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Intrinsic Expectations Persistence: Evidence from Professional and Household Survey Expectations

Jeff Fuhrer

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. It finds that the most robust feature of all of these expectations measures is that respondents inefficiently revise their forecasts, significantly underreacting to new information. As a consequence, revisions *smooth* through arriving information, and expectations *forget* past information at a rapid rate and appear to *anchor* to the unconditional mean or other salient anchors. The paper then examines the micro-data evidence bearing on the hypotheses tested by Coibion and Gorodnichenko (2015), who suggest that aggregate surveys may conform to key predictions of the sticky-information model of Mankiw and Reis (2002) and/or the noisy-information model of Maćkowiak and Wiederholt (2009). This paper finds considerably less coherence with these models in the micro data. 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 illustrated in the last sections of the paper, 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). The paper sketches a model in which agents' inefficient updating of expectations induces excess smoothness in expectations, imparting persistence to macro variables that is due strictly to the expectations formation process.

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Jeff Fuhrer is an executive vice president and senior policy advisor at the Federal Reserve Bank of Boston. His email address is jeff.fuhrer@bos.frb.org. The author thanks Susanto Basu, Olivier Coibion, Chris Foote, Yuriy Gorodnichenko, Ricardo Nunes, Giovanni Olivei, Andrei Shleifer, and seminar participants at the NBER Summer Institute for helpful comments. This paper presents preliminary analysis and results intended to stimulate discussion and critical comment. The views expressed herein are those of the author and do not indicate concurrence by the Federal Reserve Bank of Boston, the principals of the Board of Governors, or the Federal Reserve System. This paper, which may be revised, is available on the website of the Federal Reserve Bank of Boston at http://www.bostonfed.org/economic/wp/index.htm.

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Expectations lie at the heart of all current macroeconomic models. Decisions about prices, capital goods, consumer durable goods, housing, life-cycle savings choices, and monetary policy all inherently depend on expectations about future economic conditions. The idea that economic actors "look forward" or think about the future in making some 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 in question, 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. It may be the case that in these instances, rational expectations work fairly well as a description of forward-looking behavior (although this too remains an empirical question).

But evidence is mounting that suggests 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 dynamic stochastic general equilibrium (DSGE) models (habits, price indexation, complicated adjustment costs) as well as the ubiquitous presence 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 remain 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.

Several 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, *Learning and Expectations in Macroeconomics;* 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's (2003, 2006) work on rational inattention, and implemented in Maćkowiak and Wiederholt (2009) and Bordalo et al. (2018), 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), and 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 Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF) and the University of Michigan's Survey Research Center survey of consumers. An important exception is Bordalo et al. (2018), which examines a wide array of forecasts for macroeconomic variables, much like this paper. We will turn to that paper's results in section 6.

This paper examines a rich set of micro-data evidence on the expectations behavior of firms and households, both in the United States 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, 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 is understood to be the rational or model-consistent expectation of the next period's inflation rate. This Euler equation may be derived from a Calvo pricing model in which a fraction ω of price-setters who do not get the Calvo draw in period t choose to index their current prices to last 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 SPF—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 autocorrelated 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 incorporated 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.

This paper uses the individual responses in the SPF, the ECB Survey of Professional Forecasters (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 more than 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 individual respondents' forecasts over time is an advantage for the questions this paper aims to investigate. While both surveys afford such across-time comparisons to a certain extent, the SPF and the ESPF are much richer in this dimension.

Although firms' and households' expectations differ in some respects, 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 linking forecast revisions to their own forecasts for the same variable made in the previous period. This implies that they down-weight the impact of new information on their forecasts, smoothing through the information in news rather than incorporating it efficiently.[2]

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 it is not clear how much signal is reflected in the news. Coibion and Gorodnichenko (2015) provide tests of aggregate expectations that appear to generally conform to these models. We will examine implications of these models below, and conclude that

[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).

the aggregate results found by Coibion and Gorodnichenko are strongly contradicted in the micro data.[3]

Bordalo et al (2017) examine micro data from the SPF and the Blue Chip forecasters' surveys and find that forecasters generally *overreact* 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 underreaction at the aggregate level and overreaction at the individual level. However, as we show in section 6, their test of overreaction and underreaction, while informative about the predictability of forecasts (and thus about the relevance of the sticky- and noisy-information models), turns out to be a weak test of overreaction or underreaction. In contrast, the tests in this paper develop more uniform and strongly significant evidence of underreaction at the individual forecaster level, which is not consistent with 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.

As suggested above, one model that might imply sluggish expectations updating is Mankiw and Reis's (2002) sticky-information framework. Agents in that framework either (a) update their information and form a rational forecast, or (b) do not update their forecasts at all. We will show that it is uncommon for professional forecasters not to update their information sets from quarter to quarter. Rather, in the presence of updated information, they update inefficiently, slowing the incorporation of new information into forecasts by anchoring the revision to previous forecasts. Households may well update infrequently, but they are similarly shown to update quite inefficiently when they do update. The noisy information model bears similar implications, and is similarly rejected in the micro data.

[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.

Another obvious input to individual forecasts is the lagged realization of the variable of interest. It will be shown that the micro data exhibit a much stronger response to the lagged viewpoint forecast than to any of the lagged (real-time) actual data. In fact, inefficient adjustment to new information will be shown to be a much stronger feature of the data than classic adaptive least-squares learning, which here takes the form of updated ordinary least squares (OLS) projections of expectations on lagged observable data. To this point, the paper provides more 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.

This 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 can build into expectations only those characteristics that the model implies for all 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 explores the extent to which such an expectations mechanism affects the dynamics of key macroeconomic variables in a simple 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 are indeed persistent in the way described above—above and beyond the persistence of the variables they use to forecast inflation—then expectations will add their own "intrinsic persistence," in the sense articulated in the context of standard inflation models in Fuhrer (2006, 2011). It will therefore be reasonable to assume that some portion of the persistence observed in key macroeconomic time series arises from this "intrinsic expectations persistence," a finding that is 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. This assumption is tested in the empirical work in Fuhrer (2017) and illustrated in the context of stylized models below.

The paper concludes by providing some suggestive macro-modeling exercises that highlight the role that persistent expectations can play in the macroeconomy.

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 the distribution of forecasts is 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, although that is not the focus of this paper (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] Table 16 provides the results of efficiency tests for the individual forecasts, using real-time actual data to compute forecast errors, and testing the efficiency of these errors against real-time data available to the forecasters, as reported in the SPF forecast data set. It is not difficult to reject the null of efficiency, but we will examine in more detail a particularly striking form of inefficiency in what follows.

To help with interpretation of these results, it is useful to consider a simple framework for efficient forecasts and forecast revisions.[6] An efficient forecast of a variable $\boldsymbol{x}$ 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:

[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.

$$x_{t+1,t} = x_{t+t,t-1} + News_t \ . \tag{1.1}$$

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, the lagged median of forecasts made in *t-1*, and other variables contained in *Z* and observed in *t*.[7] Equivalently, the forecast revision from period *t-1* to period *t* will reflect only news:

$$R_{t+1,t} \equiv x_{t+1,t} - x_{t+t,t-1} = News_t \ . \tag{1.2}$$

If we interpret equation (1.1) as an efficiency regression:

$$x_{t+1,t} = ax_{t+t,t-1} + News_t \ , \tag{1.3}$$

and the coefficient on $x_{t+1,t-1}$ differs significantly from one (say $a < 1$), then the revision from period *t-1* to period *t* responds inefficiently to the news received in period t:

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

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 the unconditional mean for the series, or the initial forecast prior to the accumulation of news:

$$x_{t+1,t} = ax_{t+t,t-1} + News_{t+1,t} + \mu \ . \tag{1.5}$$

An efficient forecast would entail $a = 1, \mu = 0$. 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:

$$x_{t+1,t} = \sum_{i=0}^{\infty} a^i N_{t-i,t+1} + \frac{1}{1-a}\mu \ . \tag{1.6}$$

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

$$x_{t+1,t} = \sum_{i=0}^{\infty} N_{t-i,t+1} \ . \tag{1.7}$$

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. The forecast centers on the long-run estimate

[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.

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

$\frac{1}{1-a}\mu$. For most of the estimates for the inflation surveys presented below, the latter constant takes values between 1.5 and 3, reinforcing the notion that it may correspond to a long-run value for inflation. One can think of this equation (1.6) with $a<1$ and $\mu \neq 0$ as reflecting a muted response of forecasts to news, which biases the forecasts toward the unconditional mean of the series, or perhaps towards an initial estimate of ***x***, if that is what μ represents.

