelation of the efficient forecast is 0.57—in this sense, inefficient expectations increase persistence relative to rational/efficient expectations. The incorporation of such expectations into a model in which key household and firm decisions depend on expectations will induce additional persistence into the model economy that arises solely from the expectations process.

Whether one takes all of these implications literally is not critical, but the notion that forecasts exhibit a muted and inefficient response to news is central. This will imply that in models with strong dependence on expectations, rather than “jumping” or moving rapidly to new equilibria in response to shocks, the economy will adjust more gradually. We will return to this notion more formally in section 7 below, in which we demonstrate the additional persistence induced in the context of a multi-equation dynamic model. Note in addition that equation (1.2) implies that revisions will be independent across time, while equation (1.4) implies that revisions are correlated (as long as the variable X_t is correlated across time).

⁹ See Nordhaus (1987) for an exposition of these points. The figure on this page essentially replicates Nordhaus’s Figure 1. Note that section 2 illustrates the reason for correlation across time in revisions when revisions are inefficient.

¹⁰ Table A.1 shows the correlation of forecast revisions from the SPF for three key variables at several horizons. As suggested by all the results in this paper, revisions for any variable for terminal date t made from viewpoints $t, t-1, t-2, t-3$ are highly correlated, as the table clearly shows.

Properties of individual SPF forecasts

Table 2 presents results from the first set of test regressions for inflation, very simple efficiency regressions for individual forecasts like those characterized in equation (1.5). The regressions include the forecasters' idiosyncratic (real-time) estimates of lagged inflation, a measure of the previous period's central tendency of the SPF forecast for the same variable (a variable that summarizes the information in the previous period's forecasts), and lagged individual forecasts.¹¹

$$\pi_{t+1,t}^i = a\pi_{t-1}^i + b\pi_{t+1,t-1}^i + cC(\pi_{t+1,t-1}^i) + dZ_t^i + \delta_i + \varepsilon_t^i, \quad (1.10)$$

where $\pi_{t+1,t}^i$ is the i^{th} forecaster's forecast of consumer price index (CPI) inflation for period $t+1$ made in period t ; π_{t-1}^i is the i^{th} forecaster's estimate of lagged inflation as of period t , $\pi_{t+1,t-1}^i$ is the i^{th} forecaster's forecast for the same horizon $t+1$ made last period ($t-1$), $C(\pi_{t+k,t-1}^{SPF})$ is a measure of the lagged central tendency of forecasts for the same variable for period $t+1$ using the previous period's information set, here taken to be the median of the forecasts, Z_t^i is a vector of other forecaster-specific variables, which includes real-time individual estimates of lagged unemployment, output growth, and the Treasury bill rate, and δ_i denotes forecaster-specific fixed effects.¹² Standard errors are corrected for heteroskedasticity, autocorrelation, and correlation among panels using the method developed in Driscoll and Kraay (1998).¹³ The regression (1.10) is estimated as a panel for the sample from 1981:Q4 to 2018:Q1.

As shown in Table 2, the individual forecasters' own lagged-viewpoint forecasts always enter significantly, but the coefficients on the lagged-viewpoint date forecasts range from 0.3 to 0.5, markedly different from the efficient value of one. Forecasters' estimates of lagged inflation sometimes enter significantly, but with relatively small coefficients. The fifth line in each panel of the table presents the test for the efficiency of forecasts. For all variables and all horizons, the hypothesis $a=1$ is rejected overwhelmingly.

¹¹ Observations later in the sample show a considerably smaller dispersion of estimates of lagged inflation.

¹² We consider other proxies for the lagged central tendency of forecasts, but the median forecast dominates other options.

¹³ The data for the GDP deflator begin earlier, in 1968:Q4, but we focus on the CPI because (a) the SPF does not collect sufficient lags of the GDP deflator to form a lagged inflation measure, and (b) long-run inflation expectations are not collected for the GDP deflator. Despite these limitations, similar test regressions using the GDP inflation measure develop very similar results.

While these simple regressions provide an interesting first look at the data, they suffer from the difficulty that it is not possible to control for all the possible inputs to any individual forecast. An easier-to-interpret version of the regression casts it in terms of revisions, as suggested above. The revision differences out all of the information in the $t-1$ period forecast, and thus focuses on the incorporation of news into successive forecasts.¹⁴ Subtracting the lagged-viewpoint forecast from both sides, one can write the revision form of equation (1.10)

$$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = (a-1)\pi_{t+1,t-1}^{i,SPF} + b\pi_{t-1}^i + cC(\pi_{t+1,t-1}) + dZ_t^i + \delta_i + \varepsilon_t^i \quad (1.11)$$

In many of the regressions presented below, we use the specification:

$$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = (a-1)[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + b\pi_{t-1}^i + c'C(\pi_{t+1,t-1}) + dZ_t^i + \delta_i + \varepsilon_t^i \quad (1.12)$$

In this version, the forecast revision can be a function of the discrepancy between the $t-1$ viewpoint forecast and the $t-1$ central tendency, along with other variables. This regression allows us to examine the extent to which, other things equal, the current forecast is revised downward toward the lagged central tendency when the previous forecast lies above it. There is no reason that an efficient forecast should be revised in this way: An efficient revision should indeed incorporate the news in the lagged central tendency, but it should not do so relative to the discrepancy between the previous forecast and the central tendency. Note that the lagged central tendency of forecasts is included separately in the regressions as a simple means of testing the discrepancy restriction—if we cannot reject $c' = 0$, we fail to reject the restriction. The larger is the coefficient on the lagged discrepancy, the slower is the adjustment to new information. Table 3a reports the results from revision regressions from equation (1.12), where the variables are as defined for table 2.¹⁵ Regression (1.12) is estimated as a panel regression for the sample 1981:Q3 to 2018:Q1, with standard errors corrected as noted above.

All regressions develop negative and precise estimates of $(a-1)$, strongly rejecting efficiency (i.e. the implied estimate of a is well below one). In addition, when forecaster i 's $t-1$ period forecast of inflation in period $t+k$ is above the central tendency of all $t-1$ vintage forecasts, the i^{th} forecaster

¹⁴ Focusing on revisions also avoids the many difficulties that arise in working with forecast errors, as the appropriate definition of the “actual” data to use in computing the forecast error is fraught with difficulty. We will return to forecast error regressions along the lines of Coibion and Gorodnichenko (2015) below.

¹⁵ In an earlier version of the paper, we also examined other candidates for the central tendency reference: (1) the median of all forecasts for period $t+1$ made in period $t-1$ (this is the measure used in table 2); (2) the forecasts for the same origin and horizon made by the forecasters who have been in the dataset longest, as a proxy for the largest and (perhaps) most-respected forecasters in the sample; and (3) the average of forecasts for period $t+1$ made in period $t-1$ by the three forecasters with the lowest RMSE, computed real-time for the preceding 8 quarters. These measures were dominated by the median of individual forecast. For the balance of the paper, we will use the median as the measure of the central tendency.

tends to gradually revise his next forecast for the same period toward the central tendency. This result appears quite robust across control variable sets and time periods. The right-hand columns of Table 3a show the results for additional forecast horizons. For all forecast horizons, with all sets of controls, the coefficient on the lagged discrepancy from the median varies between -0.52 and -0.59. The results are uniformly strong, suggesting that individual forecasters are quite inefficient, and can be thought of as revising *all* of their forecasts gradually in response to news.¹⁶ As noted above, the inclusion of the lagged median forecasts as appropriate for the forecast horizon allows the regression to undo the restriction that median forecasts enter only as a discrepancy relative to individual forecasts. In some cases, these estimates are not significantly different from zero, but in all cases, the estimated inefficiency in the forecast revision $a - 1$ is negative, large and statistically significant.¹⁷

Figure 3 displays a bin scatter plot of forecast revisions for several variables at several forecast horizons against the lagged forecast (the first term on the right-hand side in (1.12)), controlling for the lagged median, and the negative correlation is clear. Figure 4 displays a histogram of the coefficients for equation (1.12) estimated for each forecaster in the sample. While there is clearly some heterogeneity in the degree of inefficiency and the “speed of adjustment” to new information, it is also clear that the mass of estimates is solidly centered between zero and minus one, with a modest standard error. The aggregate regression is not the artifact of a few outliers.

Table 3b provides parallel results for the unemployment forecasts from the SPF, using the revisions to the one- to three-quarter-ahead forecasts for the unemployment rate. Once again, the evidence of inefficient revisions that respond slowly to new information is strong, and changes little with the addition of other forecaster-specific controls. The right-hand columns display results for the longer forecast horizons, and the results are similarly strong. Regardless of the set of control variables, the revision in the forecast for period $t+k$ between periods $t-1$ and t always responds significantly and sizably to the lagged-viewpoint forecast and to the median of all forecasts last period. Tables 3c-3g display parallel results for real GDP growth, and for several financial variables—the 3-month Treasury bill rate, the 10-year Treasury yield, and the BAA Corporate bond

¹⁶ Because the quarterly forecasts extend out only four quarters, we are only able to compute lagged forecast revisions out to quarter $t+3$.

¹⁷ Note that the discrepancies for horizons $t+2$ and $t+3$ are adjusted accordingly ($\pi_{t+2,t-1}^i - \pi_{t+2,t-1}^{Median}, \pi_{t+3,t-1}^i - \pi_{t+3,t-1}^{Median}$, respectively). Results for the four-quarter average forecast from t to $t+3$ produce similar results—for example, the coefficient on the discrepancy is -0.46 for inflation, with p -value of 0.000.

yield, for the growth in components of GDP, for the GDP deflator, and for the growth in nonfarm payroll employment. The results are strikingly similar.¹⁸

Figures 5a-e display evidence on the time-variation in the key regression coefficient in Figure 3, for inflation, unemployment, GDP growth, the 3-month Treasury bill, and the 10-year Treasury yield. Each panel shows estimates of $(a - 1)$, using twenty-quarter rolling samples from 1969-2018:Q1, depending on data availability. The coefficients generally fall between -0.4 and -0.8, most commonly from -0.55 to -0.75. The values are quite stable from 1981 through 2000. For some variables (notably inflation), there is a modest decline in the magnitude in the mid-2000s to about -0.4, but in more recent samples, the estimate has reverted to about -0.7. The standard errors on these coefficients, not shown, are about 0.01, so these fluctuations are statistically significant. It is remarkable that the magnitude and stability of this revision coefficient is so similar across all variables and time periods. It is particularly notable that both financial and real variables display the same pattern of under-reaction to news, which differs from the findings of over-reaction in Bordalo *et al* (2018a,b).

The role of common information

It is likely that the forecast revisions are correlated with the lagged median forecast simply because the median forecast, not observed when forecasters submit their $t-1$ forecasts, contains information that forecasters should use to update their forecasts. Of course, revisions to individual forecasts should not reflect the common information known to forecasters at the time of forecast. However, revisions to individual forecasts might reflect revisions to the common information known at the time of the forecast. Note, however, that the omission of such information should not bias the coefficient on the lagged-viewpoint individual forecasts, as news that is only observable as of period t cannot be correlated with the $t-1$ individual forecasts, by definition.

To control for this possibility, Table 4 presents regressions of the individual forecast revisions on the lagged discrepancies from Table 3, adding the revision in the median forecast, which could reflect revisions due to changes in commonly held information. The last aggregate forecast revision that we know can be observed by individual forecasters is the change in the median forecast from viewpoint $t-2$ to viewpoint $t-1$; this is the first added regressor in the table. As the

¹⁸ This result differs from that of Bordalo *et al* (2018b), who find a systematic over-reaction by CFOs to information relevant for forecasting financial variables, versus the systematic under-reaction found here. For the variables available in the SPF, there appears to be little difference between the forecast properties for nonfinancial and financial variables.

results in the table indicate, while the lagged aggregate revision is sometimes significant, this addition has no impact on the key result from above: Individual forecasters continue to revise their forecasts gradually and inefficiently in response to the lagged discrepancy between their forecast and the median forecast.

But forecasters may also revise the current forecast based on revisions in common information for period t that is not observable to the econometrician. While the contemporaneous revision to the aggregate forecast cannot be observed by individual forecasters in real time, some of the information that it contains may be observed by forecasters at time t . Thus contemporaneous aggregate forecast revisions are included in the right-hand columns of Table 4 as a generous proxy for contemporaneous revisions in unobserved common information. While the coefficients on this variable are larger and quite significant—estimated magnitudes fall between 0.8 and 0.9, with near-zero p -values—the coefficients on the individual forecast discrepancies are essentially the same as those using the lagged aggregate revision, and are qualitatively unchanged from the regressions that omit the aggregate revision. As a way of controlling for the fact that the contemporaneous revision is not observable to individual forecasters at the time it is collected, the final column of the upper panel of the table provides estimates in which the current aggregate revision is instrumented by lags of aggregate revisions for periods t and $t+1$. The results are virtually identical to the others.

The bottom panel of Table 4 replicates these results for the unemployment forecasts in the SPF. As with the inflation forecasts, the inclusion of lagged, contemporaneous or instrumented contemporaneous revisions has no effect on the correlation between the individual forecast revisions and the lagged discrepancy from the median forecast. If anything, the inclusion of controls for revisions in common information strengthens the key results from Table 3.¹⁹

Learning versus inefficient revisions

¹⁹ Table A.2 in the appendix presents regressions that add a host of additional revision variables. The revisions include revisions to the aggregate forecasts, both lagged and contemporaneous; revisions to individual lagged inflation, unemployment, Treasury bill and output growth estimates; revisions to current-period forecasts of the same four variables; and revisions to other forecast variables for other forecast horizons. The table essentially provides a way of decomposing the sources of news relevant to a given forecast as of period t , using all of the information in the forecast dataset. As the table indicates, none of these variables alter the conclusion that revisions respond inefficiently to new information, including any information newly revealed in the lagged central tendencies. The coefficients for the inflation variable are a bit smaller than in the baseline; the coefficients for the unemployment variable are the same size. The significance is not at all affected. Given the “kitchen sink” nature of this regression, this is a strong result.

A vast literature has examined the properties of models in which agents must learn about their economic environments, possibly converging to rational expectations equilibria over time (see the citations above). Can the results in this paper distinguish between anchoring to a lagged central tendency and learning behavior?

The answer appears to be “yes,” although this is a tentative conclusion. Learning models typically posit least-squares or recursive least-squares learning, in which expectations are formed by time-varying projections of observables on lagged data. Such projections may be viewed as the reduced form for an expectations process that could converge, with sufficient observations and stability of the economic environment, to the restricted reduced form consistent with the rational expectations solution for the model economy (see the work pioneered by Evans and Honkapohja, as summarized in their landmark 2001 book).

Table 5 examines regressions that include the lagged discrepancy variables discussed above, along with individual real-time estimates of lagged macro variables, as a way of determining whether the results presented above are in some way a proxy for learning about the reduced-form projection of the variables of interest on lagged observables. The left-hand columns focus on inflation forecasts, and the right-hand columns focus on unemployment forecasts. The leading columns in these blocks simply reprise the results from above, which show that for the full sample, the inclusion of lagged actual variables does not change the dependence on the lagged discrepancy. The next sets of columns estimate these regressions over shrinking samples going forward in five-year blocks. These columns show that this feature of the forecasts is extremely stable over time. The results in Table 5 suggest strongly that the tendency to revise forecasts inefficiently, leading to intrinsic persistence in expectations, is quite distinct from the formation of expectations from lagged real-time realizations of inflation, unemployment, output or interest rates. The coefficient on the discrepancy variables remains uniformly negative and overwhelmingly significant. There is some evidence of a linkage from expectations to lagged and current real-time actuals, but these coefficients are generally smaller and less significant. The presence of these variables does not reduce the size of the response to the discrepancy, suggesting that learning and inefficiently gradual responses to new information remain distinct in these regressions.

Figure 6 presents results that allow period-by-period time-variation in the projections, which conforms more to the spirit of the learning literature. The figure shows estimated coefficients for rolling estimates of the equation from Table 5 for the revision to the one-quarter inflation forecast. The top panel shows the coefficient on the lagged discrepancy, and the bottom panel shows the

coefficients on lagged real-time inflation. The coefficients are estimated precisely throughout. There is a modest amount of time-variation, but there is no evidence in these estimates that the tendency for forecasters to move their forecast toward the lagged central tendency is a proxy for least-squares learning projections on lagged observables.

Altogether, the results summarized in Tables 2–5 suggest that forecasters revise their current-period forecasts inefficiently, incorporating news (including the lagged central tendency of all forecasts) slowly. In so doing, they introduce intrinsic persistence to their forecasts, dramatically slowing their adjustment to new information. This finding holds for all forecast horizons for inflation, unemployment, and other forecasted variables in the SPF dataset. The result holds when including controls for lagged information, revisions to aggregate forecasts that might reflect revisions to unobserved common information, and revisions to estimates of lagged and current variables that might be used as inputs to individual forecasts.

The dependence of forecast revisions on lagged forecasts suggests dynamics in expectations that cannot be captured by full-information rational expectations models. The results presented in table 6 and in figure 6 suggest that this behavior is not a stand-in for least-squares learning. A richer information structure combined with sluggish incorporation of new information is required to motivate these findings; a simple example of such a structure is discussed in Section 8 below.

2. Evidence from the European SPF

The ESPF surveys are organized somewhat differently from the Philadelphia Fed’s SPF. The available forecast horizons change during the history of the survey, which began in 1999. The forecasts employed in this paper include the current year and the one- and two-year ahead forecasts for inflation, unemployment, and output growth. The relationship between forecasts from quarter to quarter is not the same as in the SPF; the current forecast year remains the same for all four quarters of a calendar year, whereas the quarterly-focused SPF’s current quarter changes with the survey quarter. As a consequence, some care must be taken in defining forecast revisions in the ESPF. More details on the ESPF may be found on the ECB website, referenced in the appendix.

Tables 6-8 provide estimation results for forecast revisions that parallel those for the SPF dataset. For each forecast variable (inflation, unemployment and output growth), we examine the predictability of the revision in the current-year and one-year-ahead forecast. As with the SPF forecasts, we are particularly interested in whether the revisions efficiently incorporate new information. To do so, we run regressions like those in tables 3, focusing on the correlation between

the revisions and the discrepancy between the previous quarter’s individual forecast and the median of all previous quarter’s forecasts. As above, these regressions can provide evidence of inefficient revisions that imply sluggish adjustment to new information. Recognizing the difference in the timing convention between the SPF and the ESPF, we estimate regressions of the form

$$\pi_{y,t}^{i,ESPF} - \pi_{y,t-1}^{i,ESPF} = \gamma[\pi_{y,t-1}^{i,ESPF} - C(\pi_{y,t-1})] + b\pi_{t-1} + cZ_t^i + \delta_i + \varepsilon_t^i; k = 0,1 \quad (2.1)$$

where now the revision denoted by $\pi_{y,t}^{i,ESPF} - \pi_{y,t-1}^{i,ESPF}$ refers to the change from last quarter to this quarter in the forecast for year k made by forecaster i . The discrepancy from last period denoted by $\pi_{y,t-1}^{i,ESPF} - C(\pi_{y,t-1})$ is the difference between the forecast for year k made last quarter by forecaster i and the central tendency of all forecasts for year k made last quarter. In this section, we consider only the median as the measure of central tendency. The ESPF does not collect individual forecasters’ assessments of last quarter’s/year’s observations, so we use the real-time estimates of lagged inflation (and unemployment and real growth) in the regressions that follow. Of course, the observations for these real-time estimates do not vary across forecasters.

The control variables in Z_t^i differ from those in the US SPF, as the ECB survey collects what they call “assumption” variables for the price of oil, the exchange value of the euro relative to the dollar, the ECB policy rate assumption, and (for some observations) a labor cost measure. These “assumption” variables are collected for the same forecast horizons as the three main variables of interest. Tables 6-8 display simple versions of the test regression (2.1) which omit Z_t^i , as well as versions that include assumption variables, lagged revisions, lagged discrepancies, and current values of the forecasts for the other variables in the survey.²⁰ The regressions all span the available data for the Euro SPF from 1999:Q1 to 2018:Q1.

The robust conclusion from these results is the same as that for the US’s SPF: Individual forecasters adjust their forecasts in this period to the information revealed in the median of all forecasts last period, but they do so gradually and inefficiently, tying current forecasts to previous forecasts. The results are as strong as the U.S. results for inflation, with somewhat smaller coefficients for the unemployment rate. Table 9 includes the revisions to the aggregate (median) forecasts, in an attempt to control for the influence of common information on individual forecasts

²⁰ An important difference between the ECB dataset and the Philadelphia Fed’s SPF is that the former does not capture the real-time estimate of lagged inflation.

as with the SPF data. Again, the response to the lagged forecast discrepancy is unaffected by the inclusion of these strong proxies for revisions to common information.

3. Evidence from households

Table 10 provides evidence on the revisions of forecasts from the University of Michigan’s Survey Research Center Survey of Consumers. This monthly survey is largely a cross-sectional survey of about 500 randomly selected households per month. However, a subsample (about one-fifth) of respondents is interviewed again six months later, and the unique identifiers assigned to each respondent allow us to track this subset of households from the first to the second interview. This limited panel feature of the data allows us to examine the revisions in inflation expectations.

Table 10 displays the results from the test regressions

$$\pi_{t+1y,t}^{i,Mich} - \pi_{t+1y,t-1}^{i,Mich} = a\pi_{t-1,t} + b[\pi_{t+1y,t-1}^{Mich} - C(\pi_{t+1y,t-1}^{Mich})] + cC(\pi_{t+1y,t-1}^{Mich}) + dZ_t^i + \delta_i + \varepsilon_t^i, \quad (3.1)$$

where $\pi_{t+1y,t}^{i,Mich}$ is the i^{th} forecaster’s one-year-ahead inflation expectation made in period t and $\pi_{t+1y,t-1}^{i,Mich}$ the corresponding expectation made in the previous period $t-1$, $\pi_{t-1,t}^i$ is the real-time estimate for lagged actual inflation for the vintage of data collected for period t , $C(\pi_{t+1y,t-1}^{Mich})$ is the median of all forecasters’ one-year-ahead inflation forecasts made in period $t-1$, and Z represents a vector of other controls that include survey respondents’ continuous and qualitative assessments of unemployment, family income, current and expected financial prospects, and general business conditions.²¹ ²²

The bottom panel of Table 10 provides the results of the simple test for forecast revision efficiency, as discussed above for the SPF forecasts. The sample spans 1978:Jan through 2017:Apr. The results for the test regression, for both the one-year and the five-year inflation forecasts, are unequivocal: The sub-sample of Michigan respondents does not use the information in their previous forecasts efficiently (the test $a = 1$ in the test regression

$$\pi_{t+1y,t}^{i,Mich} = a\pi_{t+1y,t-1}^{i,Mich} + bC(\pi_{t+1y,t-1}^{Mich}) + \varepsilon_t^i \text{ rejects with overwhelming significance).}$$

²¹ The assessments of one-year and five-year inflation and family income expectations are numeric; other variables are encoded according to better/worse/same or similar qualitative categories.

²² Unlike the data for the surveys of professional forecasters, these data may well be subject to measurement error. Importantly, individual responses for inflation expectations are rounded to the nearest integer. A classical measurement error argument would suggest that the coefficients in the regressions in equation (3.1) are biased *downward*, which implies an even more inefficient adjustment of expectations over time. That is, if the estimated coefficient of about -0.7 in Table 11 is biased towards zero, then the true coefficient is even more negative, and the implied a is even smaller. A small Monte Carlo simulation gauging the effect of rounding on such a regression finds a small downward bias in the estimated coefficient on the discrepancy, on the order of -0.03 for a true coefficient of -0.50.

Table 10 provides the results from equation (3.1), as in equation (1.12) above for the SPF data. Because the time dimension of individual survey participants' responses is limited, we examine in this table the extent to which the pooled-cross section results vary over time. With a sizable number of observations for each cross-section, we are also able to examine whether these revision regressions correspond only to times of economic tumult (recessions), or times of relative calm, or both.

Here again, the results are strong and consistent across controls and time periods. The respondents inefficiently use the information in their previous forecasts of inflation. The coefficient on the lagged discrepancy between individual forecasts and the median forecast varies narrowly between -0.68 and -0.72 for all of the specifications presented in the table, indicating a small coefficient on the lagged viewpoint date forecast and a sizable coefficient on the lagged median forecast. While it certainly seems plausible that Michigan respondents do not produce efficient forecast revisions, it seems somewhat less plausible that households exhibit the kind of consistency that the SPF participants show in responding to previous periods' central tendencies. On the other hand, the number of observations is almost two orders of magnitude larger, so our confidence in the statistical significance of the results is high, even if the individual behaviors of household respondents may vary significantly around the estimated results.

Some may question the likelihood that the household respondents in the Michigan survey anchor their expectations to the previous central tendency. However, the revision results in Table 11 are based on the subset of survey participants who are re-sampled six months later. This subgroup may make some effort at that point to check the newspaper, the news, or the Internet to discover what people are saying about inflation, and they may revise their expectations toward that observation, as suggested by the regression results. This kind of "paying attention when it counts"—a variant of rational inattention models (see, for example, Sims 2006)—might suggest that consumers considering an important decision may also pay attention to prevailing forecasts/economic opinions/commentary at these key decision points.

4. **"Anchoring" inflation expectations**

Many economists embrace the notion that inflation expectations may be "well-anchored" to the central bank's inflation goal, especially in the context of a credible inflation-targeting monetary regime. By this, economists often mean that long-run inflation expectations do not deviate far from the central bank's announced inflation goal. In addition, they often assert that such anchored

expectations provide a firm anchor for realized inflation, perhaps explaining why the variation of inflation in the wake of the Great Recession has been relatively small.

Note that in rational expectations models, if the price-setting agents know the central bank's target, their expectations will be perfectly anchored, in the sense that all well-behaved models that embed such a price-setting mechanism will converge to the central bank's goal. Of course, the rate of convergence will depend upon key parameters governing other aspects of the model, including the monetary authority, the consumption Euler equation, and so on. But one can envision an environment in which price-setters are uncertain about the central bank's goal, or about the central bank's commitment to a known goal. In this case, it is possible for long-run expectations to become un-anchored from the central bank's target. While most speak of "anchored expectations" with somewhat less specificity than this, it has nonetheless become a mantra of central bankers to speak about the importance of anchored expectations that assure an ultimate return of inflation to the central bank's inflation target.

If anchoring to long-run expectations is an important feature of inflation and inflation expectations, then the omission of this variable from the regressions above could bias the estimates presented in Tables 2–10. However, the SPF and Michigan datasets allow us to examine the extent to which short-run inflation expectations are anchored to long-run expectations. Figure 7 displays the median 10-year CPI inflation forecast from the SPF from the date it was first collected (1991:Q4) through 2018:Q1.

Table 11 presents results from regressions that augment those in Section 2 with the revision to the median 10-year CPI inflation forecast, which enters with a lag, as it would not be observable to all forecasters contemporaneously. The top panel of the table presents results from these regressions for the full sample. The long-run forecast revision typically does not enter significantly, but regardless, it does not alter the strong but sluggish reversion to the lagged discrepancies reported throughout. The bottom panel displays the same regressions for the period from 2000 to the present. While a few of the coefficients on the lagged 10-year forecast revision change in magnitude, none are significant, and the effects on the response to the lagged discrepancy are trivial.

The household data afford some opportunity to examine the question of anchoring as well. For most of the sample, a 5-year inflation forecast is collected by the SRC, so we use this as a proxy for the long-run forecast around which short-run expectations might be anchored. For expositional clarity, and because the 1- and 5-year expectations have a 20 percent overlap, we construct the

implied expectation for years 2–5 and use it as the long-run anchoring proxy.²³ As Table 12 shows, short-run expectations remain tied to the lagged central tendency regardless of which other regressors are included. There appears to be some linkage to the lagged median 2–5-year expectation, but the magnitude is modest. Whether this constitutes anchoring to the central bank’s inflation goal or part of the solution to a filtering problem, in much the same way as the link to the 1-year expectation, is difficult to tell. Overall, then, while the evidence for sluggishly incorporating the information in lagged aggregate expectations remains strong, the evidence for anchoring to the long-run expectation is modest, at best.

5. Sticky information?

The important work of Coibion and Gorodnichenko (2015) finds high-level support in aggregate surveys of expectations for the sticky information model of Mankiw and Reis (2002), and for the noisy information model of Maćkowiak and Wiederholt (2009) and others. While the paper provides a host of useful empirical results, the key insight is that both models imply that forecast revisions are sufficient to explain forecast errors (in the sense that all other variables lose their significance in aggregate forecast error regressions). The logic follows directly from the definition of the sticky information setup (the noisy information case is discussed in the next section). The average expectation for variable x at date t will be a geometrically weighted average of the rational expectations formed at the current and all lagged viewpoint dates:

$$x_{t+1,t} = (1 - \lambda) \sum_{k=0}^{\infty} \lambda^k E_{t-k} x_{t+1} \quad (5.1)$$

The average expectation as of date $t-1$ is given by a parallel equation

$$x_{t+1,t-1} = (1 - \lambda) \sum_{k=0}^{\infty} \lambda^k E_{t-k-1} x_{t+1}, \quad (5.2)$$

which implies that the revision from the $t-1$ to the t period forecast is given by

$$R_{t+1} \equiv x_{t+1,t} - x_{t+1,t-1} = (\lambda - 1)(x_{t+1,t-1} - E_t x_{t+1}). \quad (5.3)$$

Note that the coefficient λ estimated in Coibion and Gorodnichenko (2015) is the coefficient in the regression of revisions on the lagged viewpoint (average) forecast, and thus is the aggregate

²³ The two- to five-year expectation is computed as one fourth the difference between five times the five-year expectation and the one-year expectation, i.e., $X_{t+2,\dots,5}^e = 0.25[5(X_{t+1,\dots,5}^e) - X_{t+1}^e]$; $X_{t+1,\dots,5}^e = 0.2[X_{t+1}^e + \dots + X_{t+5}^e]$.

version of the coefficient a estimated in the individual forecaster revision regressions above. The estimates of λ obtained in G&C center on about 0.5, and thus correspond quite well to the estimates of a obtained from individual forecasts here. This equation also implies that the forecast errors are related only to the revision, as indicated in equation (5) of their paper

$$x_{t+1} - x_{t+1,t} = v_{t+1,t} + \frac{\lambda}{1-\lambda} [x_{t+1,t} - x_{t+1,t-1}] , \quad (5.4)$$

where $v_{t+1,t}$ is the rational expectations error defined as the difference between realized x_{t+1} and the rational expectation. As Coibion and Gorodnichenko emphasize, under the assumptions of the sticky information model, agents either do not revise at all, or they revise to the rational expectation, so it is only on average that equations (5.1)-(5.4) are expected to hold.

The evidence above, augmented by evidence in this section, suggests that the sticky information model is not a good approximation to expectations behavior in these surveys. First, the sticky information model suggests that in any given quarter, a significant number of agents do not update their information sets, so that their forecasts in period t equal those in period $t-1$. It is not credible that professional forecasters do not update their information sets for six months at a time. For households, this might well be a good approximation to their updating frequency, but then the premise that households that do update information sets make rational forecasts is suspect. Likely or not, we will test both propositions below.

To begin with, we can provide a crude measure of the fraction of professional forecasters and households who do not update their information set, using the fraction whose forecast revision is precisely zero (see Andrade and Le Bihan (2013) who examine the same issue for the European SPF dataset). Of course, at the quarterly frequency, some forecasters may well have fully updated their information set but, from time to time, they may judge that the information received is not sufficient for them to alter their forecasts.²⁴ So for the professionals, this fraction is likely biased upward from the true share who does not update their information set. Table 13 provides these shares. For one-quarter-ahead inflation forecasts from the SPF, about 18 percent of forecasters' revisions are zero. The number is about the same for unemployment rate forecasts. For the four-quarter average forecast, the primary horizon studied in Coibion and Gorodnichenko (2015), the fraction of unrevised forecasts drops quite a bit to about six or seven percent; equivalently, 93-94 percent of forecasters have revised their four-quarter forecasts from one quarter to the next, and it is

²⁴ This possibility is increased slightly by the fact that some of the forecasters in the survey always report forecasts to the nearest one-tenth of a percentage point.

likely that at least that many have updated their information sets. The difference between the fractions for the one-quarter and four-quarter average forecasts likely reflects the fact that while any one quarter's forecast might not be revised from one quarter to the next, the likelihood is small that none of the four quarterly forecasts is changed. Thus this number probably provides a better indication of whether forecasters update information from one quarter to the next. The numbers are similar but still noticeably higher for the Euro SPF forecasters, in the three right-hand panels. The Michigan survey participants, not surprisingly, have a higher incidence of zero revisions, at about one-third. Infrequent updating of information may indeed make more sense for households. Figure 8 displays the histogram of revisions to the 4-quarter inflation forecasts from the SPF.

Because the Coibion-Gorodnichenko test regression applies only to the average of forecasts, it is not replicated here. However, the crux of the sticky information model is that agents who update their information sets should at that point form rational expectations with all the information available at that time. Thus, another simple test of the sticky information model is a regression of (real-time) forecast errors on information available at the time of the forecast to forecasters who update. Using the imperfect proxy of nonzero forecast revisions to identify information updaters, we regress forecast errors on $t-1$ period information, notably the forecast revisions and the lagged median forecast that has been used throughout. Forecast errors are defined relative to real-time actual data, using the convention that the “actual” is the real-time estimate of the variable at the appropriate forecast horizon, as of the data vintage eight quarters after the period the forecast was made. Table 14 provides the results of these regressions for both the SPF and the Michigan surveys.²⁵ In both cases, lagged median forecasts, revisions, and other variables enter significantly, and the R-squareds for the SPF forecasts are sizable. The column that includes “additional $t-1$ period information” adds other individual lagged forecast variables and lagged median forecasts, all of which are available to the forecasters.²⁶ For these columns, the R²s get fairly large, ranging from 0.14 to 0.25. Thus a lot of individual forecast error variation is explained by information that was available at the time of forecast. The Michigan forecasts similarly evince very significant coefficients on lagged median forecasts (and lagged individual forecasts, not shown); the R-squareds are even

²⁵ For forecast horizons beyond one period, efficient forecast errors should be $MA(b-1)$, where b is the horizon. The information in the compound forecast error will be orthogonal to the regressors in this table, as the regressors are all dated $t-1$ or earlier. However, the regression residuals may exhibit some moving average behavior, and for that reasons, standard errors are corrected for the potential presence of moving average behavior.

²⁶ We include only information dated $t-1$ to avoid potential correlation with the idiosyncratic t -period noise that may be included in the error term in the “noisy information” test below. The R²s if one includes t -period individual forecasts rise noticeably for several of the variables.

higher than those for the SPF inflation forecasts, which is striking given the noise in these household responses.²⁷

Of course, because most all SPF forecasters update information frequently, the results presented in the previous sections also constitute a wealth of evidence rejecting the sticky information model, as all of these results also reflect grossly inefficient forecasts. Thus the results in the paper suggest an inefficient use of information by all forecasters, but that appears not to be well-represented as the outcome of agents who infrequently update their information sets, but form rational forecasts when they do. Evidence on the frequency of updating suggests the professionals are not surprisingly quite up-to-date on their macro information. Nonetheless, they use it inefficiently. About two-thirds of household revisions are non-zero after six months, suggesting the possibility of infrequent updating on their part. But even those who do revise their forecast show significant signs of inefficiency. For both these reasons, then, the sticky information model receives little support from the micro data.

6. Noisy information?

It is possible that the results presented so far may map more neatly into a noisy information framework, in which agents receive noisy idiosyncratic signals about the variables they wish to forecast. In this case, they will not adjust completely to the news in current information, but will instead revise their forecast with some weight on the new information and some on their previous forecast, with the weights depending on their perceptions of the relative signal-to-noise ratios in the two inputs.

Following the simple framework in Coibion and Gorodnichenko (2015) but adapting for our notation and for one-period-ahead forecasts, we can derive some implications for the results in the paper. First, posit an autoregressive process for a variable

$$x_t = \rho x_{t-1} + \varepsilon_t; -1 \leq \rho \leq 1 . \quad (6.1)$$

²⁷ The SPF forecast errors are defined relative to real-time data for the vintage of data eight quarters after the realization date, using the real-time data provided on the Survey of Professional Forecasters site. For the Michigan survey, we employ the same timing convention, using the Philadelphia Fed's eight-quarter forward real-time vintages for the monthly 12-month percentage change in the CPI.

This process may be readily generalized by allowing x to be a vector of variables, including lags of the vector x , and ρ a conformable matrix. Agents in the economy cannot (ever) observe x_t without noise, but instead receive a noisy signal y_t^i

$$y_t^i = x_t + \omega_t^i, \quad (6.2)$$

where ω_t^i is assumed *iid* across time and individuals. Under these circumstances, agents will compute forecasts for periods t and $t+h$ as

$$\begin{aligned} x_{t,t}^i &= Gy_t^i + (1-G)x_{t,t-1}^i \\ x_{t+h,t}^i &= \rho^h x_{t,t}^i \end{aligned}, \quad (6.3)$$

where G is the Kalman gain, based on the relative signal-to-noise ratios in y_t^i and $x_{t+1,t-1}^i$. These equations imply that the forecasts for period $t+1$ made in periods $t-1$ and t are

$$\begin{aligned} x_{t+1,t}^i &= \rho x_{t,t}^i = \rho[Gy_t^i + (1-G)\rho x_{t-1,t-1}^i] \\ x_{t+1,t-1}^i &= \rho^2 x_{t-1,t-1}^i \end{aligned}, \quad (6.4)$$

which in turn implies, after some simplification, that the revision in the $t+1$ forecast between viewpoint dates $t-1$ and t is

$$x_{t+1,t}^i - x_{t+1,t-1}^i = \rho G(y_t^i - \rho x_{t-1,t-1}^i) \quad .^{28} \quad (6.5)$$

This forecast update equation depends on the Kalman gain and the difference between the newly-received signal for x_t and last period's forecast. When $G=1$, the difference between these estimates of x_t is just the news about x_t , which is \mathcal{E}_t , so the revision reduces to $\rho\mathcal{E}_t$. In the regressions in Tables 3-11 above, the weight on the lagged forecast is estimated to be negative, sizable, and remarkably significant, consistent with equation (6.5).

Coibion and Gorodnichenko show that one can also use these definitions to derive a forecast error regression like equation (5.4) above, such that the average forecast errors are related only to the average forecast revisions. In this case, the coefficient on the forecast revisions may be interpreted as a simple function of the gain parameter. As they point out, the coefficient on different forecast variables will vary with the Kalman gain, which depends in turn on the signal-to-noise ratio

²⁸ When $G=1$, $y_t^i = x_t = \rho x_{t-1} + \mathcal{E}_t$, and $x_{t-1,t-1}^i = x_{t-1}$, and in this case of course the forecast revision reduces to $\rho\mathcal{E}_t$, the news about x_t that is revealed in period t . This in turn is consistent with the definition of an efficient full-information revision in equation (1.1) above.

of the variable and its persistence. But one can also show that the individual forecast errors in this noisy information setup should be rational forecast errors:

$$x_{t+h} - x_{t+h,t}^i = \varepsilon_{t+h,t} \quad (6.6)$$

as forecasters are using the information available to them efficiently, optimally filtering out the noise to form rational forecasts. As a consequence, the rational forecast error $\varepsilon_{t+h,t}$ should be uncorrelated with any information that is available to the forecaster and dated t or earlier. If the forecaster error is found to be correlated with information available at the time of the forecast, the forecaster could not have efficiently filtered that information in forming the forecast.

It is difficult to reconcile the noisy information story with the findings presented in Table 14, which encompass the test regression for this model in equation (6.6). Forecast errors should only be predictable on average across forecasters; individual forecasters should be making rational forecasts, conditional on their information sets. If it can be shown that individual forecast errors are inefficient, given information known to the individual forecasters, the model is violated. As can be seen in table 14, forecast errors are still quite predictable by a number of variables, all of which are provided by (and thus known to) the individual forecasters (including forecast revisions in most cases).²⁹

Table 15 provides a set of test regressions for a wider array of forecast variables, and a broader set of $t-1$ and t - period information that should be uncorrelated with the rational forecast errors at the individual level. All of the variables in these regressions are available to the forecaster as of period t —indeed, all but the lagged median forecast are current and previous period’s forecasts made by the individual forecasters.