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 $j=1,\ldots,t$. 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 $x_{t+k,0}$:

$$x_{t+k,t} = x_{t+k,0} + \sum_{j=1}^{t} R_{t+k,j} \,. \tag{1.8}$$

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 is[9]:

$$\begin{aligned} R^E_{t+k,j} &= N_j \\ R^I_{t+k,j} &= \rho R^I_{t+k,j-1} + (1-\rho) N_j \end{aligned}, \tag{1.9}$$

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 [0.90, 0.75, 0.60] yields the simulated expectations series in Figure 2.[10]

It is clear from Figure 2 that expectations that incorporate news inefficiently 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. In turn, the

[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, and as the table clearly shows, revisions for any variable for terminal date t made from viewpoints t, t-1, t-2, t-3 are highly correlated.

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 implies 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, 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).

Properties of individual SPF forecasts

The first set of results examines efficiency regressions for individual inflation forecasts like those characterized in equation (1.5). The first regressions examine forecasts made in period *t* as a function of the forecasters' idiosyncratic (real-time) estimates of lagged inflation, measures 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 (both lagged viewpoint date for the *t+1* forecast and the lagged one-period-ahead forecast).[11] Table 2 presents results from the first set of test regressions, which take the general form

$$\pi^i_{t+1,t} = a\pi^i_{t-1} + b\pi^i_{t+1,t-1} + cC(\pi^i_{t+1,t-1}) + d\pi^i_{t,t-1} + eZ^i_t + \delta_i + \varepsilon^i_t\,, \tag{1.10}$$

where $\pi^i_{t+1,t}$ is the i^{th} forecaster's forecast of consumer price index (CPI) inflation for period *t+1* made in period *t*; π^i_{t-1} is the i^{th} forecaster's estimate of lagged inflation as of period *t*; $\pi^i_{t+1,t-1}$ is the i^{th} forecaster's forecast for the same horizon *t+1* made last period (*t-1*); $\pi^i_{t,t-1}$ is the i^{th} forecaster's forecast for period *t* made in period *t-1* (the previous period's one-period-ahead forecast); $C(\pi^{SPF}_{t+k,t-1})$ 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^i_t is a

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

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 heteroscedasticity, autocorrelation, and correlation among panels using the method developed in Driscoll and Kraay (1998).[13]

Note that one can think of regression (1.10) as embedding two types of change regressions. First, one can subtract the *t-1* forecast for period *t+1* from the both sides of the equation to obtain the *revision* to the *t+1* forecast ($\pi^i_{t+1,t} - \pi^i_{t+1,t-1}$) from viewpoint *t-1* to viewpoint *t*. Second, one can subtract the *t-1* forecast for period *t* from the left-hand side to obtain ($\pi^i_{t+1,t} - \pi^i_{t,t-1}$), the *difference* in one-period forecasts, made from successive viewpoint dates. We will examine evidence below for both types of regressions, focusing primarily on the revisions.

The regression is estimated as a panel for the sample from 1981:Q4 to 2018:Q1. As indicated in Table 2, in these regressions, the strongest explanatory variables are the lagged central tendency of the distribution of forecasts and the individual forecasters' own lagged forecasts. Forecasters' estimates of lagged inflation often enter significantly, but with relatively small coefficients. Other lagged variables that might reasonably reflect *t*-period news about the forecast similarly enter with small and often insignificant coefficients. The coefficients on the lagged viewpoint date forecasts range from 0.3 to 0.5, markedly different from the efficient value of 1.0. The estimated coefficient on the median forecast for *t+1* made in period *t-1* ranges from 0.28 to 0.73 across the specifications in the table. Other results with additional controls, not shown in this table, verify that this strong dependence on the lagged viewpoint date forecasts and the lagged central tendency of the previous period's forecast for the same period is robust to the inclusion of essentially any other variable in the forecast dataset.[14]

The right-hand columns of Table 2 show the same regressions for forecasts at horizons *t+2, t+3, t+4*. The results are the same. The bottom panel of the table replicates these same regressions for the unemployment forecasts from the SPF. Again, the lagged central tendencies and lagged viewpoint date forecasts are consistently correlated with the individual forecasts for all horizons.

[12] We consider other proxies for the lagged central tendency of forecasts when we estimate revision regressions below.
[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.
[14] For example, including current, *t+1* and *t+2* forecasts for unemployment, the Treasury bill, and output growth yields a coefficient on the lagged median forecast of 0.41 with a *p*-value of 0.000.

Here, the coefficients on the lagged central tendency range from 0.44 to 0.86, and the lagged viewpoint date forecast develop coefficients that range from 0.3 to 0.5.

Thus in Table 2, all of the estimates develop a coefficient on the lagged viewpoint-date forecasts that is quantitatively far from (and less than) 1. Table 2a presents results that more simply and directly test the efficiency of forecast revisions in this respect, using an augmented version of equation (1.5), as indicated at the top of the table. For all variables and all horizons, the hypothesis $a=1$ is rejected overwhelmingly.[15]

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 t-period forecast. The lagged median forecast may enter simply because it proxies for a host of other—presumably common—information that becomes available in period t, and thus influences individual forecasts made in that period. The influence of common information in the individual forecasts will be explored in greater depth below.

An easier-to-interpret version of the regression casts it in terms of revisions, as suggested above. The revision explicitly focuses on the incorporation of news into successive forecasts, not assuming efficiency as the lagged viewpoint date forecast appears in the regression.[16] Working with revisions is also preferable in some ways to working with forecast errors, because it avoids the arbitrary decisions that are required to define "real-time" actual data.[17] Subtracting the lagged-viewpoint forecast from both sides, one can write the revision form of equation (1.10)

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

In most of the regressions presented below, the regression estimates take the form:

$$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = \gamma[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + b\pi_{t-1}^{i} + dZ_t^i + \delta_i + \varepsilon_t^i . \tag{1.12}$$

In this version, the forecast revision is a function of the *discrepancy* between the t-1 viewpoint forecast and the t-1 central tendency, along with other variables. This regression imposes the restriction that $(a-1)$ and c are equal and opposite in sign, or equivalently that $a+c=1$. It implies that when the last viewpoint date's forecast is revealed to be above the lagged central tendency of such forecasts, other things equal, the forecast is revised downward toward the lagged central tendency. There is no reason that an efficient forecast should be revised in this way: An efficient revision should indeed

[15] The p-values are 0 to greater than 10 decimal places.

[16] Focusing on revisions also avoids the many difficulties that arise when working with forecast errors, as the appropriate definition of the "actual" data to use in computing the forecast error is fraught with difficulty.

[17] That said, we will examine forecast error regressions in sections 5 and 6 in the context of models of information rigidities.

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.

Table 2 shows the *p*-value for a test of the restriction $a+c=1$. For the inflation forecast, the test of this restriction rejects overwhelmingly, as indicated in the top panel. For the unemployment forecasts, the restriction fails to reject in all but one case. Thus for unemployment forecasts, the data cannot reject the hypothesis that the revision relationship is an appropriate representation of the forecast data. For the remainder of the paper, we will estimate the regressions using the revision in the forecast as the dependent variable. However, because the restriction for equation (1.12) is rejected for the inflation data in the SPF, we will always include the lagged central tendency of forecasts in the regressions, along with the discrepancy between the individual and the central tendency forecasts:

$$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = \gamma[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + b\pi_{t-1}^{i} + cC(\pi_{t+1,t-1}) + dZ_t^i + \delta_i + \varepsilon_t^i . \qquad (1.13)$$

In this way, one can interpret the coefficient γ as the difference between a in equation (1.5) and 1. The total effect of the lagged central tendency on the revision is the sum of $-\gamma$ and c. When $c=0$, this means the sole influence of the central tendency is via an "error-correction" of the current forecast to the discrepancy between the previous forecast and the central tendency. When $c \neq 0$, the central tendency has an influence beyond that of a simple error correction. In either case, a finding of $a<1$ implies an inefficient incorporation of the news in the central tendency—or in any other *t*-period news variables—into the current forecast.

Thus the coefficients on the lagged discrepancy in the revision regressions reveal the inefficiency with which expectations incorporate the new information contained in the lagged central tendency and other variables.[18] The larger is the coefficient on the lagged discrepancy, the more (negative) weight the revision places on the lagged forecast, and the slower is the adjustment to new information. Table 3a reports the results from revision regressions from equation (1.13), where the variables are as defined for Table 2. The table examines two 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), and (2) the forecasts for the same origin and horizon made by the forecasters who have

[18] This relationship is obviously akin to the error-correction relationship between nonstationary variables. Note that in this case, the error correction cannot really go both ways: It's not possible for the median forecast to error-correct toward all of the individual forecasts, but the converse can be true.

been in the dataset longest, as a proxy for the largest and (perhaps) most respected forecasters in the sample.[19]

Regression (1.13) is estimated as a panel regression for the sample 1981:Q3 to 2018:Q1, with standard errors corrected as noted above.[20] The results show clearly that among measures of the central tendency of the previous forecast, the lagged median enters most reliably in inflation forecast revision regressions (the third column includes both measures; it shows that the median dominates the other concept). For the balance of the paper, we will use the median as the measure of the central tendency.[21] All regressions develop negative and precise estimates of γ. Thus the estimated *a* is always well below 1. 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 tends to gradually revise his next forecast for the same period toward the central tendency. Even more so than is the case for the regressions of forecast levels in Tables 2, this result appears quite robust across control variable sets and time periods. The right-hand columns of Table 3a, like their counterparts in Table 2, show the results of forecast revision regressions 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 the news in previous median forecasts.[22] 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 0, but in all cases, the estimated inefficiency in the forecast revision, $a-1$, is negative, large and statistically significant.[23]

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[19] In an earlier version of the paper, we also examined the average of forecasts for period *t+1* made in period *t-1* by the three forecasters with the lowest root mean square error (RMSE), computed real-time for the preceding eight quarters. This measure was also dominated by the median of individual forecast.

[20] The use of the longest-participating forecast members involves taking into account information that could not be known in the current quarter. However, it is meant to capture the idea that a few of the forecasters in the sample are large, nationally recognized forecasting firms and thus tend to participate regularly and over a long period. The RMS forecast error measure is truly real time, with the smallest RMS error up to the regression date determining which forecasters are in this group.

[21] There is some evidence in favor of including the RMSE measure for unemployment forecasts, although it does not dominate the median.

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

[23] Note that the discrepancies for horizons *t+2* and *t+3* are adjusted accordingly ($\pi^{i}_{t+2,t-1} - \pi^{Median}_{t+2,t-1}, \pi^{i}_{t+3,t-1} - \pi^{Median}_{t+3,t-1}$, 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.

Figure 3 displays a scatter plot of the left-hand-side variable (the forecast revision) against the lagged discrepancy (the first term on the right-hand side in [1.13]), and the negative correlation is clear. Figure 4 displays a histogram of the coefficients for equation (1.13) 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 0 and –1, 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 in the median forecast 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. Regressions using the SPF's forecasts of the 3-month Treasury bill and real GDP growth, not shown, produce very similar results. Tables 3c through 3f 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 yield. The results are strikingly similar.[24]

Figures 5a through 5e 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. The top panel shows estimates of $(a-1)$, using 20-quarter rolling samples from 1969 through 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 second panel of the figure shows the estimated coefficients over time. 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 are so similar across all variables and time periods. It is particularly notable that both financial and real variables display the

[24] This result differs from that of Bordalo et al. (2017), who find a systematic *overreaction* by CFOs to information relevant for forecasting financial variables, versus the systematic *underreaction* found here. For the variables available in the SPF, there appears to be little difference between the forecast properties for nonfinancial and financial variables.

same pattern of underreaction to news, which differs from the findings of overreaction in Bordalo et al. (2017). This may reflect a difference between the behavior and incentives of analysts and professional forecasters.

Table 4 provides similar results for the forecast *difference*—that is, the dependent variable is the change in the *k*-period-ahead forecast from quarter to quarter (for example, the *t+1* forecast made in period *t* minus the *t*-period forecast made in period *t-1*). Additional columns in the table display regressions with a number of controls, and with increasing forecast horizons from *t*+1 through *t+3*. Thus the dependent variables are the *t+k* forecast made in period *t* minus the *t+k-1* forecast made in period *t-1*.

Interpreting this regression is somewhat less straightforward than it is with the forecast revision regression. In general, *k*-period-ahead forecasts for persistent variables should be somewhat correlated over time. The question is whether the changes in *k*-period-ahead forecasts reflect the same kind of gradual adjustment to new information that the revisions in Table 3 exhibit. To clarify interpretation, consider a simple process for *x*[25]

$$x_t = \rho x_{t-1} + e_t \ .$$

The forecasts for *t* and *t+1* made in periods *t-1* and *t* respectively should be related by

$$x_{t+1,t} - x_{t,t-1} = \rho(x_t - x_{t-1}) = \rho(\rho - 1)x_{t-1} + \rho e_t \, . \tag{1.14}$$

Thus the change in the forecast should be related to the lagged information that determines *x,* albeit with a relatively small coefficient (in this simple example, the coefficient can be no larger than –0.25 for $0 \le \rho \le 1$). As $\rho \to 1$, this coefficient goes to 0. The change should also be related to the news about x_{t+1} that is revealed in period t, that is, e_t . If one can properly account for the lagged information and the influence of news received in period *t* about the forecast for *t+1*, there should be no role for the lagged forecast in explaining the change in the forecast. Of course, important *t-1* information that is not fully captured by the previous forecast (or by other *t-1* regressors in the test regression), if it is correlated with the previous forecast, will contaminate this regression. Conditional on these caveats, if $x_{t,t-1}$ enters on the right side of equation (1.14) with a sizable coefficient that differs significantly from 0, this may indicate an inefficient linking of the current *k*-period forecast to last period's, analogous to the issue with the revision.

The forecast change regressions displayed in Table 4 show a strong link between the change in forecasts and the lagged forecast, similar to those in Table 3. The change in the *k*-period-ahead

[25] This derivation can be generalized by allowing *x* to depend on a vector of factors X*;* the logic remains the same.

forecast responds strongly and significantly to the *k*-period-ahead forecast from last period, after controlling for the lag of the forecast variable, and for the lagged median of the *k*-period-ahead forecasts (as one proxy for new information about the *t+1* forecast). This correlation holds up when controlling for additional lagged information, and for news about the forecast as proxied by lagged median forecasts of *x* and other variables in the data set. While it is a weaker test than the forecast revision, these results indicate that, in addition to updating forecasts with information about the change in inflation from period *t* to period *t-1* (much of which may be contained in the lagged median forecast), the forecasts are inefficiently tied to the previous *k*-period-ahead forecast. Thus the change in the *k*-quarter-ahead forecast for successive forecast periods forecasts appears to be adjusted gradually over time to incorporate new information. Such behavior also constitutes a source of intrinsic persistence in expectations. The macroeconomic implications of these results, and those for forecast revisions, are discussed in section 7.

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 the forecast. However, revisions to individual forecasts might reflect *revisions* to the *common* information known at the time of the forecast.[26] To control for this possibility, Table 5 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 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

[26] The omission of such information should not bias the coefficient on the lagged-viewpoint individual forecasts, as, by definition, news that is observable only as of period *t* cannot be correlated with the *t-1* individual forecasts.

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 5 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 they 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 5 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.[27]

Learning versus inefficient revisions

A vast literature examines 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 learning or recursive least-squares learning, in which expectations are formed by time-varying projections of observables on lagged data. Such projections may be viewed

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[27] 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.

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, *Learning and Expectations in Macroeconomics*).

Table 6 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 6 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 6 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 through 6 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 7 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.

2. Evidence from the European SPF

The ECB Survey of Professional Forecasters (ESPF) is organized somewhat differently from the Philadelphia Fed's Survey of Professional Forecasters (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-year-ahead and two-years-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 7 through 9 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 forecasts. 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 Table 3, focusing on the correlation between the revisions and the discrepancy between the previous quarter's individual forecast and the median of all previous quarters' 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

$$\pi_{y1,t}^{i,ESPF} - \pi_{yk,t-1}^{i,ESPF} = \gamma[\pi_{yk,t-1}^{i,ESPF} - C(\pi_{yk,t-1})] + b\pi_{t-1} + cZ_t^i + \delta_i + \varepsilon_t^i; k = 0,1, \tag{2.1}$$

where now the revision denoted by $\pi_{yk,t}^{i,ESPF} - \pi_{yk,t-1}^{i,ESPF}$ 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 $\pi_{yk,t-1}^{i,ESPF} - C(\pi_{yk,t-1})$, 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 forecaster's 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 it calls "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 7 through 9 display simple versions of the test regression (2.1) that 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.[28] 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 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 10 includes the revisions to the aggregate (median) forecasts, in an attempt to control for the influence of common information on individual forecasts 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 11 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

[28] 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.