As in table 14, the R^2 s are sizable, suggesting information clearly available to (indeed, provided by) the forecasters at the time the forecasts are made has significant predictive power for what should be rational forecast errors. This is a strong test of the noisy information proposition: Because the explanatory variables are largely the forecasts made by the individual forecasters, not only is this information trivially available to the forecaster, under the null hypothesis these are forecasts that have optimally used the information available to each forecaster. Thus none of these variables should have any predictive power for the forecast error. In contrast to previous research, these results are strongly at odds with a noisy information model in which agents optimally filter

²⁹ In this case, one would not restrict the sample to those forecasts that are revised from the previous viewpoint date. Replicating Table 16 for the full sample does not change the results.

signal from noise in incoming data, forming rational forecasts given the information available to them. Indeed, these results reject *any* model in which agents are assumed to efficiently filter information to form forecasts. If the filtering of information were efficient, then that information could not be used to predict individual forecast errors.

Taking a step back, it seems unlikely that professional forecasters face a serious problem of signal extraction of the type modeled in this section. To be sure, the data that they collect from government and other agencies is somewhat noisy, and subject to revision. But it is difficult to motivate a gain coefficient G that is consistent with the estimates presented in this paper. That is, the notion that the uncertainty about the true signal in the latest GDP, unemployment or inflation release is large enough to shrink one's forecast roughly fifty percent toward the previous forecast stretches credulity. In some economic circumstances, the noisy information model may make perfect sense. But it does not seem well-suited for the professional forecaster—or any forecaster who is projecting aggregate data largely by way of official aggregate statistics. The noise involved here is small, and the information is largely common, rather than idiosyncratic.

Shleifer *et al* results and mis-estimated persistence

It is important to note that the coefficients on the revisions in these regressions are typically negative, which in the tests of Bordalo, Gennaioli, Ma and Shleifer 2018a (based in turn on Coibion and Gorodnichenko 2015), are interpreted as indicating over-reaction to information at the individual forecaster level. While the rejection of the simple noisy information model holds nonetheless, the implication for over- versus under-reaction might appear difficult to square with the results from the many revision regressions presented above, all of which found significant under-reaction.

Table 16 separates the components of the revision in the Shleifer *et al* test regressions—the current period forecast and the previous period's forecast. The results in Table 16 show that it is not the revision that predicts the forecast error, but the t -period forecast (obviously a component of the revision).³⁰ That is, the regressions show that when the t -period forecast is systematically high, the associated forecast error must be negative, and vice versa. The revision *per se* holds no predictive power for the forecast error once the t -period forecast's effect is isolated. Because the result is not related to the revision, it says nothing about under- or over-reaction of forecasts to news—it is not

³⁰ The inclusion of the lagged viewpoint-date forecast in the regressions in table 15 serves the same purpose: It shows that the coefficient on this term is approximately equal and opposite in sign to the coefficient on the lagged viewpoint-date forecast that is part of the revision. Thus not surprisingly, these regressions also suggest that it is only the t -period viewpoint date forecast that is negatively correlated with the forecast error.

the response to news that is embodied in the forecast revision that predicts forecast errors. It is simply that systematically higher (lower) forecasts produce negative (positive) errors, thus inducing a negative correlation between the forecast and the error. In these data, the Shleifer *et al* regression is simply not a very powerful test for the presence of under- or over-reaction of forecasts, unlike the revision regressions presented above.³¹

Where does this correlation come from? A simple fixed bias in the forecast would not produce the result in these regressions, as the bias would be absorbed into the intercept in the forecast error regressions. But a mis-estimate of the persistence of the series in question could lead to such a negative correlation. Consider a simple model for an AR(1) process as discussed in section 2. Allow the forecaster to use an idiosyncratic estimate of the persistence parameter

$$\begin{aligned} x_t &= \rho x_{t-1} + \varepsilon_t \\ x_{t+1,t}^i &= \hat{\rho}_i x_t \end{aligned} \quad (6.7)$$

The forecast error for the $t+1$ forecast when $\hat{\rho}_i = \rho$ is just the unpredictable component ε_{t+1} . But when the estimated autocorrelation coefficient differs from the underlying process, the forecast error is

$$Error_{t+1}^i = x_{t+1} - x_{t+1,t}^i = (\rho - \hat{\rho}_i)x_t + \varepsilon_{t+1} \quad (6.8)$$

For positively autocorrelated series (as all in these datasets are), when the individual autocorrelation estimate exceeds the underlying process's autocorrelation, the error will be systematically negatively correlated with the forecast; when the estimate falls short of the underlying process's autocorrelation, the error will be systematically *positively* correlated with the forecast:

$$Cov(Error_{t+1}^i, x_{t+1,t}^i) = (\rho - \hat{\rho}_i)\hat{\rho}_i Var(x) \quad (6.9)$$

Figure 11 displays the distributions of regression coefficients for the test regression of individual forecast errors on individual forecast revisions, for a sample of the variables at several forecast horizons, at the individual forecaster level. The pattern of results in Table 16 is largely replicated at the individual forecaster level, with the bulk of the coefficients for (e.g.) inflation negative, although this is not uniformly the case. As in the overall regressions for unemployment in table 16, most of the individual regressions develop a positive coefficient, suggesting under-reaction of forecasts, using the Shleifer *et al* criterion.

³¹ One can think of the Shleifer *et al* regression as a restricted version of the unrestricted regression presented in Table A.3, in which the t - and $t-1$ period forecasts enter with equal and opposite signs. As the table indicates, this restriction is almost always violated, and the importance of the $t-1$ period forecast is minimal. Thus the regressions say little about under- or over-reaction to news, as they do not reflect an underlying relationship between revisions and forecast errors.

This intuition would be more compelling if there were evidence that forecasters systematically mis-estimate the persistence of the variables they forecast. To test this proposition, we estimate the implied persistence in the forecasts of each forecaster for each variable in the SPF dataset. Because the out-quarter forecasts largely depend on propagating the forecast from the initial quarter forward using the persistence of the series (as in equation (6.3) above), we can pool the forecasts for each variable, for each forecaster, into a simple three-equation system to estimate the persistence underlying the forecasts:

$$\begin{aligned}x_{t+2,t}^i &= \rho^i x_{t+1,t}^i + e_{2t}^i \\x_{t+3,t}^i &= \rho^i x_{t+2,t}^i + e_{3t}^i \\x_{t+4,t}^i &= \rho^i x_{t+3,t}^i + e_{4t}^i\end{aligned}\tag{6.10}$$

Note that ρ^i is constrained to be equal across the three equations. Figure 12 displays the distribution of biases in these estimated autocorrelations by forecaster, relative to estimates of the autocorrelation in the data series that are being forecasted. The mapping between the distribution of biases and the estimated coefficients in the Shleifer *et al* test regressions is quite good: Variables for which the distribution of estimated ρ 's skews positive (CPI inflation, output growth, GDP inflation, consumption growth, residential and nonresidential structures growth) tend to develop negative coefficients on the current-period forecast in the Shleifer *et al* test regression (Table 16). Those with a negative or insignificant skew in the distribution of estimated ρ 's develop positive or insignificant coefficients in the Shleifer test regression. To be sure, this test is simple—the system (6.10) is estimated over the full sample, when the autocorrelation properties of some of these variables have no doubt changed over time; and the two- to four-quarter-ahead forecasts no doubt incorporate information beyond that captured in the autoregressive properties of the series. As a test of the sub-sample sensitivity of these results, appendix figure A.1 shows that the correlation between the biases in estimated ρ 's and test coefficients in equation (6.9) holds up in the latter half of the sample (1998-2018) as well. The combined results of Table 16 and Figure 12 suggest a very different explanation for the Shleifer *et al* results, and one that does not imply over-reaction to news.³² Thus

³² A simple robust regression linking the median bias in autocorrelation to the median test coefficient develops a coefficient of -1.6, with a p -value of 0.021, confirming the negative correlation apparent in the figure. Figure A.2 provides a bin-scatter plot of test regression coefficients versus ρ biases by forecaster id. The figure shows a downward sloping pattern by forecaster, with the exception of unemployment and employment, and an ambiguous slope for the 3-month Treasury bill. This corresponds to the pattern in the test regression results of Table 16, as well as the histograms in figure 12.

the “diagnostic expectations” model of Shleifer *et al*, which implies over-reaction at the micro level and under-reaction at the aggregate level, is generally rejected by these tests.

Overall, it seems fair to conclude that forecasters, both household and professional, do not make rational forecasts, even accounting for possible information frictions. They simply use information inefficiently, significantly reducing their responses to relevant news. This is not an artifact of the simple staggered information or noisy information environments described in the literature, as these models’ predictions appear to be strongly violated at the micro level. Any noisy information model that implies that agents efficiently use the information available to them to form expectations, rationally accounting for the noise in that information that they filter out, is inconsistent with the results in this and the preceding section.

7. Implications for macroeconomic modeling

Here, we briefly examine the macroeconomic implications of expectations that embody inefficient revisions in a simple dynamic macroeconomic model. To build intuition, we begin by breaking down the results into their most fundamental implications.

Expectations that embody a muted response to new information may be said to exhibit “excess smoothness.” Because equation (1.1) implies that efficient revisions should follow a Martingale process, as expectations jump immediately in response to news, inefficient revisions of the type studied above imply a muted or smoothed response to news.³³

We can examine the behavior of inefficient expectations relative to their efficient counterpart in a simple model that comprises a New-Keynesian Phillips curve augmented with an AR(1) process for the output gap:

$$\begin{aligned} \pi_t &= \beta E_t \pi_{t+1} + \gamma y_t + \varepsilon_t \\ y_t &= \rho y_{t-1} + u_t \end{aligned} ,$$

the solution for the rational expectation in the first equation is $E_t \pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} y_t$, and for the same

quantity at viewpoint date $t-1$ is $E_{t-1} \pi_{t+1} = \frac{\rho^2\gamma}{1-\rho\beta} y_{t-1}$, so that the efficient revision is

³³ Recall that the inefficiency documented here implied under-reaction to news. Had we estimated $a > 1$ in the fundamental regression, this would have implied over-reaction to news.

$E_t \pi_{t+1} - E_{t-1} \pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} u_t$. If we contrast solutions for inflation using rational expectations versus a model in which inefficient expectations (denoted by F) update information as in the example above $F_t \pi_{t+1} = aF_{t-1} \pi_{t+1} + \frac{\rho\gamma}{1-\rho\beta} u_t$; $a < 1$, we can show that as expected, the resulting inflation series exhibits muted and smoothed responses to the news about output u_t , much like the exercise with fixed-endpoint forecasts described above.

We take the $t-1$ expectation for y to be the efficient expectation $E_{t-1} \pi_{t+1} = \frac{\rho^2\gamma}{1-\rho\beta} y_{t-1}$, and then update the expectation at period t using $F_t \pi_{t+1} = aE_{t-1} \pi_{t+1} + \frac{\rho\gamma}{1-\rho\beta} u_t$. Figure 9 displays the efficient and inefficient expectations for inflation formed in this way over a 40-period sample using random draws for the shocks u_t for various values of a .³⁴ The smoothing that arises over time from this type of inefficient expectations formation is evident for all values of $a < 1$ in this figure. This figure is not, however, a complete description of how such expectations might affect inflation, as expectations do not feed into inflation in this exercise; they are simply computed as a stand-alone at each point in time given the news shocks for output, the efficient $t-1$ expectation for inflation, and the rational expectations solution for the model (which is of course not quite appropriate if expectations are not being formed rationally!).

To provide a more complete description of how inefficient expectations affect outcomes in a macro model, we construct a model in which the $t+1$ -quarter expectation made in period t inefficiently uses the information in the expectation for quarter $t+1$ made from expectation viewpoint $t-1$, and/or the lagged aggregate one-quarter-ahead expectation. The empirical results in Tables 2–11 provide evidence of both types of anchoring, although, as suggested above, there is a conceptual difference between the two inefficiencies.

We examine a simple but fully-articulated DSGE model that embeds such expectations behavior throughout. The model includes a Phillips curve that mixes rational and inefficient expectations

$$\pi_t = b\pi_{t+1,t}^I + (1-b)E\pi_{t+1} - \gamma\tilde{U}_t, \quad (7.1)$$

³⁴ The other parameters in the model $[\rho, \beta, \gamma]$ take the values $[0.9, 0.99, 0.1]$.

where $\pi_{t+1,t}^I$ is the inefficient expectation for inflation in period $t+1$ using information up to period t , and \tilde{U}_t is the unemployment gap (or the output gap, or real marginal cost; for these purposes all of these driving variables are equivalent).³⁵ We add an “IS” curve of similar form

$$\tilde{U}_t = (1-b)U_{t+1,t}^I + bEU_{t+1} - \sigma(f_t - \pi_{t+1,t}^{Agg} - \bar{\rho}), \quad (7.2)$$

where the inefficient expectation for the driving variable appears in parallel fashion to (7.1), f_t is the short-term nominal policy rate, and $\bar{\rho}$ is the short-term equilibrium real interest rate. The policy rate is determined by a conventional (albeit non-inertial) policy rule.³⁶

$$f_t = \bar{\rho} + \bar{\pi} + a_\pi(\pi_t - \bar{\pi}) - a_u\tilde{U}_t. \quad (7.3)$$

We can envision an economic agent who forms expectations as suggested by the empirical results in the paper,

$$\pi_{t+1,t}^I = \omega E\pi_{t,t-1} + (1-\omega)E\pi_{t+1,t-1} - c\tilde{U}_{t-1} + \varepsilon_t \quad (7.4)$$

and similarly for expectations of the unemployment/output gap

$$U_{t+1,t}^I = \omega EU_{t,t-1} + (1-\omega)EU_{t+1,t-1} + d(f_t - \pi_{t+1,t}^I - \bar{\rho}) + \eta_t. \quad (7.5)$$

Equations (7.4) and (7.5) are very close analogues of the expectations regressions in Sections 2–4 above, in which individual expectations for period $t+1$ depend on lagged central tendencies of period t and period $t+1$ forecasts made in period $t-1$. We could motivate this model from the level of individual forecasters, but for simplicity, we assume that the coefficients ω , c and d are the same across all forecasters.³⁷ In this case, aggregation is trivial, and the individual version of equations (7.4) and (7.5) are essentially the same as the aggregate.³⁸

Importantly, none of the individual agents who form inertial expectations in the model know the true model, and none know the current value of the aggregate expectation. In addition, they do not attempt to form higher-order expectations (expectations of other agents’ expectations). Such augmentations, while perhaps reasonable, would extend this simple example well beyond the scope of this paper. Equations (7.4)-(7.5) allow expectations to be formed inertially, with more weight on

³⁵ Of course the rational expectations are computed consistent with some fraction of expectations formation defined by $\pi_{t+1,t}^I$ in equation (7.1), as long as $b \neq 1$. When $b = 1$ as in Figure 9 below, the model depends completely on the rational expectation.

³⁶ The model abstracts from policy inertia to isolate the impact of expectations on model dynamics.

³⁷ Allowing for greater and perhaps systematic heterogeneity in expectations, as might be suggested by Figure 3, could impart additional dynamics to the system, but those enhancements lie beyond the scope of this paper.

³⁸ The use of multiple forecasters comports well with the empirical work in the preceding sections. However, for these purposes, we could just as well use a representative agent.

the lagged one-period-ahead expectation or the lagged two-period-ahead expectation, as the weight ω varies between zero and one. Equation (7.1) allows inflation to depend more or less on inertial versus rational expectations, as b increases and decreases in size respectively, and the same is true for the unemployment gap in equation (7.2).

Figure 13 examines the properties of this simple model (equations (7.1), (7.2), (7.3), (7.4) and (7.5)) in response to a disinflation shock. That is, the model variables begin at a steady state with the equilibrium real rate and inflation at two percent, while the inflation target is dropped to 0 percent at the beginning of the simulation. The simulation traces the paths of the key model variables in response to this unexpected downshift in the inflation goal, for various values of the parameters ω and b . Inspection of equations (7.4)-(7.5) suggests that, for values of ω like those estimated in the empirical section, this backward-referential expectations behavior can impart considerable persistence to output, inflation, and the policy rate. Figure 13 displays the quantitative implications of this intuition. The green line, which assumes rational expectations exhibits no persistence. The black, red and blue lines, which employ different weights on lagged t and $t+1$ aggregate expectations (ω and $(1-\omega)$, respectively), exhibit considerable persistence in response to a disinflation shock. Thus all of the persistence in this model may be attributed to the contribution from inertial expectations of the type uncovered in the micro survey data.

The conclusion from this simple exercise is that if expectations are formed in a manner consistent with the micro evidence, such intrinsic expectations inertia can account for a sizable fraction of the persistence exhibited by the macroeconomic data. Whether the data suggest that this or other forms of persistence best account for the inertial responses that are present in aggregate data is a topic for additional research.

8. A model of “expectations smoothing”

The results in sections 5 and 6 suggest that the sticky and noisy information models are inconsistent with the microeconomic survey data from a variety of household and professional surveys. The “diagnostic expectations” model of Shleifer *et al* is also inconsistent with these results, as the overwhelming evidence points to *under*-reaction to information at the micro level, not *over*-reaction as in their findings. Section 6 provides a reconciliation of the results in this paper and those in Shleifer *et al*, suggesting that the test regressions presented in this paper have significantly greater ability to distinguish between under- and over-reaction to news.

What form of expectation behavior is consistent with the striking regularities that we find in the micro data? The facts which the theory must confront are:

- a. Forecasts are strongly inefficient at the micro level; in particular, forecasts under-use newly-available information in a way that cannot be attributed to sticky information sets, optimal filtering of noisy information, diagnostic expectations, or learning;
- b. This is true for both financial and nonfinancial variables, for professional and household forecasters, across all available samples, in Europe and in the U.S.
- c. While we develop some evidence of heterogeneity in expectations, the dominant feature among individual survey respondents is a common way of processing information, rather than heterogeneity. Thus contrary to sticky or noisy information theories, in which staggered updating of information or uniquely noisy information sets produce heterogeneity, these results do not suggest that heterogeneity is the key feature of the data to be explained.

One could develop an even more contorted information story to explain the results in this paper. But the gross inefficiencies in individual forecasts suggest that agents are not optimally filtering idiosyncratic information. Instead, we take the simple approach of characterizing their behavior as “expectations smoothing,” in which rather than allowing expectations to “jump” in response to incoming information, expectations adjust more smoothly, linking to a reference point while gradually incorporating news. This notion of expectations smoothing links directly to the concepts of “anchoring and insufficient adjustment,” first advanced in Kahneman and Tversky (1974). They note that in many circumstances, individuals’ estimates of probabilistic outcomes are biased toward their initial estimates—thus “anchoring”—and that adjustments to these initial estimates in the face of evidence typically underweight the new information in favor of the initial estimate.³⁹ This kind of behavior appears to be precisely what we observe in survey-based forecasts of households and professional forecasters.

At the risk of over-simplifying, a simple representation of expectations smoothing begins with a reference point $\mathfrak{R}_{t+k,t}$. Agents can then be viewed as forming (and revising) expectations for realizations of variable x in period $t+k$ at viewpoint date t as

$$\begin{aligned} x_{t+k,t} &= \gamma x_{t+k,t-1} + (1-\gamma)\mathfrak{R}_{t+k,t} + N_{t+k,t} \\ x_{t+k,t} - x_{t+k,t-1} &= (\gamma-1)x_{t+k,t-1} + (1-\gamma)\mathfrak{R}_{t+k,t} + N_{t+k,t} \end{aligned} \tag{8.1}$$

³⁹ Importantly in this context, Kahneman and Tversky (1974, see p. 1128) note that anchoring occurs “not only when the starting point is given to the subject, but also when the subject bases his estimate [starting point] on the result of some incomplete computation.”

In equation (8.1), $1-\gamma$ denotes the weight of attachment to the reference point, and correspondingly γ the extent to which news N_t is down-weighted (relative to one, see equation (1.6) above).⁴⁰ As discussed in section 2 above, the efficient forecast (in the absence of information frictions) sets γ to one, so that news accumulates fully and revisions are not anchored to the reference point. Equivalently, $\gamma-1$ indexes the extent to which revisions over-weight the previous forecast (relative to zero). The key feature of equation (8.1) is that it implies a smoothed incorporation of news at each period.