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 11 displays the results from the test regressions

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

where $\pi_{t+1y,t}^{i,Mich}$ is the i^{th} forecaster's one-year-ahead inflation expectation made in period *t,* $\pi_{t+1y,t-1}^{i,Mich}$ is 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.[29] [30]

The bottom panel of Table 11 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 subsample of Michigan respondents does not use the information in their previous forecasts efficiently (the test $a=1$ in the test regression $\pi_{t+1y,t}^{i,Mich} = a\pi_{t+1y,t-1}^{i,Mich} + bC(\pi_{t+1y,t-1}^{Mich}) + \varepsilon_t^i$ rejects with overwhelming significance).

Table 11 provides the results from equation (3.1), as in equation (1.13) above for the SPF data. Because the time dimension of individual survey participant's 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), only to times of relative calm, or to both.

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[29] 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.

[30] 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 toward 0, 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.

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 the Michigan responses 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 12 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 unanchored 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 through 11. 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 12 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 five-year inflation forecast is collected by the University of Michigan's Survey Research Center, 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 one- and five-year expectations have a 20 percent overlap, we construct the implied expectation for years two through five and use it as the long-run anchoring proxy.[31] As Table 13 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 two- through five-year expectation, but the magnitude is

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

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 one-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 Coibion and Gorodnichenko's 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:

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

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

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

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

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

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 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

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

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) through (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 household forecasters who do update information sets make rational forecasts is suspect. Regardless of whether that is likely, we will test these propositions below.

To begin with, we can provide a crude measure of the fraction of professional forecasters and household forecasters 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.[32] So for the professionals, this fraction is likely biased upward from the true share who do not update their information set. Table 14 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 6 percent or 7 percent; equivalently, 93 percent to 94 percent of forecasters have revised their four-quarter forecasts from one quarter to the next, and it is 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

[32] 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.

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 on individual forecasts. 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 15 provides the results of these regressions for both the SPF and the Michigan surveys.[33] 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.[34] For these columns, the R^2s 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 higher than those for the SPF inflation forecasts, which is striking given the noise in these household responses.[35]

[33] For forecast horizons beyond one period, efficient forecast errors should be MA(*h*-1), where *h* 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.
[34] 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 R^2s, if one includes *t*-period individual forecasts, rise noticeably for several of the variables.
[35] 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 8-quarter forward real-time vintages for the monthly 12-month percentage change in the CPI.

Of course, because nearly 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, though that appears not to be as 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 forecasters' 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?

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

$$x_t = \rho x_{t-1} + \varepsilon_t ; -1 \le \rho \le 1 . \tag{6.1}$$

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

$$y_t^i = x_t + \omega_t^i \ , \tag{6.2}$$

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

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

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

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

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

$$x_{t+1,t}^i - x_{t+1,t-1}^i = \rho G(y_t^i - \rho x_{t-1,t-1}^i) \ . \tag{6.5}$$ [36]

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 ε_t, so the revision reduces to $\rho\varepsilon_t$. In the regressions in Tables 3 through 12 above, the weight on the lagged forecast is estimated to be negative, sizable, and remarkably significant, consistent with equation (6.5).

Coibion and Gorodnichenko (2015) 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 Coibion and Gorodnichenko point out, the coefficient on different forecast variables will vary with the Kalman gain, which depends in turn on the signal-to-noise ratio 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:

$$x_{t+h} - x_{t+h,t}^i = \varepsilon_{t+h,t} \ , \tag{6.6}$$

as forecasters are using the information available to them efficiently. 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.

It is difficult to reconcile the noisy information story with the findings presented in Table 15, which encompass the test regression for this model in equation (6.6). Forecast errors should be predictable only *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

[36] When G=1, $y_t^i = x_t = \rho x_{t-1} + \varepsilon_t$, and $x_{t-1,t-1}^i = x_{t-1}$, and in this case, of course, the forecast revision reduces to $\rho\varepsilon_t$, 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.

inefficient, given information known to the individual forecasters, the model is violated. As can be seen in Table 15, forecast errors are still quite predictable by a number of variables, including forecast revisions in most cases.[37]

Table 16 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—indeed, all but one are current or previous period's forecasts made by the individual forecasters. The exception is the lagged median forecast, which is available as of period *t*; a column in each set of results excludes the lagged median to ensure that the results are robust to the exclusion of this variable. The results above suggest that lagged median forecasts are incorporated into current forecasts, but of course, the question here is whether these and other information variables are incorporated efficiently.

As in Table 15, 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 *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 signal from noise in incoming data, forming rational forecasts given the information available to them.

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

Note, however, that as shown in Table 17, it is not the *revision* that predicts the forecast error, but the *t*-period forecast (obviously a component of the revision).[38] That is, the regressions

[37] 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.

[38] 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

show that when the *t*-period forecast is high, the associated forecast error is low, 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 no longer related to the revision, it says nothing about underreaction or overreaction of forecasts to news—it is not the response to news that is embodied in the forecast revision that predicts forecast errors. It is simply that systematically higher (lower) forecasts produce over-forecasts (under-forecasts), inducing a negative correlation between the forecast and the error. Thus in these data, the Bordalo et al. (2018) regression is not a very powerful test for the presence of underreaction or overreaction of forecasts, unlike the revision regressions presented above.[39]

At a higher level, 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 50 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 to 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 common, rather than idiosyncratic.

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.

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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.

[39] One can think of the Bordalo at al. (2018) 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 underreaction or overreaction to news, as they do not reflect an underlying relationship between revisions and forecast errors.

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.[40]

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:

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

where 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 $E_t\pi_{t+1} - E_{t-1}\pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} u_t$. 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

[40] Recall that the inefficiency documented here implied *underreaction* to news. Had we estimated $a > 1$ in the fundamental regression, this would have implied *overreaction* to news.

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*.[41] 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 through 12 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

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

where $\pi^I_{t+1,t}$ 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).[42] We add an "IS" curve of similar form

$$\tilde{U}_t = (1-b)U^I_{t+1,t} + bEU_{t+1} - \sigma(f_t - \pi^{Agg}_{t+1,t} - \bar{\rho}), \tag{7.2}$$

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[43]

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

[42] Of course, the rational expectations are computed consistent with some fraction of expectations formation defined by $\pi^I_{t+1,t}$ 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.

[43] The model abstracts from policy inertia to isolate the impact of expectations on model dynamics.

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

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

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

and similarly for expectations of the unemployment/output gap

$$U^I_{t+1,t} = \omega EU_{t,t-1} + (1-\omega)EU_{t+1,t-1} + d(f_t - \pi^i_{t+1,t} - \bar{\rho}) + \eta_t \ . \tag{7.5}$$

Equations (7.4) and (7.5) are very close analogues of the expectations regressions in sections 2 through 4, 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.[44] In this case, aggregation is trivial, and the individual version of equations (7.4) and (7.5) are essentially the same as the aggregate.[45]

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) and (7.5) allow expectations to be formed inertially, with more weight on the lagged one-period-ahead expectation or the lagged two-period-ahead expectation, as the weight ω varies between 0 and 1. 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 10 examines the properties of this simple model—equations (7.1), (7.2), (7.3), (7.4), (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 2 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) and (7.5) suggests that, for values of ω like those estimated in the empirical section, this backward-referential expectations behavior can impart considerable

[44] 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.

[45] 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.

persistence to output, inflation, and the policy rate. Figure 10 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-ω), 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 survey micro 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 Bordalo et al. (2018) is also inconsistent with these results, as the overwhelming evidence points to *underreaction* to information at the micro level, not *overreaction* as in their findings. Section 6 provides a reconciliation of the results in this paper and those in Bordalo et al. (2018), suggesting that the test regressions presented in this paper have significantly greater ability to distinguish between underreaction and overreaction to news.

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

a. Forecasts are strongly inefficient at the micro level; in particular, forecasts *underuse* 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 United States.
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 Tversky and Kahneman (1974). The authors 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 under-weight the new information in favor of the initial estimate.[46] This kind of behavior appears to be precisely what we observe in survey-based forecasts of households and professional forecasters.