In such an anchoring model, there is no presumption that information sets are not updated regularly, which might be a reasonable assumption for less-sophisticated agents, but seems implausible for more sophisticated agents. Neither is there a presumption that agents efficiently use all information, a hypothesis that is soundly rejected in all of the micro data examined here.

What deeper incentives lead to expectations smoothing? One possibility is that the incomplete use of information found in this study is the result of a process of continuous updating of the econometric models used by professional forecasters, or of the implicit models used by households. But such updating would not lead to systematic under-response to information. The response would depend on the pattern of shocks to the economic structure, and how those structural changes correspond to the model structure prior to the shock.⁴¹

9. Conclusion

There is little question that expectations lie at the heart of much economic decision-making, and thus at the heart of models of the macroeconomy that hope to reflect such decision-making. How expectations are formed is an open research question. In earlier work, Fuhrer (2017) showed that empirical estimates of a standard DSGE model preferred inertia in expectations over price indexation or habit formation as a mechanism to explain the persistence of aggregate time series for output, inflation, and interest rates. A question left open in that paper was why and how expectations might exhibit such inertia.

⁴⁰ Equations (1.5) and (1.6) make explicit the way in which news and the anchor are weighted in forecasts that follow (8.1).

⁴¹ For the professional forecaster surveys, if forecasters use econometric models, and update their coefficients regularly, their forecasts would not systematically under-react to information in the way this paper finds. Apart from gross misspecification, the models would capture the approximate response of key variables to incoming information, even as these responses change over time. This suggests that forecasters have added judgment to their model-based forecasts that leads to a systematic under-response to incoming information.

Through examination of data on individuals' and forecasting firms' forecasts, this paper suggests one possible reason for expectational inertia: Individual expectations exhibit significant inefficiency, particularly in the way in which they update information over time. In this paper, we document the inefficient updating to current information across three well-known surveys of expectations. In doing so, forecasters and households smooth their expectations' response to news, building a kind of intrinsic inertia into the expectations process.

The results in this paper allow one to distinguish between inefficient updating and a number of other behaviors. For example, the agents in this model are not using adaptive expectations, as it is clear that they incorporate quite a few sources of information, not simply forming expectations from weighted averages of lags of the variable they are forecasting. Agents are clearly not naïve, for similar reasons. In addition, while agents may well be learning about the best parameters in least-squares projections of macro variables on lagged data, this learning does not at all substitute for the inefficient updating that is endemic in the micro data.

Sections 5 and 6 examine the possibility that this apparent inefficiency is instead a manifestation of sticky or noisy information. The results in Tables 14-16 suggest that this is not the case. The reason is straightforward: Those models imply that those who update still do so rationally, given their information constraints. The regression results suggest that (a) most professional forecasters update quite frequently, which is not a surprise; (b) some households may not be updating their information sets frequently, also not a surprise; (c) those professional and household forecasters who appear to have updated do so quite inefficiently; and (d) forecast errors appear not to be consistent with a noisy information model, as it is clear that forecasters are not efficiently filtering the information available to them, resulting in quite predictable forecast errors. This result is generic for any model of noisy information in which agents are presumed to filter out the noise efficiently. Thus revisions are inefficient, but not because of sticky or noisy information.

The penultimate section of this paper shows that building expectations that smooth relevant news into a relatively standard (but admittedly simple) macroeconomic model can generate the kinds of impulse responses that are commonly found in macroeconomic VARs, without resorting to the bells and whistles that have been added to DSGE models in recent years—price indexation, habit formation, and autocorrelated structural shocks.

While the micro-data results appear quite robust, their implications for macroeconomic dynamics no doubt merit further investigation; this paper provides only simple examples of the possible implications of such expectations behavior in macro models. However, coupled with earlier

work, this paper suggests that micro data-based expectations that exhibit these kinds of inefficiencies indeed induce significant persistence into dynamic macro models, and thus might go far in explaining much of the persistence observed in macro data.

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Figure 1

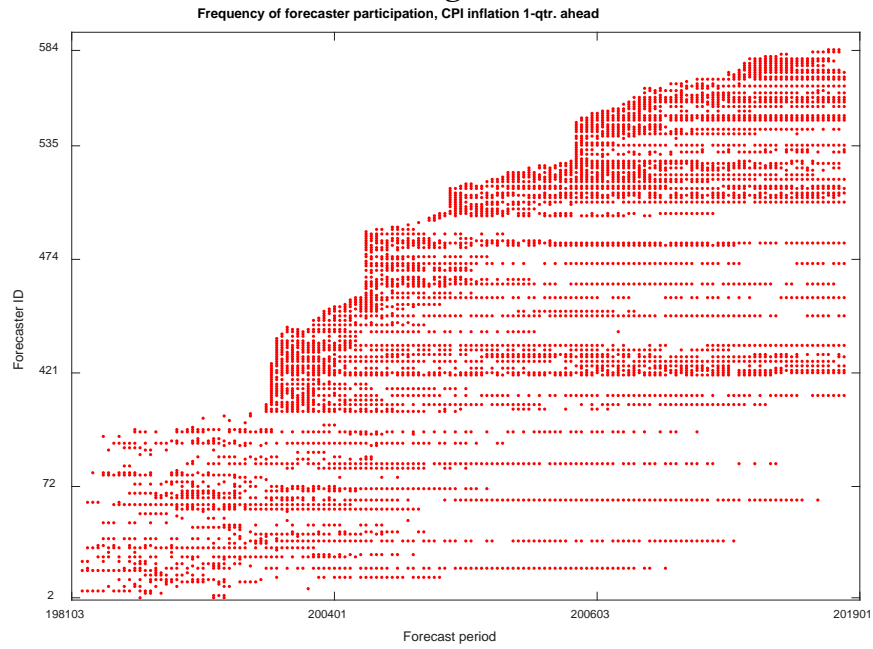


Figure 2

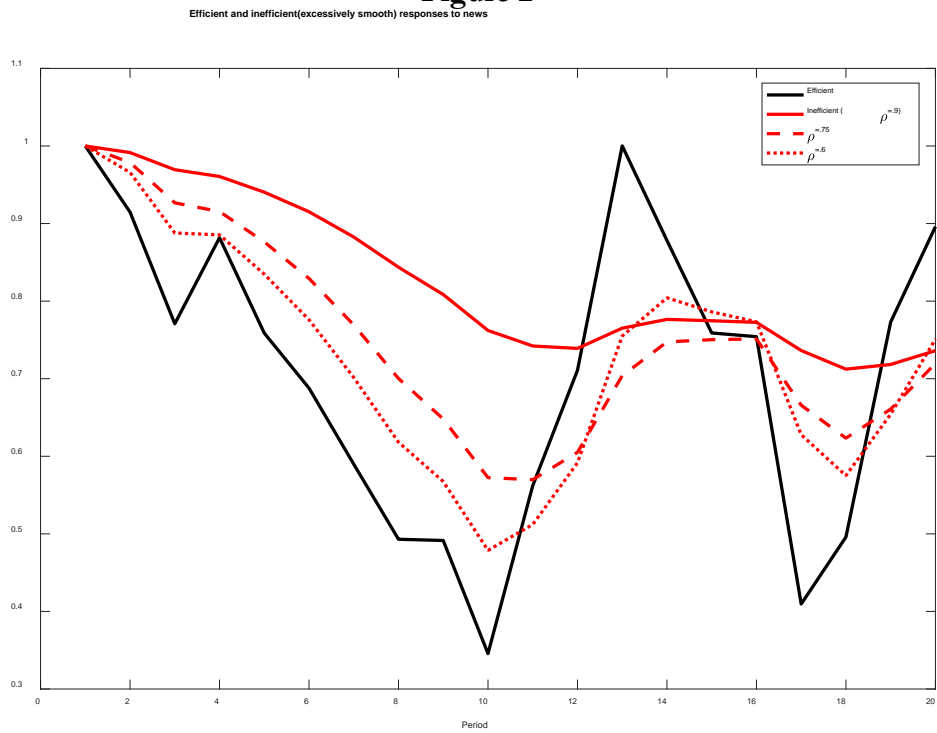


Figure 3
Bin scatter revisions and lagged forecasts

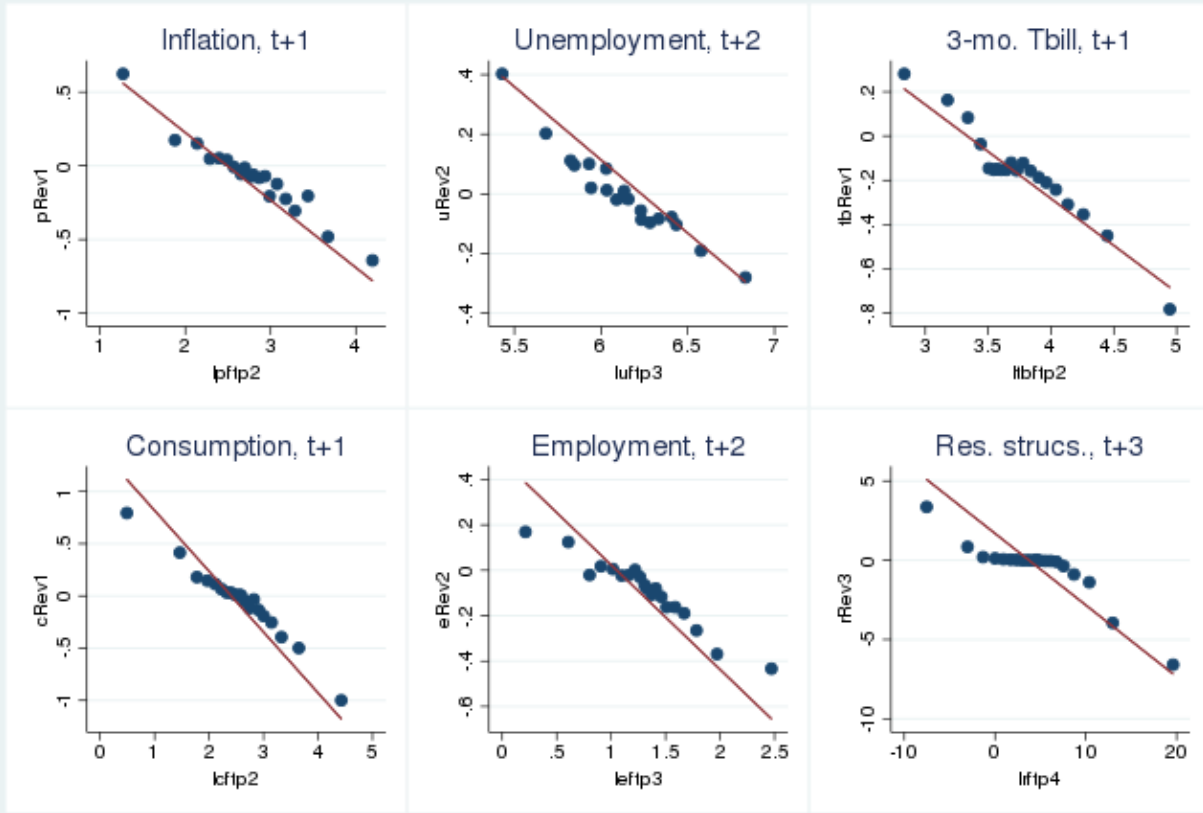


Figure 4
Distribution of individual
forecaster revision coefficients

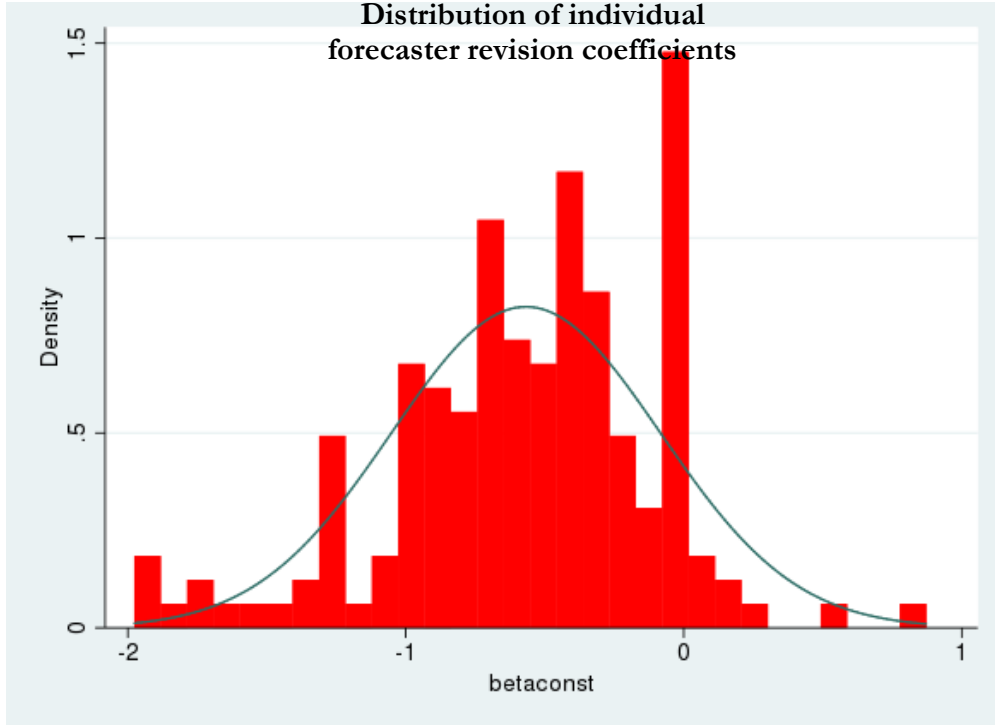


Figure 5a: Estimated inefficiency coefficients, Inflation
20-quarter rolling regressions

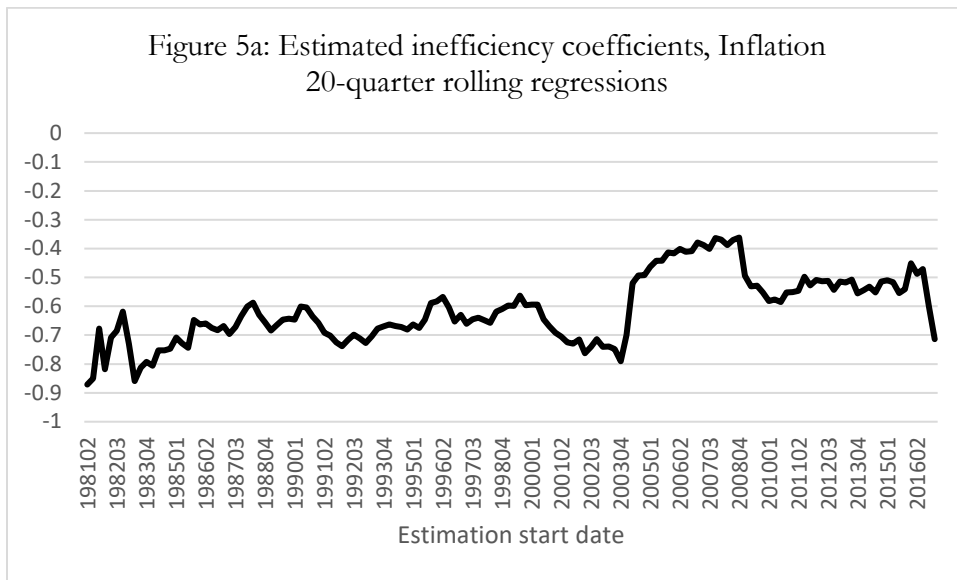


Figure 5b: Estimated inefficiency coefficients, Unemployment
20-quarter rolling regressions

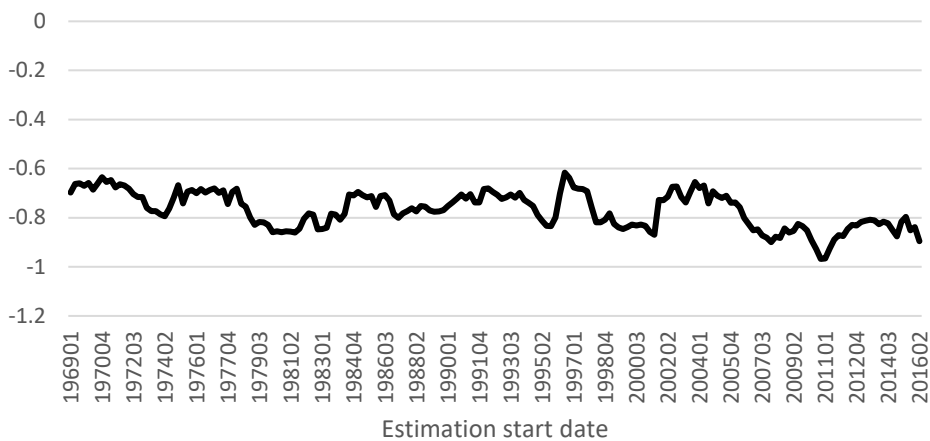


Figure 5c: Estimated inefficiency coefficients, 3-mo.
Treasury bill rate
20-quarter rolling regressions

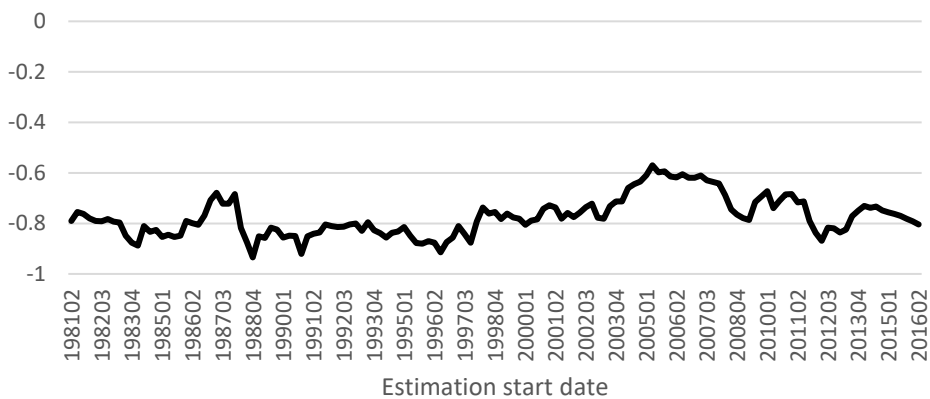
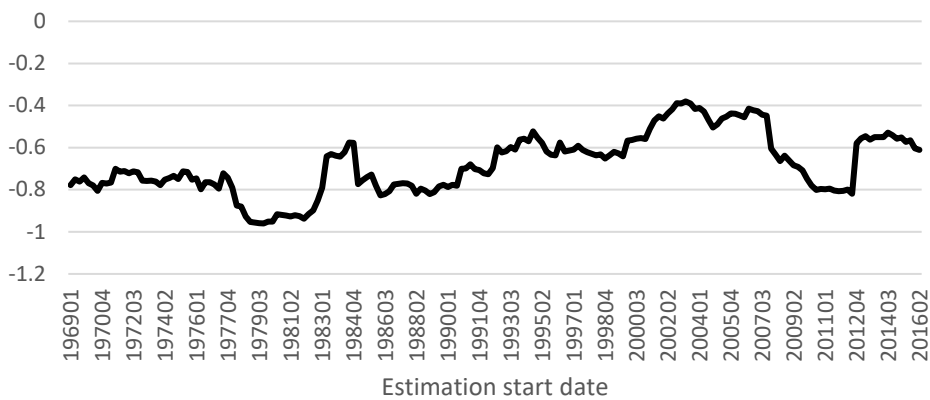


Figure 5d: Estimated inefficiency coefficient, Real GDP
growth
20-quarter rolling regressions



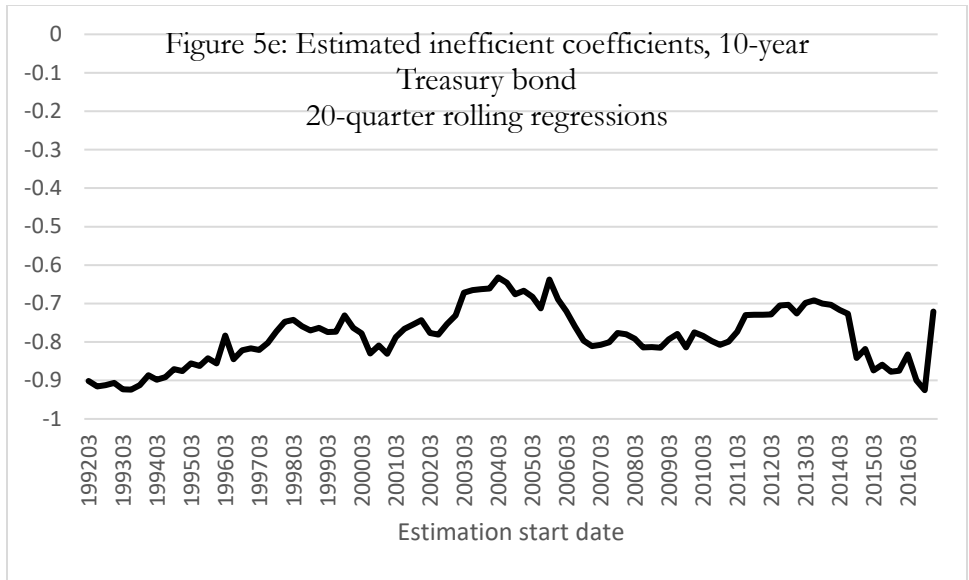


Figure 6
Adding least-squares learning variables to the regressions
(40-quarter rolling regressions)

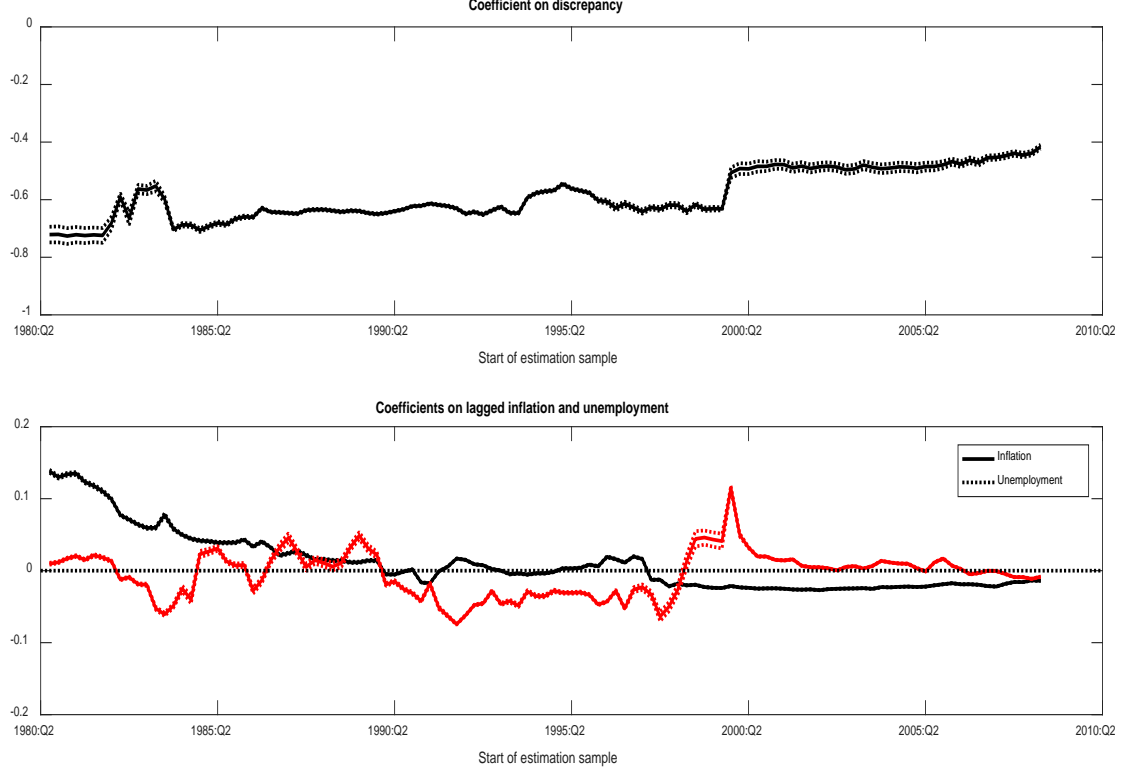


Figure 7
Median of SPF 10-year CPI inflation forecast

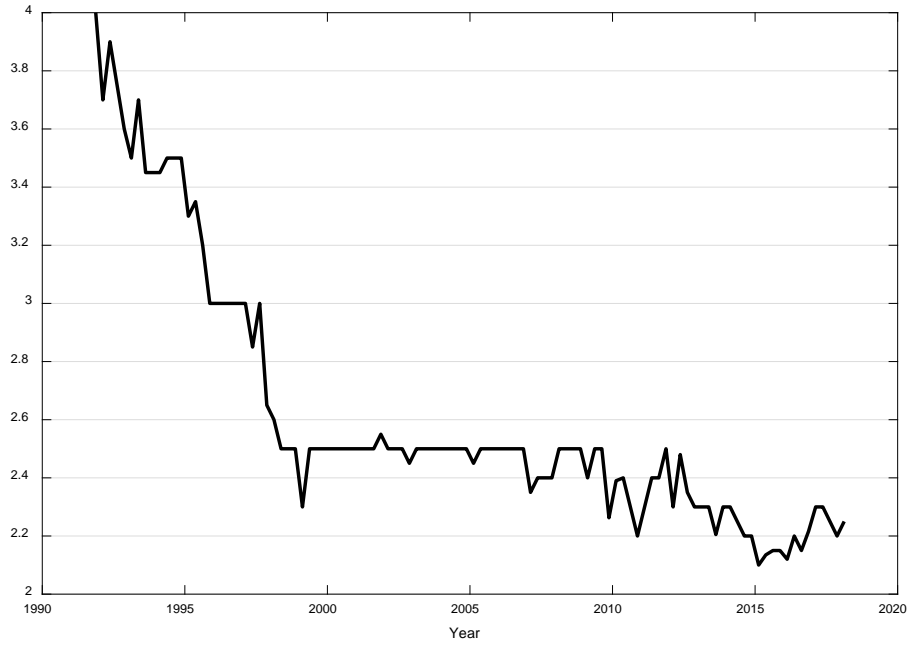


Figure 8
Histogram of 4-quarter SPF inflation revisions

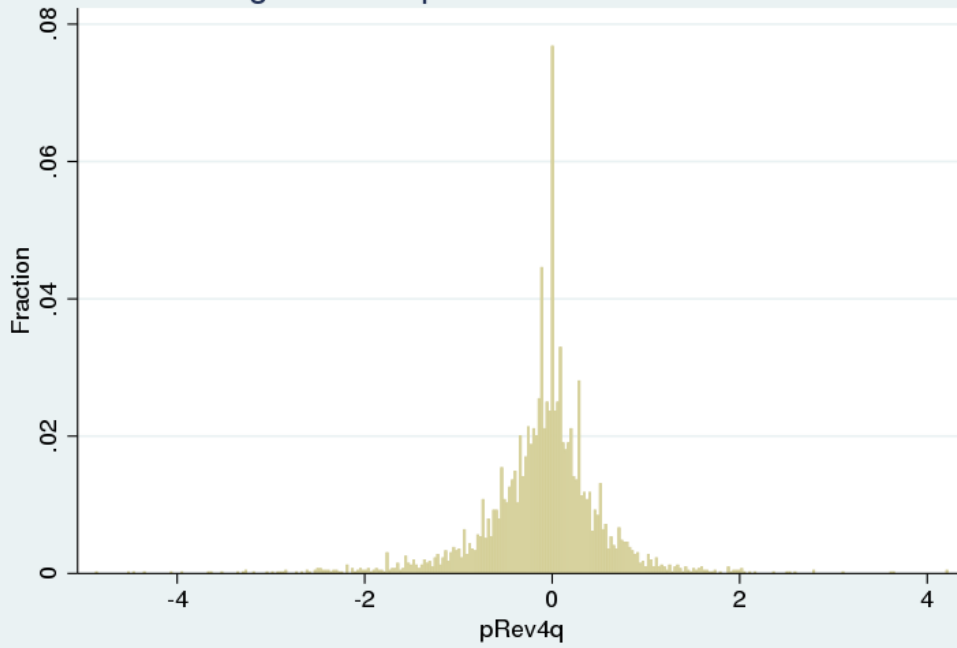


Figure 10a
Figure 9

Efficient and inefficient(excessively smooth) expectations in a simple NKPC model

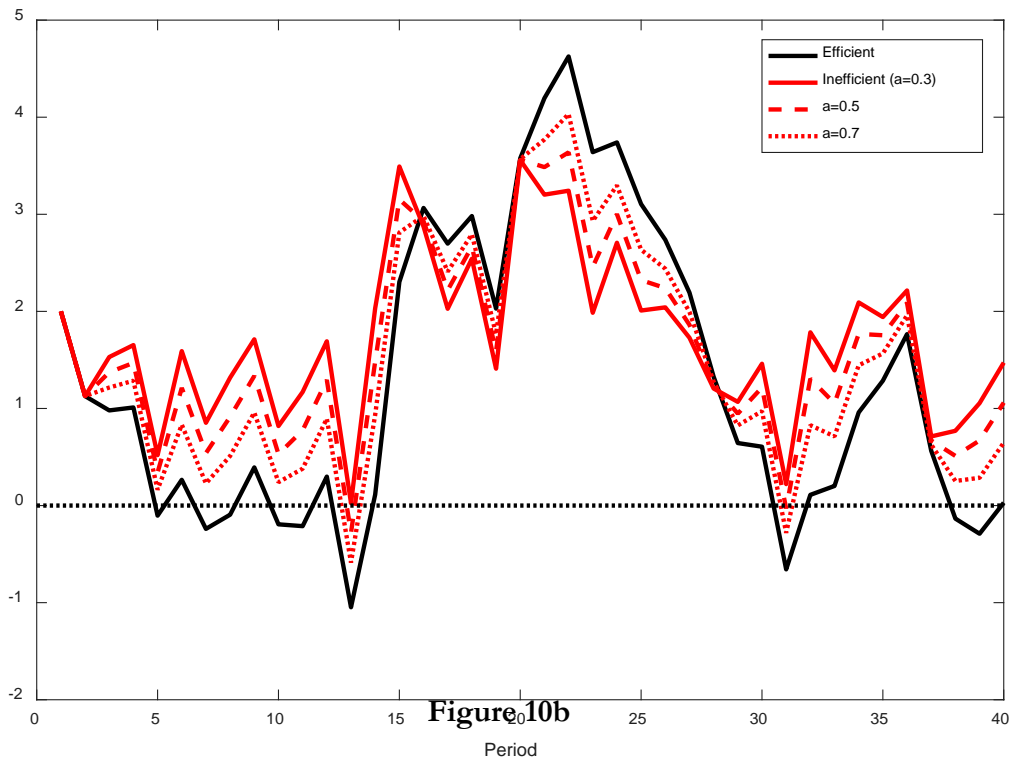


Figure 11
Histogram of forecast error regression coefficient by forecaster

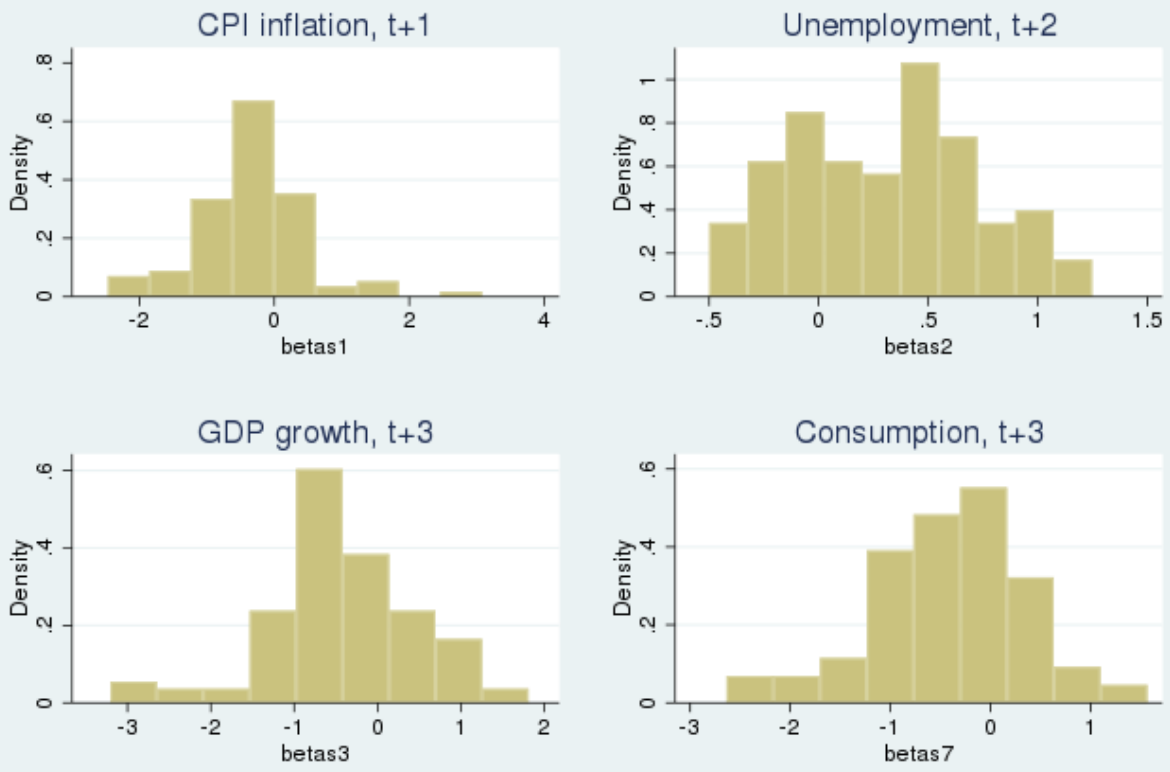


Figure 12

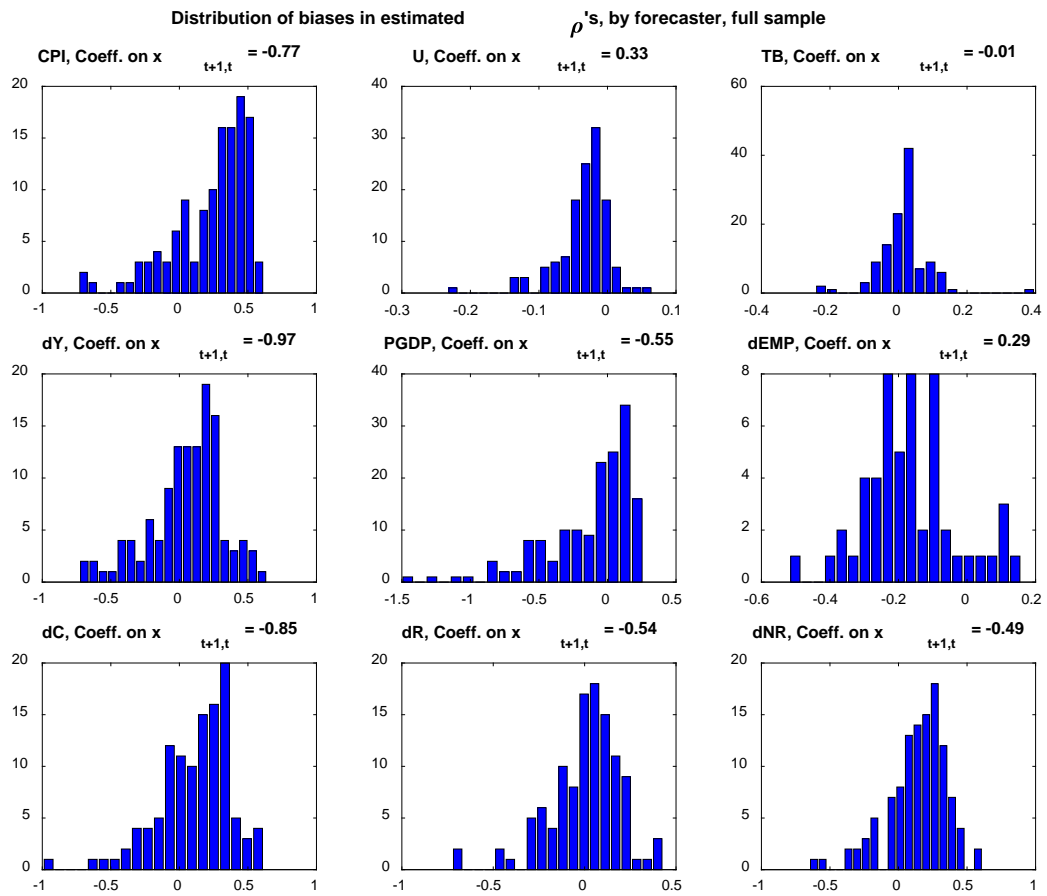


Figure 13
Simulation of simple model with and without inertial expectations effects

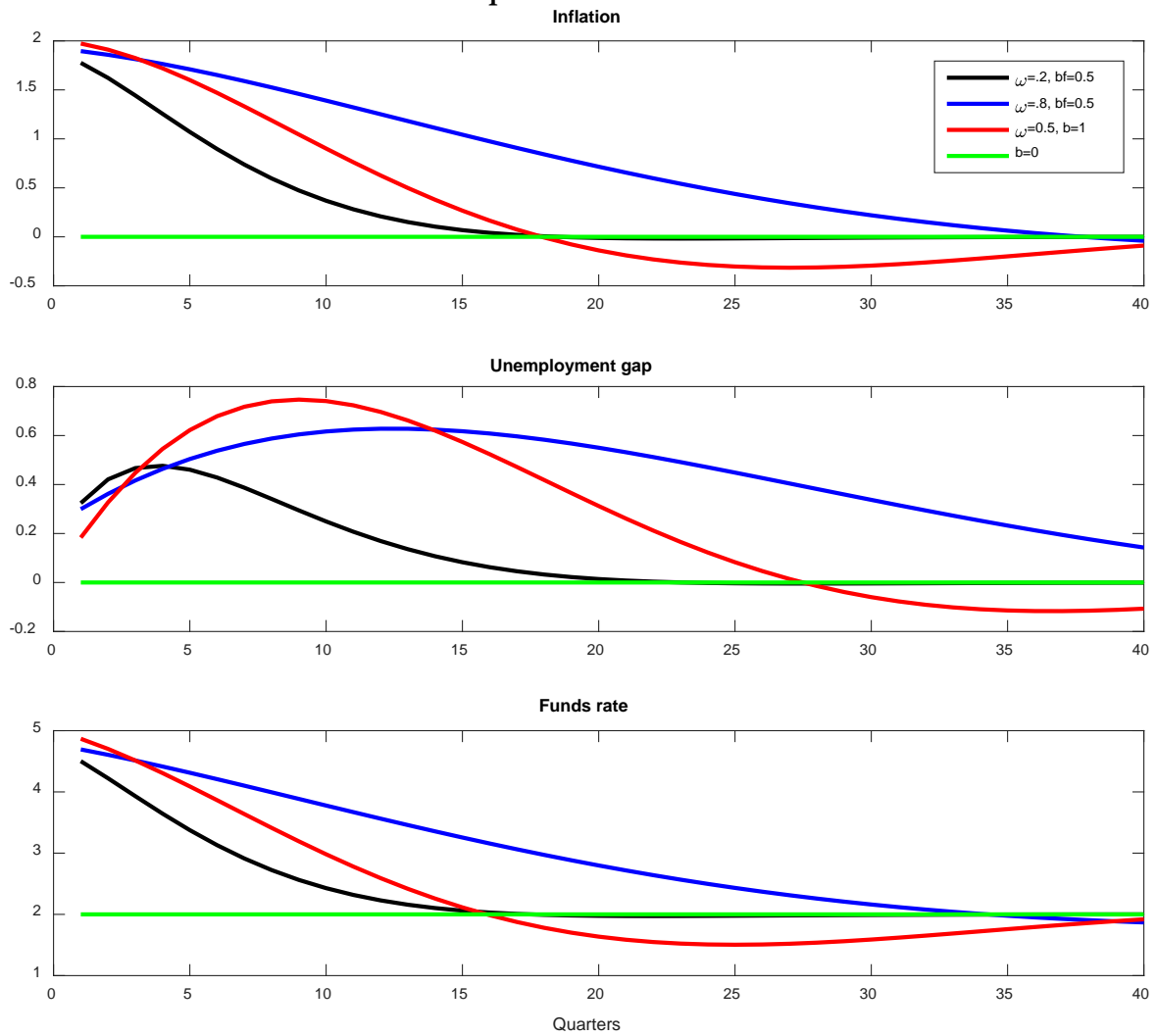


Table 1a Characteristics of SPF sample									
Forecaster participation (number of forecasts submitted)				Central tendency of forecast (1-qtr. Ahead)					
Inflation, CPI									
$N_t=146$				1968:Q4		1981:Q3		2018:Q1	
Mean	15.0			Mean	Med.	Mean	Med.	Mean	Med.
Median	8.7			-		7.9	8.0	2.0	2.0
Min, max	1, 70								
Inflation, GDP deflator									
$N_t = 196$				1968:Q4		1981:Q3		2018:Q1	
Mean	9.5			Mean	Med.	Mean	Med.	Mean	Med.
Median	5.1			3.0	3.3	7.4	8.5	1.5	1.5
Min, max	1, 71								
Unemployment									
$N_t = 196$				1968:Q4		1981:Q3		2018:Q1	
Mean	9.4			Mean	Med.	Mean	Med.	Mean	Med.
Median	4.5			3.8	3.8	7.5	7.5	4.8	4.8
Min, max	1, 71								
Firm type (percentage, $N_t=105$)¹									
Financial	45.8								
Nonfinancial	46.4								
Unknown	7.7								
¹ Firm type available only beginning in 1990:Q2 survey									