At the risk of oversimplifying, a simple representation of expectations smoothing begins with a reference point $R_{t+k,t}$. Agents can then be viewed as forming expectations for realizations of variable x in period $t+k$ at viewpoint date t as

$$x_{t+k,t} = \gamma x_{t+k,t-1} + (1-\gamma) R_{t+k,t} + N_{t+k,t} \quad . \tag{8.1}$$

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).[47] The relevant reference point could be the initial estimate of x_{t+k} prior to obtaining any information (news), or the (possibly time-varying) unconditional mean of the series x. The key feature of equation (8.1) is that it implies a smoothed incorporation of news at each period.

What deeper incentives lead to expectations smoothing?[48]

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[46] Importantly in this context, Tversky and Kahneman (1974) 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." See page 1128.

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

[48] For the professional forecaster surveys, if forecasters use econometric models and update their coefficients regularly, their forecasts would not systematically underreact 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.

Such a judgmental under-response can be motivated in an environment in which all forecasters face significant model uncertainty.

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) shows 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 is why and how expectations might exhibit such inertia.

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, especially the information revealed in previous aggregate expectations, across three well-known surveys of expectations. 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 several 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 and do not simply form expectations from weighted averages of lags of the variable they are forecasting. It is similarly clear that agents are not naïve. 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 15 and 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 still do not do so efficiently; and (d) forecast errors appear not to be consistent with a noisy information model, as a number of variables apart from the forecast revision hold significant explanatory power for the errors. 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 vector autoregressions (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

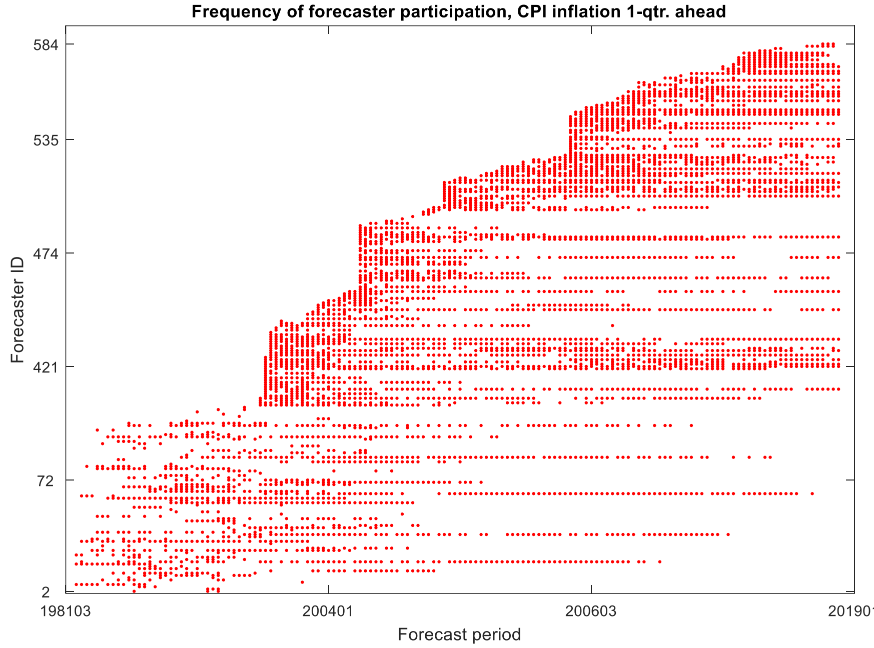


Figure 2

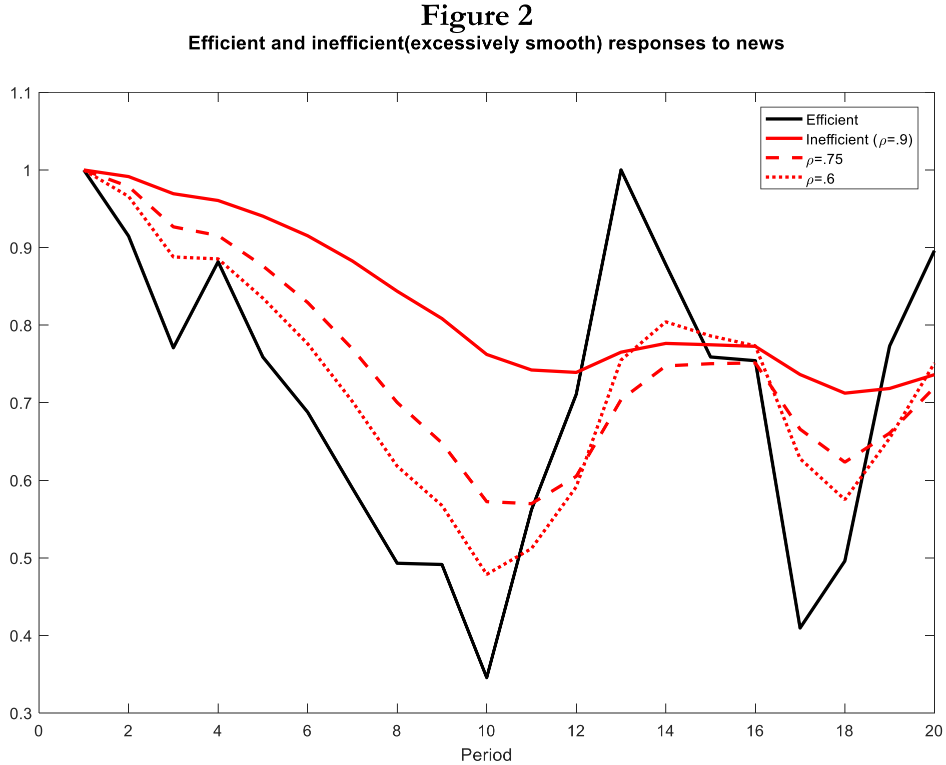


Figure 3

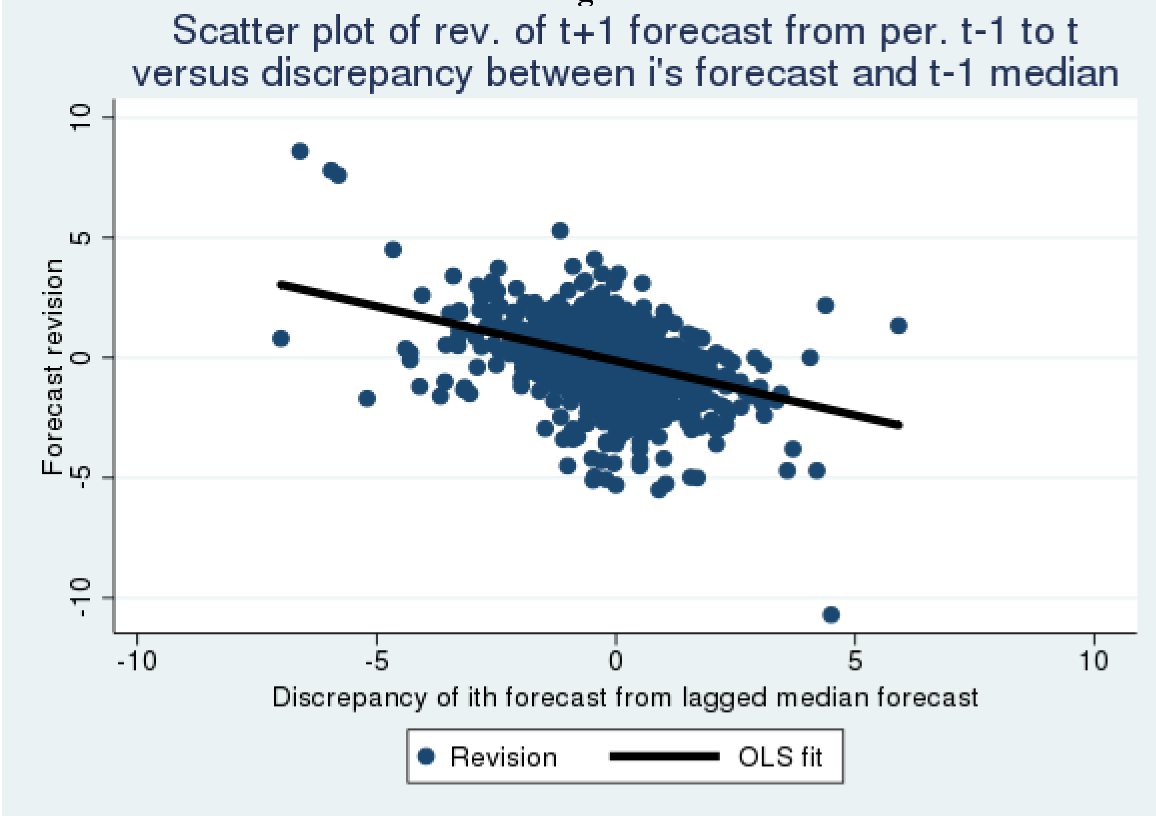


Figure 4

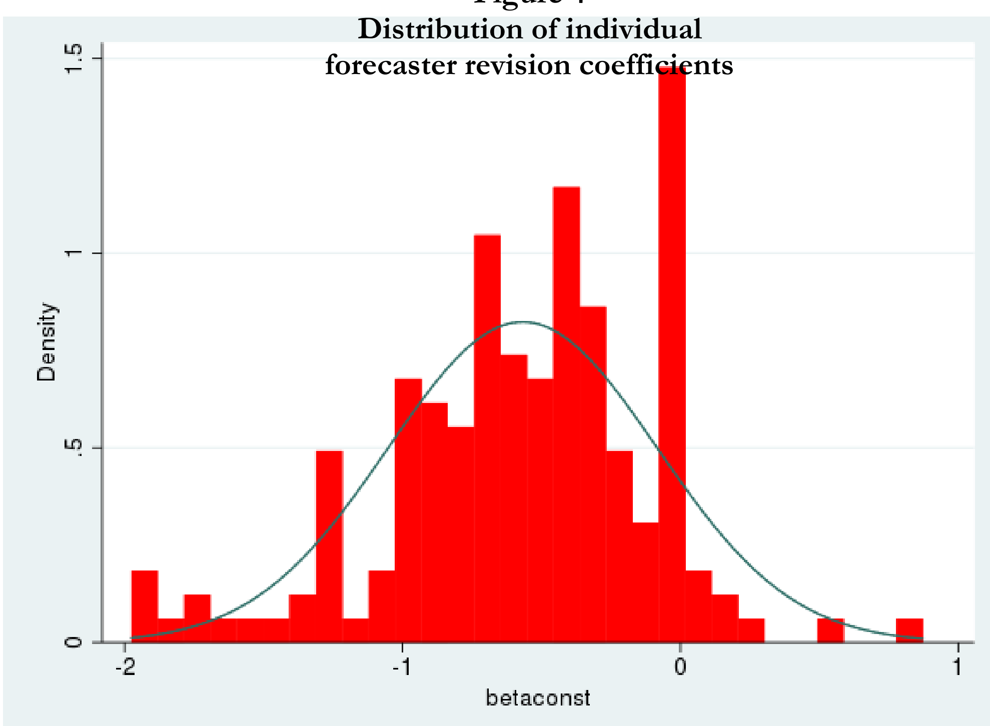


Figure 5a: Estimated inefficiency coefficients, Inflation
20-quarter rolling regressions

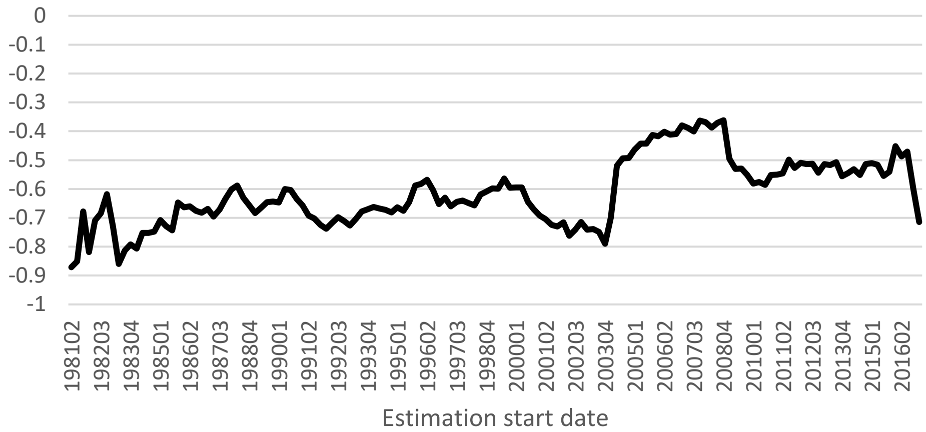


Figure 5b: Estimated inefficiency coefficients, Unemployment
20-quarter rolling regressions

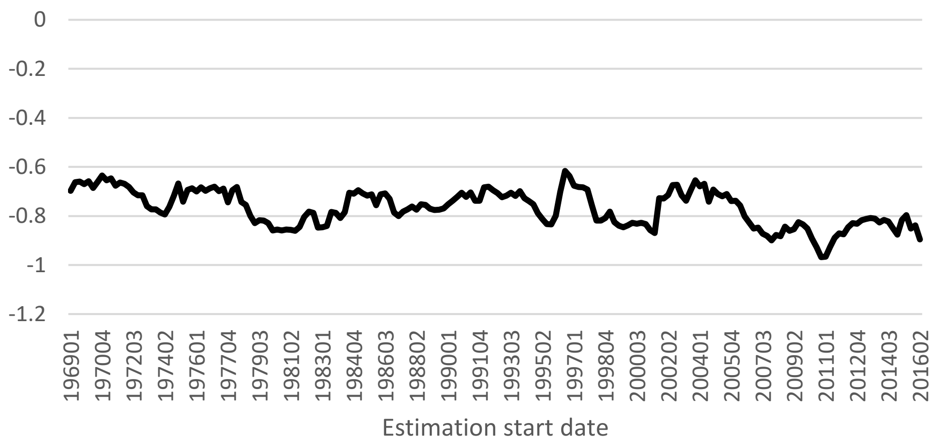
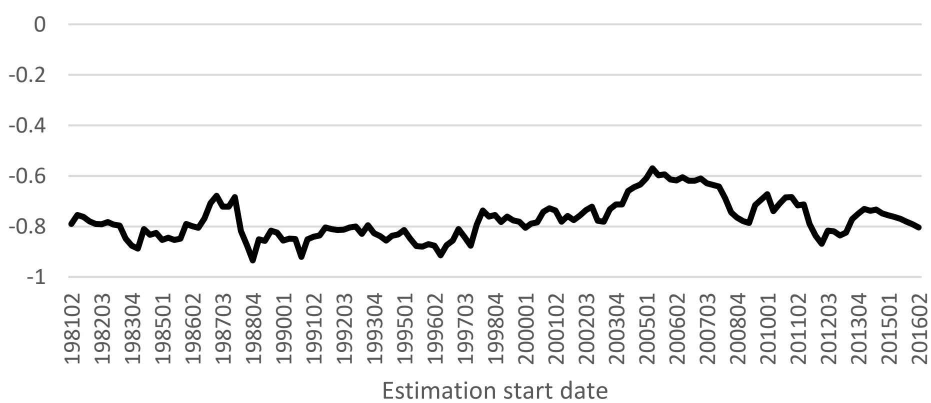


Figure 5c: Estimated inefficiency coefficients, 3-mo. Treasury bill rate
20-quarter rolling regressions



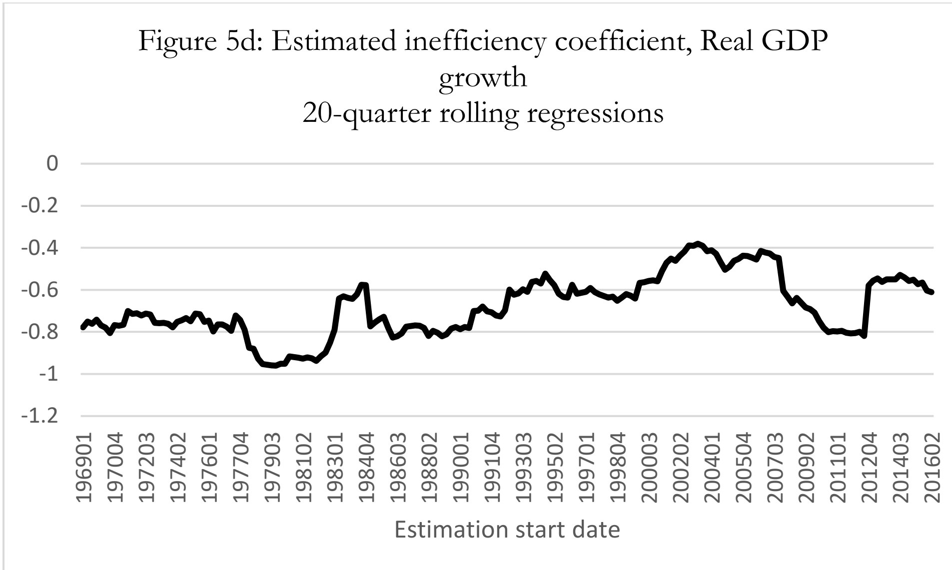


Figure 5d: Estimated inefficiency coefficient, Real GDP growth
20-quarter rolling regressions