Table 1b Characteristics of ESPF sample									
Forecaster participation (number of forecasts submitted, 1968-2016)				Central tendency of forecast (1-year ahead)					
Inflation, CPI									
$N_t=70$				1999:Q1		2007:Q3		2015:Q4	
Mean	39			Mean	Med.	Mean	Med.	Mean	Med.
Median	43			1.3	1.4	2.0	2.0	1.05	1.1
Min, max	1, 69								
Output growth									
$N = 70$				1999:Q1		2007:Q3		2015:Q4	
Mean	39			Mean	Med.	Mean	Med.	Mean	Med.
Median	43			2.4	2.5	2.3	2.3	1.7	1.7
Min, max	1, 69								
Unemployment									
$N = 70$				1999:Q1		2007:Q3		2015:Q4	
Mean	39			Mean	Med.	Mean	Med.	Mean	Med.
Median	43			10.5	10.3	6.7	6.7	10.5	10.5
Min, max	1, 69								

Table 2
Test of revision efficiency, all variables, all horizons, 1981-2018:Q1

$$x_{t+k,t}^i = ax_{t+k,t-1}^i + b\text{Median}(x_{t+k,t-1}^i) + cx_{t-1}^i + dZ_{t-1}^i$$

	Inflation				Unemployment			
	$k=1$	$k=2$	$k=3$	$k=1$	$k=1$	$k=2$	$k=3$	$k=1$
$x_{t+k,t-1}^i$	0.43 (0.000)	0.48 (0.000)	0.41 (0.000)	0.45 (0.000)	0.32 (0.000)	0.44 (0.000)	0.51 (0.000)	0.22 (0.000)
$\text{Median}(x_{t+k,t-1}^i)$	0.37 (0.000)	0.36 (0.000)	0.39 (0.000)	0.28 (0.012)	0.61 (0.000)	0.60 (0.000)	0.56 (0.000)	0.45 (0.001)
x_{t-1}^i	0.04 (0.026)	0.05 (0.000)	0.06 (0.000)	0.03 (0.093)	0.08 (0.428)	-0.03 (0.759)	-0.05 (0.570)	0.33 (0.009)
Other vbls.				Y				Y
Test: $a=1$ (\hat{p})	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	3988	3971	3883	3659	5807	5784	5503	3726
	Treasury bill rate				Output growth			
	$k=1$	$k=2$	$k=3$	$k=1$	$k=1$	$k=2$	$k=3$	$k=1$
$x_{t+k,t-1}^i$	0.26 (0.000)	0.33 (0.000)	0.47 (0.000)	0.26 (0.000)	0.26 (0.000)	0.27 (0.000)	0.27 (0.000)	0.24 (0.004)
$\text{Median}(x_{t+k,t-1}^i)$	0.34 (0.125)	0.27 (0.184)	0.17 (0.189)	0.17 (0.474)	0.85 (0.000)	0.91 (0.000)	0.72 (0.000)	0.76 (0.000)
x_{t-1}^i	0.35 (0.117)	0.36 (0.061)	0.32 (0.010)	0.52 (0.023)	0.08 (0.003)	0.04 (0.174)	0.01 (0.565)	0.12 (0.000)
Other vbls.				Y				Y
Test: $a=1$ (\hat{p})	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	3927	3819	3815	3658	5737	5714	5404	3715
	GDP deflator				Employment			
	$k=1$	$k=2$	$k=3$	$k=1$	$k=1$	$k=2$	$k=3$	$k=1$
$x_{t+k,t-1}^i$	0.26 (0.000)	0.28 (0.000)	0.23 (0.000)	0.29 (0.000)	0.47 (0.000)	0.45 (0.000)	0.36 (0.000)	0.45 (0.000)
$\text{Median}(x_{t+k,t-1}^i)$	0.67 (0.000)	0.68 (0.000)	0.68 (0.000)	0.59 (0.000)	0.84 (0.000)	0.80 (0.000)	0.83 (0.000)	0.81 (0.000)
Other vbls.				Y				Y
Test: $a=1$ (\hat{p})	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	5690	5669	5394	3729	1723	1723	1713	1579
	Consumption				Res. Structures			
	$k=1$	$k=2$	$k=3$	$k=1$	$k=1$	$k=2$	$k=3$	$k=1$
$x_{t+k,t-1}^i$	0.37 (0.000)	0.38 (0.000)	0.33 (0.000)	0.35 (0.000)	0.47 (0.000)	0.54 (0.000)	0.50 (0.000)	0.47 (0.000)
$\text{Median}(x_{t+k,t-1}^i)$	0.74 (0.000)	0.61 (0.000)	0.59 (0.000)	0.60 (0.000)	0.56 (0.000)	0.40 (0.000)	0.57 (0.000)	0.53 (0.000)
Other vbls.				Y				Y
Test: $a=1$ (\hat{p})	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	4002	3983	3872	3679	3895	3873	3764	3584

Table 3a
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures

$$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = \gamma[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + b\pi_{t-1}^i + c'C(\pi_{t+1,t-1}) + dZ_t^i + \delta_i + \varepsilon_t^i$$

Inflation results, 1981:Q3-2018:Q1

Variable	$t+1$ ($k=1$)						$k=2$	$k=3$
$\pi_{t+k,t-1}^i - \pi_{t+k,t-1}^{Median}$	-0.56 (0.000)	-0.75 (0.000)	-0.56 (0.000)	-0.57 (0.000)	-0.55 (0.000)	-0.57 (0.000)	-0.52 (0.000)	-0.59 (0.000)
π_{t-1}^i			0.02 (0.116)	0.04 (0.026)	0.04 (0.033)	-0.04 (0.001)	0.05 (0.000)	0.06 (0.000)
$\pi_{t+k,t-1}^{Median}$				-0.21 (0.000)	-0.29 (0.001)	-0.20 (0.001)	-0.16 (0.000)	-0.20 (0.000)
U_{t-1}^i					-0.01 (0.593)		-0.10 (0.263)	
R_{t-1}^i					0.04 (0.259)		0.01 (0.921)	
Kitchen sink						Y		
Adjusted R-squared	0.16	0.19	0.16	0.18	0.17	0.34	0.23	0.28
Observations	3999	2729	3988	3988	3717	3540	3971	3883

Estimation sample: 1981:Q3-2018:Q1
“Kitchen sink” includes lagged real-time unemployment and inflation, current and t+1-period forecasts of all variables, revisions for other variables, discrepancies for other variables, current and lagged revisions to aggregate forecasts.

Table 3b
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, UNEMPLOYMENT Results, SPF, 1981-2018:Q1

$$U_{t+k,t}^i - U_{t+k,t-1}^i = \delta[U_{t+k,t-1}^i - U_{t+k,t-1}^{Median}] + aU_{t-1}^i + cZ_t^i + \delta_i + \mu_t + \varepsilon_t^i$$

Variable	$t+1$ ($k=1$)						$k=2$	$k=3$
$U_{t+k,t-1}^i - U_{t+1,t-1}^{Median}$	-0.67 (0.000)	-0.75 (0.001)	-0.68 (0.000)	-0.74 (0.000)	-0.71 (0.000)	-0.56 (0.000)	-0.49 (0.000)	
U_{t-1}^i			0.08 (0.428)	0.08 (0.707)	0.13 (0.000)	-0.03 (0.759)	-0.05 (0.570)	
$U_{t+k,t-1}^{Median}$			-0.08 (0.508)	-0.07 (0.757)	-0.13 (0.000)	0.04 (0.717)	0.07 (0.524)	
$\pi_{t-1,t}^i$				-0.01 (0.667)	-0.00 (0.754)			
$R_{t-1,t}^i$				0.02 (0.276)	0.05 (0.006)			
Additional controls						Y		
Adjusted R-squared	0.20	0.19	0.21	0.23	0.78	0.16	0.15	
Observations	5817	4256	5807	3796	3542	5784	5503	

Estimation sample: 1981:Q3-2018:Q1
“Additional controls” includes all lagged real-time variables, current and t+1-period forecasts of variables, revisions for other variables, discrepancies for other variables, current and lagged revisions to aggregate forecasts.

Table 3c
Real GDP growth

	$t+1$ ($k=1$)			$k=2$	$k=3$
$\Delta Y_{t+k,t-1}^i - \Delta Y_{t+k t-1}^{Median}$	-0.73 (0.000)	-0.73 (0.000)	-0.75 (0.000)	-0.73 (0.000)	-0.73 (0.000)
$\Delta Y_{t+k t-1}^{Median}$		0.19 (0.000)	0.16 (0.295)	0.21 (0.002)	-0.00 (0.961)
Other controls?			Y		
R-squared	0.31	0.32	0.41	0.35	0.34
Observations	5742	5742	3720	5719	5409
Table 3d					
3-month Treasury Bill Yield					
	$t+1$ ($k=1$)			$k=2$	$k=3$
$R_{t+k,t-1}^i - R_{t+k t-1}^{Median}$	-0.68 (0.000)	-0.69 (0.000)	-0.69 (0.000)	-0.55 (0.000)	-0.51 (0.000)
$R_{t+k t-1}^{Median}$		-0.06 (0.026)	-0.42 (0.089)	-0.04 (0.095)	-0.03 (0.217)
Other controls?			Y		
R-squared	0.16	0.21	0.21	0.17	0.19
Observations	3947	3947	3732	3933	3823
Table 3e					
10-Year Treasury Yield					
	$t+1$ ($k=1$)			$k=2$	$k=3$
$T10_{t+k,t-1}^i - T10_{t+k t-1}^{Median}$	-0.67 (0.000)	-0.68 (0.000)	-0.67 (0.000)	-0.59 (0.000)	-0.53 (0.000)
$T10_{t+k t-1}^{Median}$		-0.04 (0.058)	-0.06 (0.002)	-0.03 (0.123)	-0.02 (0.288)
Other controls?	N	N	Y	N	N
R-squared	0.19	0.19	0.21	0.17	0.17
Observations	3176	3176	3045	3160	3047
Table 3f					
BAA Corporate bond Yield					
	$t+1$ ($k=1$)			$k=2$	$k=3$
$BAA_{t+k,t-1}^i - BAA_{t+k t-1}^{Median}$	-0.68 (0.000)	-0.66 (0.000)	-0.66 (0.000)	-0.56 (0.000)	-0.57 (0.000)
$BAA_{t+k t-1}^{Median}$		-0.15 (0.000)	-0.27 (0.006)	-0.18 (0.000)	-0.19 (0.000)
Other controls?	N	N	Y	N	N
R-squared	0.27	0.30	0.33	0.26	0.26
Observations	771	771	735	771	761

Table 3g
More revision regressions
GDP deflator, payroll employment, and real GDP components

	GDP deflator (1968:4-present)				Payroll employment (2003:4-present)			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t-1}^i - x_{t+k t-1}^{Median}$	-0.70 (0.000)	-0.70 (0.000)	-0.63 (0.000)	-0.69 (0.000)	-0.70 (0.000)	-0.53 (0.000)	-0.55 (0.000)	-0.64 (0.000)
$x_{t+k t-1}^{Median}$	-0.07 (0.297)	-0.08 (0.080)	-0.04 (0.263)	-0.10 (0.011)	0.10 (0.765)	0.20 (0.409)	0.20 (0.384)	0.19 (0.348)
x_{t-1}	0.06 (0.022)	0.03 (0.071)	0.03 (0.045)	0.03 (0.035)	0.09 (0.693)	0.04 (0.630)	0.02 (0.790)	0.00 (0.919)
R-squared	0.24	0.32	0.25	0.32	0.29	0.27	0.22	0.28
Observations	4845	4850	4830	4621	1646	1646	1646	1636
	Real C spending growth (1981:3-present)				Real res. Investment growth (1981:3-present)			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t-1}^i - x_{t+k t-1}^{Median}$	-0.69 (0.000)	-0.64 (0.000)	-0.62 (0.000)	-0.67 (0.000)	-0.64 (0.000)	-0.52 (0.000)	-0.45 (0.000)	-0.50 (0.000)
$x_{t+k t-1}^{Median}$	0.12 (0.212)	-0.15 (0.150)	-0.13 (0.037)	-0.14 (0.155)	-0.06 (0.399)	-0.04 (0.536)	-0.06 (0.397)	0.08 (0.005)
x_{t-1}	0.04 (0.442)	0.12 (0.000)	0.07 (0.005)	0.04 (0.010)	0.14 (0.000)	0.07 (0.013)	0.01 (0.727)	-0.01 (0.385)
R-squared	0.23	0.26	0.27	0.26	0.30	0.22	0.17	0.25
Observations	3929	3928	3909	3798	3820	3819	3797	3688
	Real nonres. Investment growth (1981:3-present)				Real net exports (1981:3-present)			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t-1}^i - x_{t+k t-1}^{Median}$	-0.67 (0.000)	-0.55 (0.000)	-0.62 (0.000)	-0.60 (0.000)	-0.77 (0.000)	-0.67 (0.000)	-0.58 (0.000)	-0.54 (0.000)
$x_{t+k t-1}^{Median}$	-0.01 (0.922)	-0.01 (0.898)	0.04 (0.692)	0.07 (0.517)	-0.02 (0.021)	-0.02 (0.030)	-0.02 (0.067)	-0.02 (0.076)
x_{t-1}	0.14 (0.000)	0.11 (0.000)	0.06 (0.000)	0.04 (0.002)				
R-squared	0.19	0.26	0.31	0.26	0.22	0.22	0.21	0.21
Observations	3826	3823	3804	3696	3921	3918	3898	3792

Table 4								
The effect of common information								
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, controlling for revision in aggregate forecast, 1981-2018:Q1								
$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = \gamma[\pi_{t+1,t-2}^{Median} - \pi_{t+1 t-1}^{Median}] + \delta[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + a\pi_{t-1}^i + cZ_t^i + \delta_i + \mu_t + \varepsilon_t^i$								
Inflation results								
Variable	Lagged revision				Contemporaneous revision			
$\pi_{t+1,t-1}^i - \pi_{t+1 t-1}^{Median}$	-0.56 (0.000)	-0.55 (0.000)	-0.56 (0.000)	-0.53 (0.000)	-0.58 (0.000)	-0.58 (0.000)	-0.56 (0.000)	-0.56 (0.000)
$\pi_{t+1,t-1}^{Median} - \pi_{t+1 t-2}^{Median}$		0.11 (0.386)	0.16 (0.204)	0.19 (0.172)				
$\pi_{t+1,t}^{Median} - \pi_{t+1 t-1}^{Median}$					0.91 (0.000)	0.88 (0.000)	0.87 (0.000)	0.62 (0.006)
π_{t-1}^i	0.02 (0.116)	0.02 (0.337)	0.03 (0.093)	0.03 (0.153)	-0.01 (0.506)	0.00 (0.963)	0.00 (0.917)	
$\pi_{t+1,t-1}^{Median}$			-0.24 (0.000)	-0.36 (0.000)		-0.07 (0.007)	-0.07 (0.060)	
Additional forecast variables	N	N	N	Y	N	N	Y	Instrumented
Adjusted R-squared	0.16	0.15	0.17	0.17	0.29	0.29	0.28	-
Observations	3988	3952	3952	3685	3988	3988	3717	3962
* “Additional forecast variables” includes real-time estimates of lagged unemployment, Treasury bill rate.								
Unemployment results								
Variable	Lagged revision				Contemporaneous revision			
$U_{t+1,t-1}^i - U_{t+1 t-1}^{Median}$	-0.68 (0.000)	-0.65 (0.000)	-0.67 (0.000)	-0.72 (0.000)	-0.66 (0.000)	-0.66 (0.000)	-0.70 (0.000)	-0.67 (0.000)
$U_{t+1,t-1}^{Median} - U_{t+1 t-2}^{Median}$		0.44 (0.000)	0.53 (0.000)	0.61 (0.000)				
$U_{t+1,t}^{Median} - U_{t+1 t-1}^{Median}$					0.96 (0.000)	0.96 (0.000)	0.99 (0.000)	0.99 (0.000)
U_{t-1}^i	0.01 (0.471)	-0.01 (0.401)	0.26 (0.000)	0.41 (0.000)	0.00 (0.606)	-0.01 (0.139)	-0.00 (0.935)	
$U_{t+1,t-1}^i$			-0.29 (0.000)	-0.44 (0.000)		0.02 (0.091)	0.00 (0.986)	
Additional forecast variables	N	N	N	Y	N	N	Y	Instrumented
Adjusted R-squared	0.21	0.37	0.41	0.45	0.77	0.77	0.79	-
Observations	5807	5363	5363	3764	5807	5807	3796	5371
* “Additional forecast variables” includes real-time estimates of lagged inflation, Treasury bill rate.								

Table 5										
Learning versus lagged central tendencies										
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measure, with lagged real-time actual data										
Sub-sample estimates										
	$\pi_{t+1,t}^i - \pi_{t+1,t-1}^i$					$U_{t+1,t}^i - U_{t+1,t-1}^i$				
Sample	Full sample	1990-	1995-	2000-	2005-	Full sample	1990-	1995-	2000-	2005-
$\pi_{t+1,t}^i - \pi_{t+1,t-1}^{Median}$	-0.56 (0.000)	-0.50 (0.000)	-0.49 (0.000)	-0.49 (0.000)	-0.48 (0.000)					
$U_{t+1,t}^i - U_{t+1,t-1}^{Median}$						-0.70 (0.000)	-0.70 (0.000)	-0.71 (0.000)	-0.72 (0.000)	-0.75 (0.000)
$\pi_{t+1,t}^{Median} - \pi_{t+1,t-1}^{Median}$	0.87 (0.000)	0.85 (0.000)	0.85 (0.000)	0.84 (0.000)	0.86 (0.000)					
$U_{t+1,t}^{Median} - U_{t+1,t-1}^{Median}$						0.96 (0.000)	0.93 (0.000)	0.95 (0.000)	0.94 (0.000)	0.94 (0.000)
Observations	3636	3170	2718	2182	1705	3703	3286	2816	2262	1756
Additional controls include $\pi_{t-1}^i, \pi_{t+1,t-1}^i$ for inflation, $U_{t-1}^i, U_{t+1,t-1}^i$ for unemployment										

Table 6						
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, INFLATION Results, Euro SPF, 1999-2018						
Regressor	Dependent variable (forecast revisions)					
	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$
$\pi_{yk,t-1}^i - \pi_{yk,t-1}^{Median}$	-0.56 (0.000)	-0.48 (0.000)	-0.59 (0.000)	-0.49 (0.000)	-0.52 (0.000)	-0.51 (0.000)
$\pi_{yk,t-1}^{Median}$	-0.38 (0.012)	-0.47 (0.000)	-0.47 (0.000)	-0.46 (0.000)	-0.61 (0.000)	-0.46 (0.000)
π_{t-1}	0.17 (0.001)	0.06 (0.000)	0.16 (0.000)	0.06 (0.000)	0.20 (0.000)	0.07 (0.000)
Additional controls						
$\pi_{yk,t-1}^{Median}$			Y	Y	Y	Y
Unemployment discrepancy					Y	Y
Exogenous assumptions					Y	Y
Output and unemployment forecasts					Y	Y
Adjusted R-squared	0.19	0.24	0.28	0.25	0.44	0.32
Observations	3405	1054	3200	1025	2162	739

Table 7						
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, UNEMPLOYMENT Results, Euro SPF, 1999-2018						
Regressor	Dependent variable (forecast revisions)					
	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$
$U_{yk,t-1}^i - U_{yk,t-1}^{Median}$	-0.36 (0.000)	-0.32 (0.000)	-0.23 (0.000)	-0.08 (0.504)	-0.38 (0.000)	0.06 (0.518)
$U_{yk,t-1}^{Median}$	0.20 (0.156)	-0.00 (0.998)	-0.12 (0.042)	-	0.19 (0.016)	-
U_{t-1}	-0.24 (0.115)	-0.06 (0.464)	-1.09 (0.000)	-1.08 (0.000)	-0.23 (0.007)	-0.02 (0.826)
Additional controls						
$U_{yk,t-1}^{Median}$			Y	Y	Y	Y
Inflation discrepancy					Y	Y
Exogenous assumptions					Y	Y
Output and unemployment forecasts					Y	Y
Adjusted R-squared	0.16	0.11	0.66	0.45	0.35	0.35
Observations	3230	963	3214	960	2162	728

Table 8						
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, OUTPUT GROWTH Results, Euro SPF, 1999-2018						
Regressor	Dependent variable (forecast revisions)					
	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$
$\Delta y_{yk,t-1}^i - \Delta y_{yk,t-1}^{Median}$	-0.68 (0.000)	-0.52 (0.000)	-0.73 (0.000)	-0.52 (0.000)	-0.77 (0.000)	-0.55 (0.000)
$\Delta y_{yk,t-1}^{Median}$	-0.46 (0.005)	-0.08 (0.111)	-0.57 (0.001)	-0.00 (0.968)	-0.61 (0.001)	-0.15 (0.109)
Δy_{t-1}	0.18 (0.129)	-0.02 (0.096)	0.04 (0.655)	-0.07 (0.000)	0.15 (0.043)	0.00 (0.765)
Additional controls						
$\Delta y_{yk,t-1}^{Median}$			Y	Y	Y	Y
Inflation discrepancy					Y	Y
Exogenous assumptions					Y	Y
Output and unemployment forecasts					Y	Y
Adjusted R-squared	0.16	0.13	0.30	0.21	0.41	0.30
Observations	3246	1029	3118	1003	2162	744

Table 9
Effect of common information: Response of forecast revisions to lagged discrepancies
between individual forecasts and central tendency measures, Euro SPF, with revisions to
aggregate forecast, 1999-2018

Regressor	Dependent variable (forecast revisions)					
	π		U		Δy	
	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$
$X_{y1,t-1}^i - X_{yk,t-1}^{Median}$	-0.54 (0.000)	-0.48 (0.000)	-0.51 (0.000)	-0.38 (0.000)	-0.66 (0.000)	-0.54 (0.000)
$X_{yk,t}^{Median} - X_{yk,t-1}^{Median}$	0.94 (0.000)	0.66 (0.000)	0.96 (0.000)	0.96 (0.000)	0.98 (0.000)	0.96 (0.000)
$X_{yk,t-1}^{Median}$	-0.02 (0.464)	-0.14 (0.009)	0.03 (0.171)	0.06 (0.021)	-0.02 (0.145)	0.00 (0.865)
$X_{k,t-1}^i$	0.03 (0.052)	0.02 (0.011)	-0.04 (0.087)	-0.07 (0.012)	0.01 (0.057)	-0.00 (0.476)
Adjusted R-squared	0.47	0.30	0.65	0.46	0.77	0.29
Observations	3405	1054	3230	963	3246	1029

Table 10											
Michigan Survey											
Regression of revision in 12-month inflation forecast (from current interview to 6-months previous) on discrepancy between last inflation forecast and lagged mean/median, as well as other controls											
1978:Jan-2017:Apr											
	Full sample					Sub-samples					
	With lagged discrep.	With lagged median forecast	All indiv. controls	Add aggregate revs.	Drop round resp.'s	1985-forward	1995-forward	2000-forward	2005-forward	Recess. only	Non-recess.
$\pi_{1Y,t-1}^{Mich}$ - $Median(\pi_{1Y,t-1}^{Mich})$	-0.72 (0.000)	-0.72 (0.000)	-0.69 (0.000)	-0.69 (0.000)	-0.67 (0.000)	-0.69 (0.000)	-0.70 (0.000)	-0.69 (0.000)	-0.69 (0.000)	-0.67 (0.000)	-0.69 (0.000)
$Median(\pi_{1Y,t-1}^{Mich})$		-0.41 (0.000)	-0.48 (0.000)	0.07 (0.052)	-0.11 (0.001)	-0.82 (0.000)	-0.84 (0.000)	-0.90 (0.000)	-1.00 (0.000)	-0.60 (0.000)	-0.42 (0.000)
Revision to family income, 1-yr. expec.			0.00 (0.677)	0.00 (0.736)		0.00 (0.725)	0.00 (0.010)	0.00 (0.008)	0.00 (0.073)	0.00 (0.823)	0.00 (0.718)
Revision to 5-year inflation expec.			0.20 (0.000)	0.19 (0.000)		0.21 (0.000)	0.26 (0.000)	0.28 (0.000)	0.28 (0.000)	0.21 (0.000)	0.19 (0.000)
Aggregate revision				0.80 (0.000)							
Test of EC restriction	0.000	0.000	0.000	-		0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R-squared	0.427	0.432	0.469	0.479	0.362	0.470	0.467	0.442	0.449	0.420	0.481
Observations	86404	86404	58960	58960	47763	53612	42326	32882	24246	7117	51843
Simple test of revision efficiency											
$\pi_{kY,t}^{Mich} = a\pi_{kY,t-1}^{Mich} + bMedian(\pi_{kY,t-1}^{Mich}); k = 1, 5$											
Test: $a = 1$											
	One-year forecast										
	Coefficient					p-value of test $a = 1$					
$\pi_{1Y,t-1}^{Mich}$ (a)	0.29 (0.000)					0.28 (0.000)					
$Median(\pi_{1Y,t-1}^{Mich})$ (b)						0.60 (0.000)					
	Five-year forecast										
	Coefficient					p-value of test $a = 1$					
$\pi_{5Y,t-1}^{Mich}$ (a)	0.33 (0.000)					0.30 (0.000)					
$Median(\pi_{5Y,t-1}^{Mich})$ (b)						0.76 (0.000)					

Table 11								
"Anchoring" regressions								
SPF inflation forecast revisions, varying horizons								
Revision regressions with the revision in the long-term (10-year) forecast, full sample								
	Revision				Revision			
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
$\pi_{t,t-1}^i - \pi_{t t-1}^{Median}$	-0.59 (0.000)				-0.64 (0.000)			
$\pi_{t+1,t-1}^i - \pi_{t+1 t-1}^{Median}$		-0.47 (0.000)				-0.48 (0.000)		
$\pi_{t+2,t-1}^i - \pi_{t+2 t-1}^{Median}$			-0.43 (0.000)				-0.43 (0.000)	
$\pi_{t+3,t-1}^i - \pi_{t+3 t-1}^{Median}$				-0.51 (0.000)				-0.52 (0.000)
Lagged revision in 10-year aggregate forecast	-0.43 (0.425)	0.33 (0.057)	0.19 (0.288)	0.08 (0.692)	-0.64 (0.223)	0.31 (0.120)	0.10 (0.592)	-0.06 (0.777)
Other controls	N	N	N	N	Y	Y	Y	Y
Adjusted R-squared	0.09	0.11	0.15	0.18	0.19	0.12	0.17	0.22
Observations	3252	3251	3239	3166	3000	2999	2991	2947
Post-1999 sample								
	t	$t+1$	$t+2$	$t+3$	t	$t+1$	$t+2$	$t+3$
$\pi_{t,t-1}^i - \pi_{t t-1}^{Median}$	-0.60 (0.000)				-0.65 (0.000)			
$\pi_{t+1,t-1}^i - \pi_{t+1 t-1}^{Median}$		-0.47 (0.000)				-0.47 (0.000)		
$\pi_{t+2,t-1}^i - \pi_{t+2 t-1}^{Median}$			-0.42 (0.000)				-0.42 (0.000)	
$\pi_{t+3,t-1}^i - \pi_{t+3 t-1}^{Median}$				-0.51 (0.000)				-0.52 (0.000)
Lagged revision in 10-year aggregate forecast	-1.28 (0.219)	0.26 (0.349)	0.09 (0.633)	0.00 (0.995)	-1.14 (0.246)	0.41 (0.274)	0.17 (0.310)	-0.02 (0.913)
Other controls	N	N	N	N	Y	Y	Y	Y
Adjusted R-squared		0.09	0.13	0.17	0.21	0.12	0.18	0.22
Observations	2386	2386	2380	2334	2177	2177	2175	2156

Table 12					
Michigan survey, one-year ahead inflation expectations					
Test for “anchoring” to long-run (2- to 5-year) median expectations					
	(1)	(2)	(3)	(4)	(5)
Lagged median 1-yr. expec.	0.76 (0.000)	0.71 (0.000)	0.51 (0.000)	0.50 (0.000)	0.44 (0.000)
Lagged median 2-5-yr. expec.	0.38 (0.000)	0.38 (0.000)	0.42 (0.000)	0.42 (0.000)	0.48 (0.000)
Unemp. controls		Y	Y	Y	Y
Income, financial controls			Y	Y	Y
In previous survey?				Y	Y
Interaction terms					Y
Adjusted R-squared	0.041	0.054	0.094	0.095	0.109
Observations	181363	181363	50945	50945	49232

Table 13								
Percentage of forecasters whose revision equals zero								
SPF (1981-2018)				Michigan (1978-2018)	Euro SPF (1999-2018)			
One-quarter		Four-quarter		One-year	0, 1, 2, 5-year (joint)			
Inflation	Unemp.	Inflation	Unemp.	Inflation	Infl.	Unemp	Output growth	All 3 vars.
18.7	20.2	6.2	6.9	9.4	33.6	29.2	9.2	3.3

Table 14										
Test regressions for sticky information models										
$Error_{t+k}^i \equiv x_{t+k} - x_{t+k,t}^i = \alpha x_{t+k,t-1}^{Median} + \beta R_{t+k,t}^i + \gamma x_{t+k,t-1}^i \mid R_{t+k,t}^i \neq 0$										
$R_{t+k,t}^i \equiv x_{t+k,t}^i - x_{t+k,t-1}^i$										
SPF forecasts										
	Inflation errors					Unemployment errors				
	$k=0$	$k=1$	$k=1$	$k=2$	$k=3$	$k=0$	$k=1$	$k=1$	$k=2$	$k=3$
$R_{t+k,t}^i[\beta]$	-0.10 (0.513)	-0.79 (0.000)	-0.85 (0.000)	-0.90 (0.000)	-0.88 (0.000)	0.04 (0.641)	0.15 (0.382)	-0.04 (0.672)	0.29 (0.183)	0.40 (0.075)
$x_{t+k,t-1}^i[\gamma]$	-0.31 (0.024)	-0.78 (0.000)	-0.73 (0.000)	-0.99 (0.000)	-0.88 (0.000)	-0.08 (0.389)	-0.18 (0.154)	-0.24 (0.021)	-0.19 (0.245)	-0.24 (0.088)
$Median(x_{t+k,t-1}^i)$ [α]	-0.01 (0.957)	0.12 (0.554)	1.00 (0.451)	0.35 (0.045)	0.24 (0.120)	0.07 (0.452)	0.15 (0.258)	1.44 (0.002)	0.12 (0.521)	0.11 (0.518)
Additional $t-1$ period information			Y					Y		
R-squared	0.07	0.15	0.25	0.16	0.15	0.06	0.10	0.20	0.12	0.14
Observations	3483	3241	3005	3074	2951	3407	3384	2973	3322	3171
	Output growth errors					Treasury bill errors				
	$k=0$	$k=1$	$k=1$	$k=2$	$k=3$	$k=0$	$k=1$	$k=1$	$k=2$	$k=3$
$R_{t+k,t}^i[\beta]$	-0.43 (0.000)	-0.51 (0.000)	-0.53 (0.000)	-0.73 (0.000)	-1.03 (0.000)	0.03 (0.218)	-0.10 (0.311)	-0.12 (0.265)	-0.06 (0.542)	0.00 (0.986)
$x_{t+k,t-1}^i[\gamma]$	-0.51 (0.000)	-0.64 (0.000)	-0.61 (0.000)	-0.83 (0.000)	-1.04 (0.000)	-0.00 (0.987)	-0.31 (0.000)	-0.34 (0.000)	-0.43 (0.000)	-0.49 (0.000)
$Median(x_{t+k,t-1}^i)$ [α]	0.62 (0.000)	0.56 (0.079)	0.72 (0.001)	0.29 (0.489)	0.67 (0.166)	-0.02 (0.678)	0.23 (0.006)	-0.28 (0.604)	0.26 (0.000)	0.26 (0.026)
Additional controls			Y					Y		
R-squared	0.11	0.08	0.21	0.15	0.24	0.01	0.05	0.10	0.10	0.12
Observations	4031	3968	3471	3918	3783	3392	3367	3092	3243	3182
Michigan Forecasts										
	One-year inflation forecast errors (monthly, 12-month change)									
$Median(x_{t+k,t-1}^i)[\beta]$	-0.20 (0.000)					0.08 (0.102)				
$R_{t+k,t}^i[\gamma]$	-0.41 (0.000)					-0.39 (0.000)				
Additional t and $t-1$ period information						Y				
R-squared	0.293					0.345				
Observations	61191					12255				

Table 15

Test regressions for noisy information models

$$Error_{t+k}^i \equiv x_{t+k} - x_{t+k,t}^i = \alpha Z_t + \beta R_{t+k,t}^i + \gamma x_{t+k,t-1}^i$$

$$R_{t+k,t}^i \equiv x_{t+k,t}^i - x_{t+k,t-1}^i$$

$$Z_t = [x_{t+k,t-1}^{Median}, y_{t+k,t-1}^i, y_{t+k,t}^i]$$

Inflation errors								
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=3$
$R_{t+k,t}^i$	-0.03 (0.777)	-0.10 (0.511)	-0.47 (0.000)	-0.80 (0.000)	-0.89 (0.000)	-0.86 (0.000)	-0.98 (0.000)	-0.89 (0.000)
$x_{t+k,t-1}^i$		-0.32 (0.023)		-0.81 (0.000)	-0.80 (0.000)	-0.82 (0.000)	-0.91 (0.000)	-0.91 (0.000)
$Median(x_{t+k,t-1}^i)$		-0.00 (0.997)		0.15 (0.414)	1.23 (0.358)	-	0.34 (0.043)	0.28 (0.080)
Additional Z's					Y	Y		
R-squared	0.00	0.07	0.03	0.15	0.27	0.26	0.16	0.15
Observations	3884	3884	3856	3856	3527	3527	3813	3699
Unemployment errors								
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=3$
$R_{t+k,t}^i$	0.07 (0.309)	0.03 (0.767)	0.20 (0.106)	0.13 (0.433)	-0.24 (0.010)	0.01 (0.918)	0.29 (0.186)	0.38 (0.105)
$x_{t+k,t-1}^i$		-0.13 (0.163)		-0.23 (0.064)	-0.40 (0.000)	0.01 (0.917)	-0.22 (0.149)	-0.29 (0.022)
$Median(x_{t+k,t-1}^i)$		0.12 (0.196)		0.20 (0.120)	1.33 (0.001)	-	0.15 (0.376)	0.17 (0.295)
Additional Z's					Y	Y		
R-squared	0.02	0.06	0.06	0.10	0.19	0.15	0.12	0.15
Observations	4092	4092	4063	4063	3587	3593	4018	3901
Real GDP growth errors								
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=3$
$R_{t+k,t}^i$	-0.24 (0.001)	-0.43 (0.000)	-0.14 (0.076)	-0.51 (0.000)	-0.73 (0.000)	-0.72 (0.000)	-0.73 (0.000)	-1.03 (0.000)
$x_{t+k,t-1}^i$		-0.51 (0.000)		-0.64 (0.000)	-0.80 (0.000)	-0.74 (0.000)	-0.83 (0.000)	-1.04 (0.000)
$Median(x_{t+k,t-1}^i)$		0.62 (0.000)		0.56 (0.081)	-0.08 (0.866)	-	0.28 (0.507)	0.67 (0.169)
Additional Z's					Y	Y		
R-squared	0.03	0.11	0.01	0.08	0.25	0.23	0.04	0.13
Observations	4037	4037	3986	3986	3559	3559	3940	3804
3-mo. Treasury bill errors								
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=3$
$R_{t+k,t}^i$	0.04 (0.025)	0.02 (0.271)	-0.01 (0.920)	-0.10 (0.324)	-0.21 (0.022)	-0.22 (0.045)	-0.06 (0.560)	0.00 (0.996)
$x_{t+k,t-1}^i$		-0.01 (0.905)		-0.29 (0.000)	-0.17 (0.060)	-0.17 (0.085)	-0.41 (0.000)	-0.50 (0.000)
$Median(x_{t+k,t-1}^i)$		-0.02 (0.762)		0.22 (0.004)	-0.26 (0.646)		0.25 (0.000)	0.28 (0.017)
Additional Z's					Y	Y		

R-squared	0.01	0.01	0.00	0.04	0.12	0.12	0.10	0.12		
Observations	3846	3843	3844	3830	3479	3479	3698	3668		
GDP deflator errors										
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=2$	$k=3$	$k=3$
$R_{t+k,t}^i$	-0.40 (0.000)	-0.68 (0.000)	-0.29 (0.000)	-0.67 (0.000)	-1.03 (0.000)	-0.99 (0.000)	-0.42 (0.000)	-0.79 (0.000)	-0.37 (0.000)	-0.82 (0.000)
$x_{t+k,t-1}^i$		-0.74 (0.000)		-0.72 (0.000)	-0.97 (0.000)	-0.90 (0.000)		-0.85 (0.000)		-0.85 (0.000)
$Median(x_{t+k,t-1}^i)$		0.60 (0.000)		0.40 (0.002)	1.11 (0.061)	-		0.44 (0.002)		0.36 (0.037)
Additional Z's					Y	Y				
R-squared	0.12	0.28	0.04	0.14	0.68	0.59	0.07	0.17	0.05	0.14
Observations	4845	4845	4823	4823	1539	1556	4775	4775	4540	4540
Employment growth errors										
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=2$	$k=3$	$k=3$
$R_{t+k,t}^i$	-0.02 (0.940)	-0.39 (0.004)	0.29 (0.351)	-0.26 (0.214)	-0.79 (0.000)	-0.61 (0.000)	0.20 (0.534)	-0.27 (0.256)	-0.02 (0.908)	-0.48 (0.008)
$x_{t+k,t-1}^i$		-0.49 (0.000)		-0.56 (0.000)	-0.93 (0.000)	-0.59 (0.000)		-0.50 (0.013)		-0.63 (0.000)
$Median(x_{t+k,t-1}^i)$		1.08 (0.000)		1.60 (0.000)	2.64 (0.000)	-		1.96 (0.001)		2.52 (0.002)
Additional Z's					Y	Y				
R-squared	0.00	0.42	0.03	0.36	0.74	0.63	0.01	0.31	0.00	0.26
Observations	1625	1625	1602	1602	1479	1479	1576	1576	1542	1542
Consumption growth errors										
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=2$	$k=3$	$k=3$
$R_{t+k,t}^i$	-0.42 (0.000)	-0.68 (0.000)	-0.45 (0.000)	-0.80 (0.000)	-0.99 (0.000)	-0.89 (0.000)	-0.38 (0.000)	-0.77 (0.000)	-0.47 (0.000)	-0.92 (0.000)
$x_{t+k,t-1}^i$		-0.76 (0.000)		-0.84 (0.000)	-1.01 (0.000)	-0.93 (0.000)		-0.81 (0.000)		-0.91 (0.000)
$Median(x_{t+k,t-1}^i)$		0.87 (0.000)		1.13 (0.000)	0.10 (0.891)	-		0.78 (0.037)		0.88 (0.024)
Additional Z's					Y	Y				
R-squared	0.12	0.29	0.08	0.26	0.61	0.52	0.05	0.20	0.09	0.24
Observations	3904	3904	3877	3877	1533	1550	3830	3830	3697	3697
Nonresidential structures growth errors										
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=2$	$k=3$	$k=3$
$R_{t+k,t}^i$	-0.28 (0.003)	-0.51 (0.000)	-0.22 (0.045)	-0.49 (0.001)	-0.97 (0.000)	-0.83 (0.000)	-0.33 (0.000)	-0.69 (0.000)	-0.36 (0.000)	-0.76 (0.000)
$x_{t+k,t-1}^i$		-0.65 (0.000)		-0.69 (0.000)	-0.94 (0.000)	-0.87 (0.000)		-0.70 (0.000)		-0.87 (0.000)
$Median(x_{t+k,t-1}^i)$		0.91 (0.000)		0.92 (0.003)	-0.03 (0.981)	-		0.94 (0.039)		0.93 (0.105)
Additional Z's					Y	Y				
R-squared	0.10	0.21	0.01	0.08	0.50	0.42	0.01	0.07	0.02	0.11
Observations	3802	3802	3774	3774	1531	1548	3728	3728	3599	3599
Residential structures growth errors										
	$k=0$	$k=0$	$k=1$	$k=1$	$k=1$	$k=1$	$k=2$	$k=2$	$k=3$	$k=3$