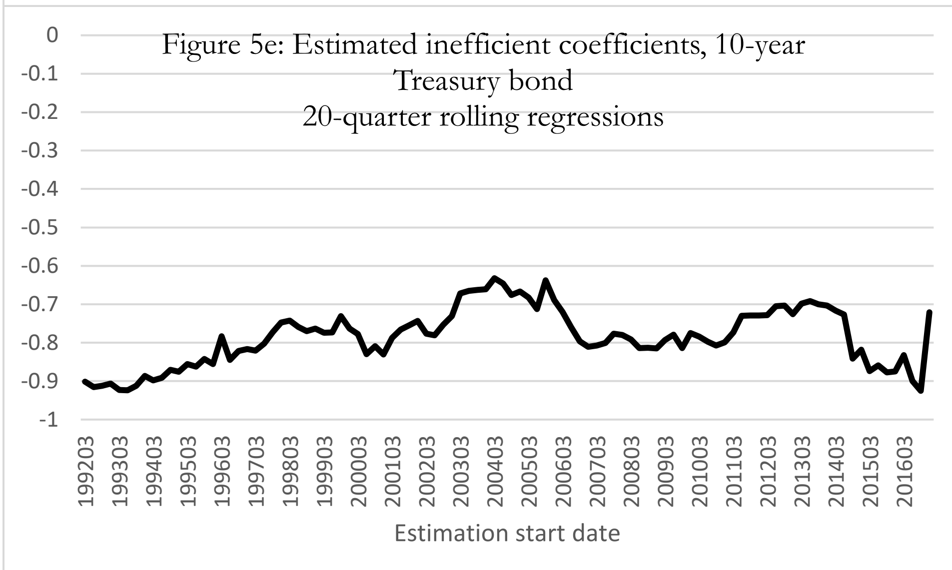


Figure 5e: Estimated inefficient coefficients, 10-year Treasury bond
20-quarter rolling regressions

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

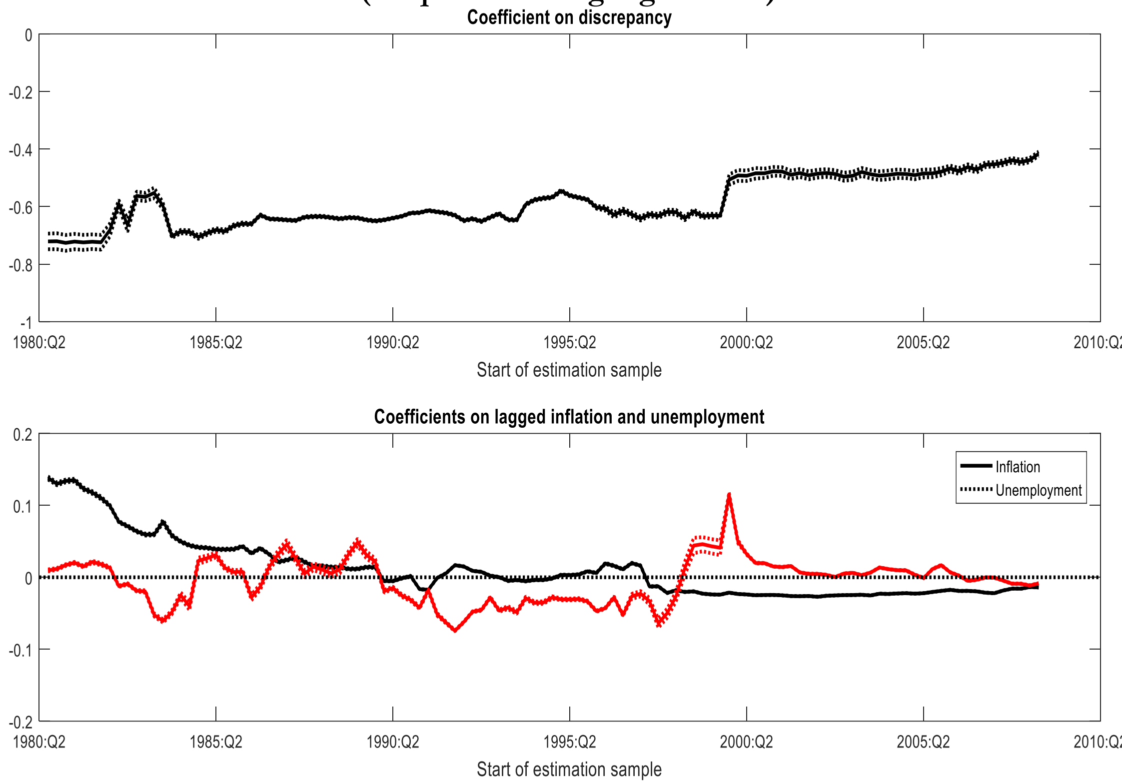


Figure 7
Median of SPF 10-year CPI inflation forecast

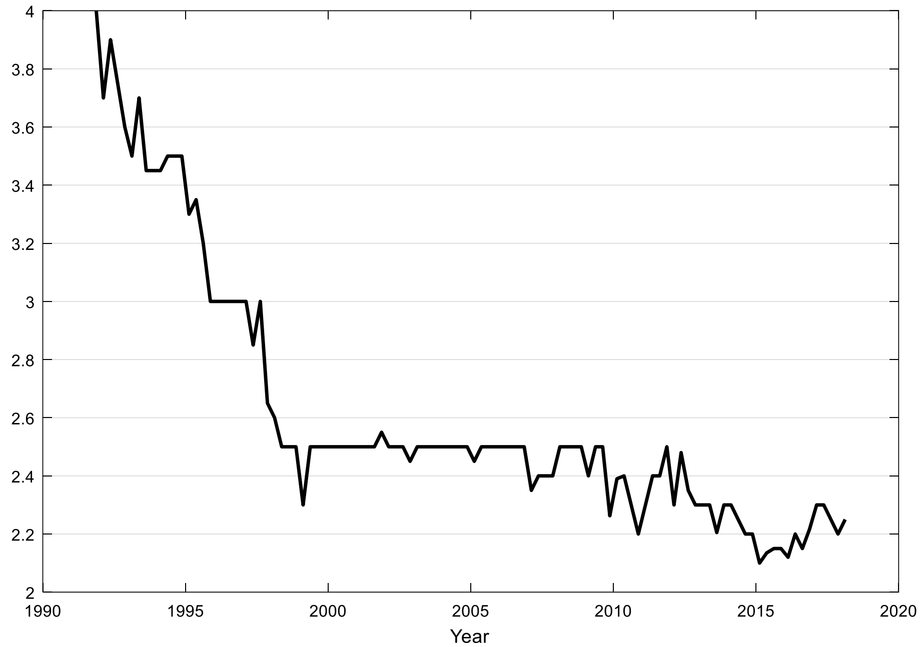


Figure 8

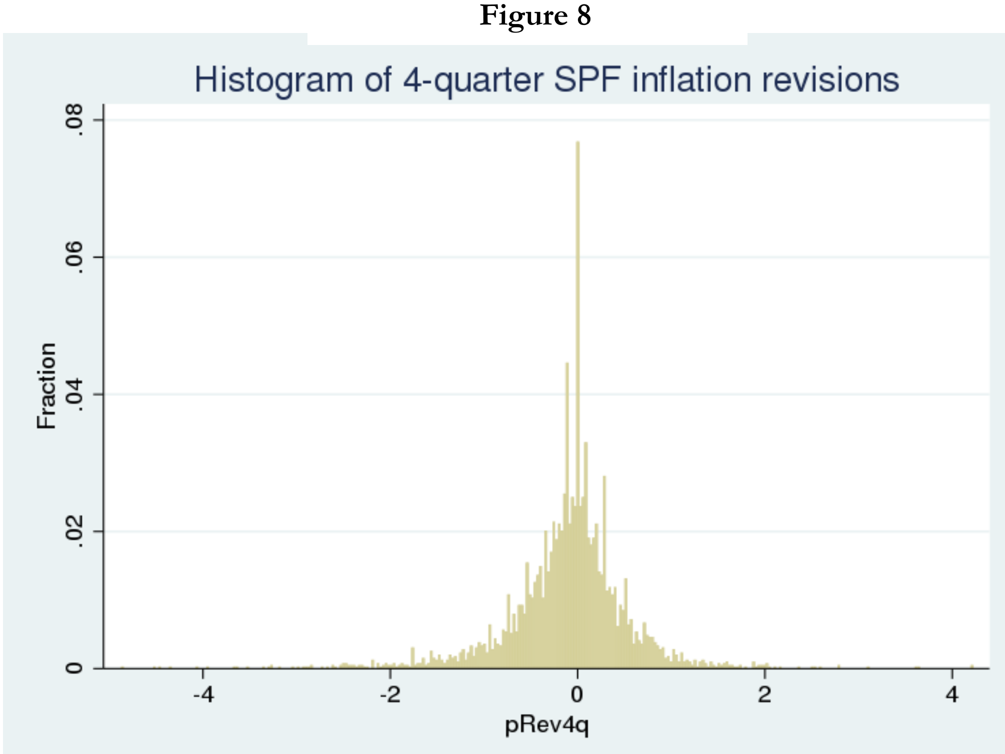


Figure 9
Efficient and inefficient(excessively smooth) expectations in a simple NKPC model