$R_{t+k,t}^i$	-0.56 (0.000)	-0.84 (0.000)	-0.27 (0.002)	-0.57 (0.000)	-0.81 (0.000)	-0.79 (0.000)	-0.31 (0.000)	-0.63 (0.000)	-0.46 (0.000)	-1.04 (0.000)
$x_{t+k,t-1}^i$		-0.88 (0.000)		-0.74 (0.000)	-1.00 (0.000)	-1.06 (0.000)		-0.78 (0.000)		-1.08 (0.000)
$Median(x_{t+k,t-1}^i)$				0.83 (0.001)	0.04 (0.986)	-		0.62 (0.031)		1.45 (0.000)
Additional Z's					Y	Y				
R-squared	0.14	0.49	0.01	0.12	0.35	0.30	0.02	0.13	0.03	0.23
Observations	3796	3796	3770	3770	1529	1546	3722	3722	3593	3593

Table 16								
Shleifer <i>et al</i> test (2017)								
Regress forecast errors on components of revision from $t-1$ to t (allow forecasts to enter separately)								
$x_{t+h} - x_{t+h,t}^i = ax_{t+h,t}^i + bx_{t+h,t-1}^i + \varepsilon_{t+h}^i$								
	Inflation				Unemployment			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	-0.10 (0.474)	-0.77 (0.000)	-0.91 (0.000)	-0.83 (0.000)	0.06 (0.363)	0.20 (0.134)	0.33 (0.053)	0.43 (0.023)
$x_{t+k,t-1}^i$ (b)	-0.22 (0.016)	0.04 (0.741)	0.16 (0.060)	0.06 (0.558)	-0.08 (0.255)	-0.23 (0.079)	-0.40 (0.024)	-0.56 (0.008)
Test: $a+b=0?$	0.000	0.000	0.000	0.000	.036	.015	.0062	.0033
Observations	3884	3856	3813	3699	4092	4063	4018	3901
	GDP growth				3-mo. Tbill rate			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	-0.30 (0.003)	-0.40 (0.021)	-0.70 (0.000)	-0.97 (0.000)	0.01 (0.598)	-0.01 (0.869)	0.05 (0.537)	0.08 (0.494)
$x_{t+k,t-1}^i$ (b)	0.08 (0.059)	-0.07 (0.127)	-0.07 (0.320)	0.07 (0.302)	-0.03 (0.024)	-0.06 (0.422)	-0.21 (0.000)	-0.32 (0.002)
Test: $a+b=0?$.040	.0063	0.000	0.000	0.012	0.0045	0.000	0.000
Observations	4037	3986	3940	3804	3843	3832	3698	3668
	GDP deflator				Payroll employment growth			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	-0.54 (0.000)	-0.55 (0.000)	-0.68 (0.000)	-0.72 (0.000)	-0.06 (0.621)	0.29 (0.194)	0.30 (0.329)	0.15 (0.656)
$x_{t+k,t-1}^i$ (b)	0.18 (0.000)	0.07 (0.219)	0.08 (0.147)	0.07 (0.204)	0.41 (0.000)	0.15 (0.131)	0.26 (0.002)	0.27 (0.054)
Test, $a+b=0?$	0.000	0.000	0.000	0.000	0.001	0.047	0.091	0.333
Observations	4845	4823	4775	4540	1625	1602	1576	1542
	Real cons. growth				Real nonres. Investment growth			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	-0.55 (0.000)	-0.67 (0.000)	-0.70 (0.000)	-0.85 (0.000)	-0.29 (0.010)	-0.28 (0.055)	-0.49 (0.001)	-0.62 (0.000)
$x_{t+k,t-1}^i$ (b)	0.12 (0.034)	0.12 (0.007)	0.03 (0.542)	0.08 (0.121)	0.20 (0.009)	0.02 (0.835)	0.12 (0.161)	-0.00 (0.955)

Test, $a+b=0?$	0.002	0.000	0.000	0.000	0.518	0.103	0.037	0.000
Observations	3904	3877	3830	3697	3802	3774	3728	3599
	Real res. Investment growth							
	t	t+1	t+2	t+3				
$x_{t+k,t}^i$ (a)	-0.78 (0.000)	-0.41 (0.003)	-0.54 (0.000)	-0.74 (0.000)				
$x_{t+k,t-1}^i$ (b)	0.03 (0.546)	0.06 (0.497)	0.04 (0.649)	0.23 (0.006)				
Test, $a+b=0?$	0.000	0.012	0.000	0.000				
Observations	3796	3770	3722	3593				

Appendix

Data sources

SPF, ESPF and Michigan Survey Data

All of the SPF survey data used in this study come from the Philadelphia Fed's website (<http://www.phil.frb.org/research-and-data/real-time-Center/survey-of-professional-forecasters>). The documentation for all of the series employed in this paper may be found here: (<http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf>).

The ESPF data come from the European Central Bank's website <http://www.ecb.europa.eu/stats/prices/indic/forecast/html/index.en.html>. The documentation for all of the series in the paper may be found here: http://www.ecb.europa.eu/stats/prices/indic/forecast/shared/files/SPF_dataset_description.pdf

The individual responses for the Michigan survey are available upon request from the University of Michigan's Survey Research Center data archive, and may be found here: <http://data.sca.isr.umich.edu/sda-public/cgi-bin/hsda?harsda+sca>

Figure A.1

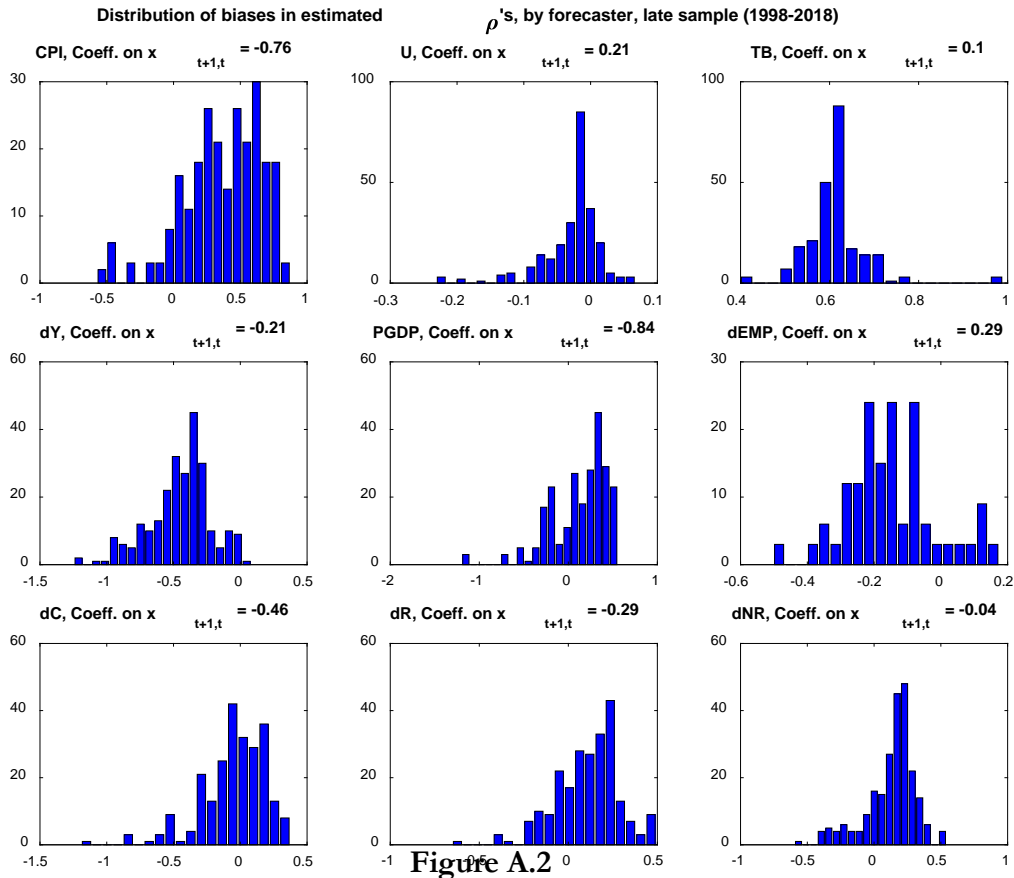


Figure A.2

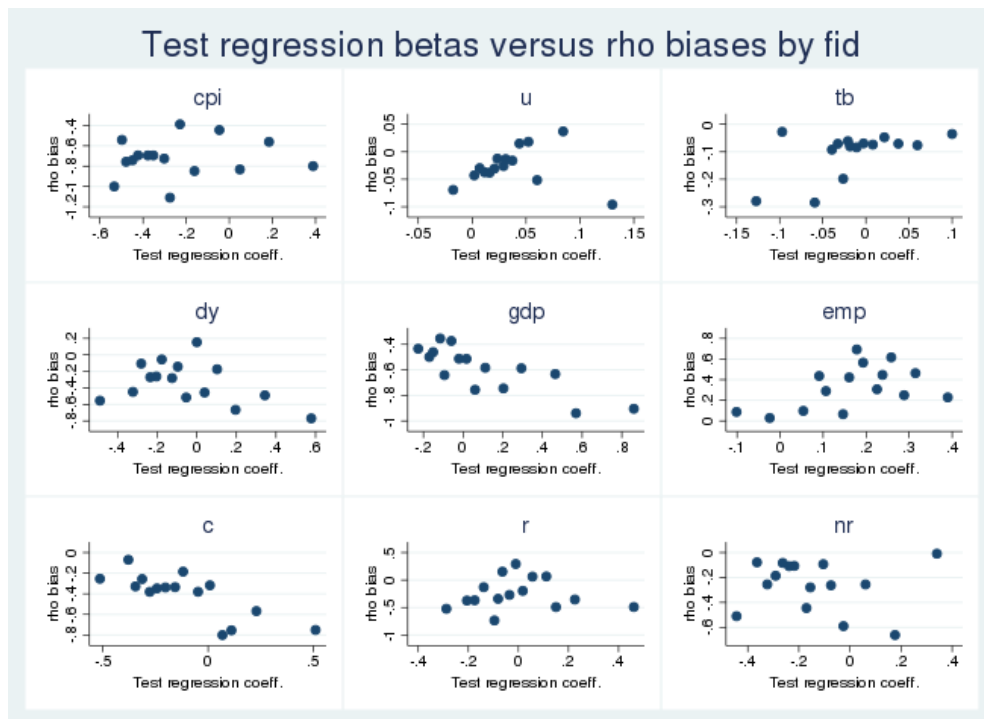


Table A.1									
Correlation of revision from viewpoint $t-1$ to t with revisions from $t-k$ to t for all k available in SPF dataset, for various terminal dates									
	Inflation forecasts			Unemployment forecasts			Treasury bill forecasts		
	Terminal date			Terminal date			Terminal date		
Viewpoint	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
t-2	0.86	0.71	0.55	0.75	0.74	0.76	0.71	0.75	0.74
t-3	0.82	0.57	-	0.64	0.62	-	0.55	0.60	-
t-4	0.80	-	-	0.56	-	-	0.47	-	-
Observations	2177	2523	3000	3003	3524	4250	2129	2478	2958

Table A.2						
Effect of common information and all other revisions						
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, controlling for revision in aggregate forecast and in lagged and period-t estimates						
$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = \gamma[\pi_{t+1,t-2}^{Median} - \pi_{t+1,t-1}^{Median}] + \delta[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + a\pi_{t-1}^i + cZ_t^i + \delta_i + \mu_t + \varepsilon_t^i$						
	$\pi_{t+1,t}^i - \pi_{t+1,t-1}^i$	$\pi_{t+2,t}^i - \pi_{t+2,t-1}^i$	$\pi_{t+3,t}^i - \pi_{t+3,t-1}^i$	$U_{t+1,t}^i - U_{t+1,t-1}^i$	$U_{t+2,t}^i - U_{t+2,t-1}^i$	$U_{t+3,t}^i - U_{t+3,t-1}^i$
$\pi_{t+k,t-1}^i - \pi_{t+k,t-1}^{Median}$	-0.35 (0.000)	-0.36 (0.000)	-0.43 (0.000)	-0.40 (0.000)	-0.35 (0.000)	-0.37 (0.000)
$\pi_{t+k,t-1}^{Median} - \pi_{t+k,t-2}^{Median}$	-0.07 (0.440)	0.02 (0.867)	-0.15 (0.078)	0.18 (0.001)	0.30 (0.000)	0.27 (0.000)
Adjusted R-squared	0.197	0.233	0.265	0.631	0.580	0.550
Observations	2779	2761	2678	2813	2791	2699
Contemporaneous revisions to aggregate forecasts						
$\pi_{t+k,t-1}^i - \pi_{t+k,t-1}^{Median}$	-0.58 (0.000)	-0.54 (0.000)	-0.55 (0.000)	-0.64 (0.000)	-0.57 (0.000)	-0.51 (0.000)
$\pi_{t+1,t}^{Median} - \pi_{t+1,t-1}^{Median}$	0.84 (0.000)	0.79 (0.000)	0.73 (0.000)	0.90 (0.000)	0.85 (0.000)	0.86 (0.000)
Adjusted R-squared	0.297	0.282	0.296	0.790	0.731	0.709
Observations	2779	2761	2678	2813	2791	2699
Additional variables include revisions of lagged inflation, unemployment, Treasury bill, output growth; Revisions to current period forecasts for the same; $t-1$ viewpoint date forecast of inflation or output for period $t+k$; and t -period individual estimates of lagged inflation, unemployment, Treasury bill, and output growth.						

Table A.3										
Revision regressions, unconstrained (no discrepancy, just lagged forecast and lagged median)										
	Inflation						Unemployment			
	t	t+1	t+2	t+3	4-qtr.	t	t+1	t+2	t+3	
$X_{t+k,t-1}^i$	-0.70 (0.000)	-0.57 (0.000)	-0.53 (0.000)	-0.59 (0.000)	-0.37 (0.000)	-0.87 (0.000)	-0.67 (0.000)	-0.56 (0.000)	-0.49 (0.000)	
$X_{t+k,t-1}^{Median}$	0.56 (0.000)	0.42 (0.000)	0.43 (0.000)	0.45 (0.000)	0.36 (0.000)	0.87 (0.000)	0.68 (0.000)	0.57 (0.000)	0.51 (0.000)	

Observations	3998	3999	3982	3893	3884	5819	5817	5794	5513
	GDP growth					3-mo. Treasury bill			
	t	t+1	t+2	t+3	4-qtr.	t	t+1	t+2	t+3
$x_{t+k,t}^i$	-0.31 (0.000)	-0.42 (0.000)	-0.55 (0.000)	-0.64 (0.000)	-0.25 (0.000)	-0.47 (0.000)	-0.44 (0.000)	-0.43 (0.000)	-0.51 (0.000)
$x_{t+k,t-1}^{Median}$	0.21 (0.020)	0.36 (0.000)	0.51 (0.000)	0.65 (0.000)	0.22 (0.002)	0.41 (0.000)	0.37 (0.000)	0.37 (0.000)	0.49 (0.000)
	5745	5751	5728	5417	5407	3946	3933	3827	3823
4-qtr. = average of quarters 0, 1, 2, 3									

Table A.4								
Shleifer <i>et al</i> test (2017), 1998:1-2018:1								
Regress forecast errors on components of revision from $t-1$ to t (allow forecasts to enter separately)								
$x_{t+h} - x_{t+h,t}^i = ax_{t+h,t}^i + bx_{t+h,t-1}^i + \varepsilon_{t+h}^i$								
	Inflation				Unemployment			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	0.00 (0.985)	-0.76 (0.000)	-1.01 (0.000)	-0.95 (0.000)	0.09 (0.412)	0.21 (0.298)	0.39 (0.095)	0.51 (0.029)
$x_{t+k,t-1}^i$ (b)	-0.30 (0.006)	-0.10 (0.608)	0.13 (0.342)	0.20 (0.049)	-0.10 (0.327)	-0.25 (0.220)	-0.46 (0.058)	-0.64 (0.015)
Test: a+b=0?	0.000	0.000	0.000	0.000	.059	.0061	.0046	.0059
Observations	2454	2425	2393	2318	2549	2522	2488	2418
	GDP growth				3-mo. Tbill rate			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	-0.19 (0.259)	-0.21 (0.435)	-0.44 (0.136)	-0.89 (0.000)	0.04 (0.046)	0.10 (0.061)	0.16 (0.136)	0.29 (0.041)
$x_{t+k,t-1}^i$ (b)	0.01 (0.862)	-0.13 (0.303)	-0.09 (0.421)	0.07 (0.571)	-0.06 (0.005)	-0.17 (0.001)	-0.29 (0.000)	-0.50 (0.000)
Test: a+b=0?	.20	.15	0.035	0.000	0.12	0.057	0.035	0.025
Observations	2552	2495	2461	2368	2373	2372	2278	2252
	GDP deflator				Payroll employment growth			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x_{t+k,t}^i$ (a)	-0.72 (0.000)	-0.84 (0.000)	-0.80 (0.000)	-0.82 (0.000)	-0.06 (0.621)	0.29 (0.194)	0.30 (0.329)	0.15 (0.656)
$x_{t+k,t-1}^i$ (b)	0.08 (0.275)	0.11 (0.082)	0.07 (0.072)	-0.02 (0.568)	0.41 (0.000)	0.15 (0.131)	0.26 (0.002)	0.27 (0.054)
Test, a+b=0?	0.000	0.000	0.000	0.000	0.0012	0.047	0.091	0.333
Observations	2489	2462	2428	2371	1625	1602	1576	1542
	Real cons. growth				Real nonres. Investment growth			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3

$x_{t+k,t}^i$ (a)	-0.44 (0.026)	-0.46 (0.030)	-0.48 (0.012)	-0.72 (0.000)	-0.24 (0.128)	-0.04 (0.838)	-0.32 (0.069)	-0.54 (0.001)
$x_{t+k,t-1}^i$ (b)	0.15 (0.129)	0.10 (0.363)	0.06 (0.514)	0.13 (0.132)	0.20 (0.118)	-0.19 (0.260)	-0.02 (0.865)	-0.01 (0.949)
Test, a+b=0?	0.072	0.057	0.028	0.0038	0.841	0.293	0.201	0.047
Observations	2521	2493	2455	2363	2414	2387	2354	2268
	Real res. Investment growth							
	t	t+1	t+2	t+3				
$x_{t+k,t}^i$ (a)	-0.77 (0.000)	-0.29 (0.155)	-0.55 (0.000)	-0.80 (0.000)				
$x_{t+k,t-1}^i$ (b)	0.08 (0.209)	-0.11 (0.346)	0.03 (0.795)	0.25 (0.011)				
Test, a+b=0?	0.000	0.016	0.0023	0.0012				
Observations	2416	2389	2353	2266				