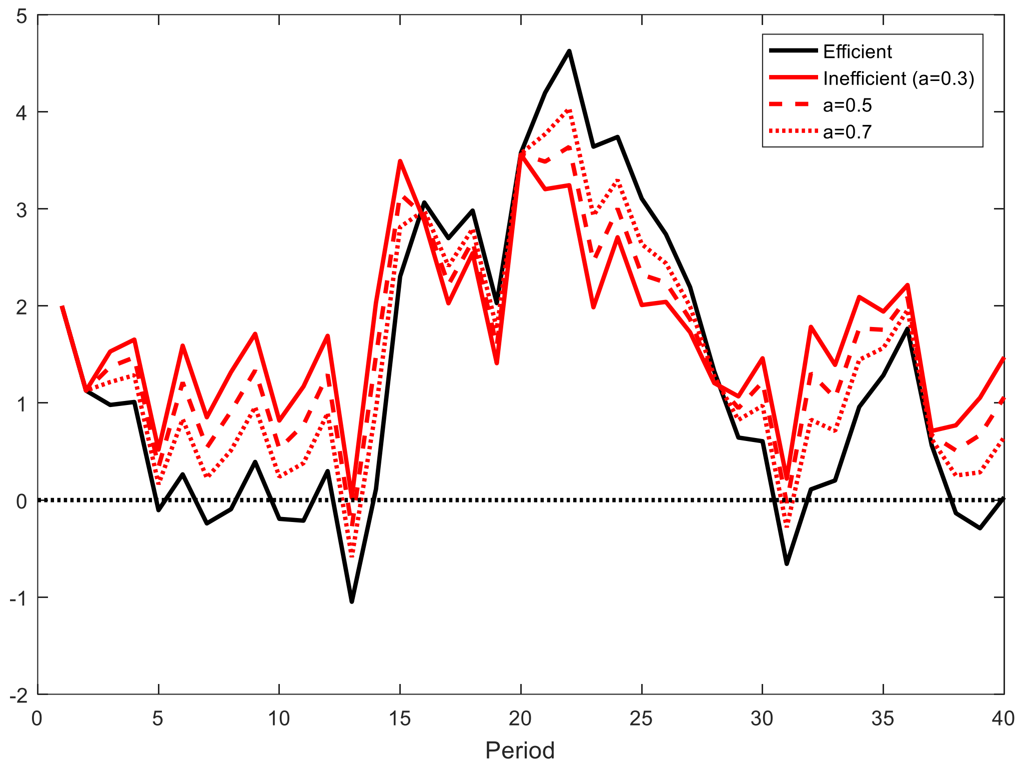


Figure 10
Simulation of simple model with and without inertial expectations effects

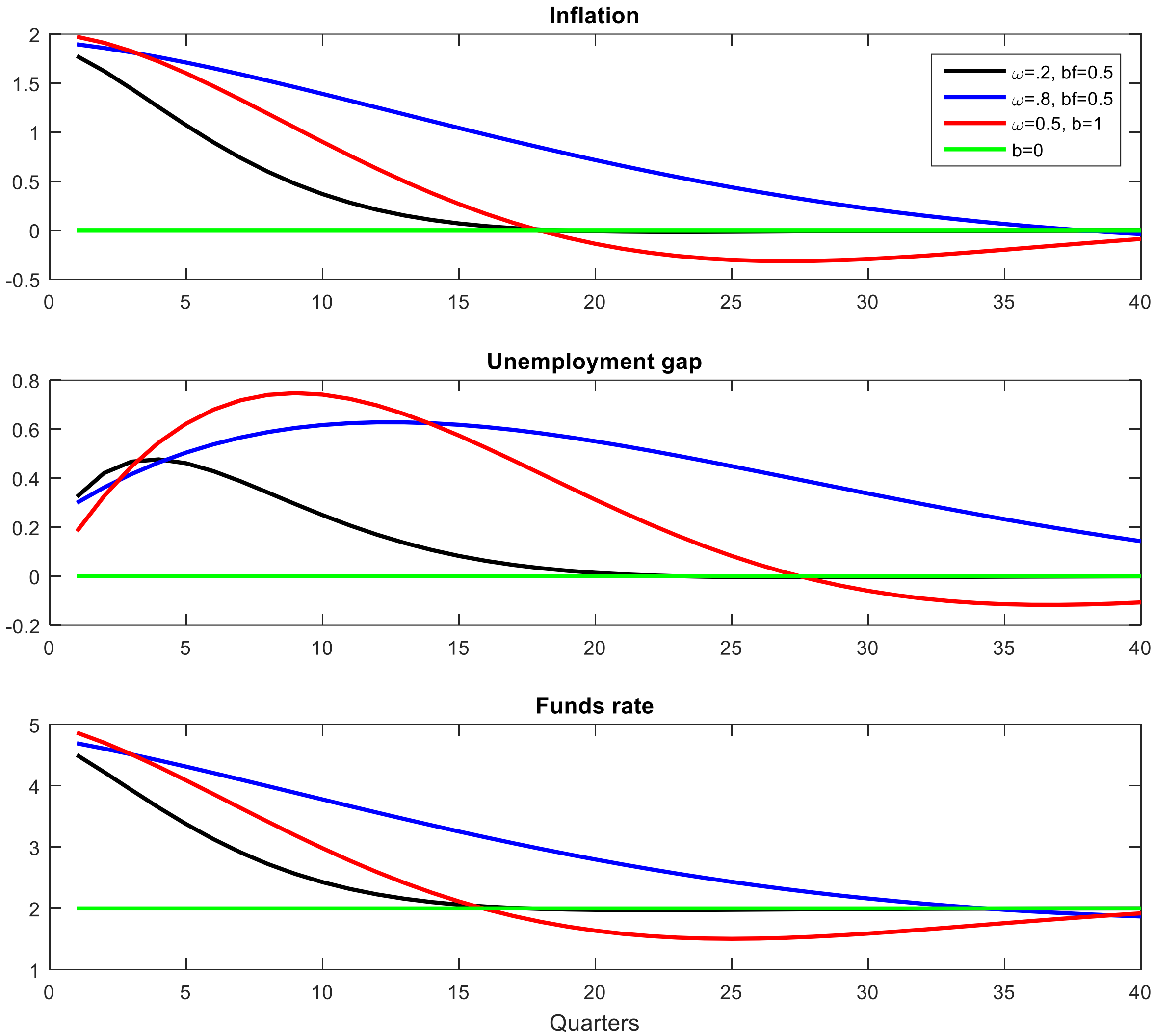


Table 1a Characteristics of SPF sample							
Forecaster participation (number of forecasts submitted)		Central tendency of forecast (1-qtr. Ahead)					
Inflation, CPI							
N_t=146		1968:Q4		1981:Q3		2018:Q1	
Mean	15.0	Mean	Med.	Mean	Med.	Mean	Med.
Median	8.7	-		7.9	8.0	2.0	2.0
Min, max	1, 70						
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_f=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

Inflation forecast dependence on lagged forecast, central tendency, various controls and horizons

$$\pi^i_{t+k,t} = a\pi^i_{t-1} + b\pi^i_{t+k,t-1} + cC(\pi^i_{t+k,t-1}) + d\pi^i_{t,t-1} + eZ^i_t + \delta_i + \varepsilon^i_t$$

Variable	*t+1* (*k=1*)				(*k=2*)	(*k=3*)	(*k=4*)
π^i_{t-1}	0.14 (0.006)	0.06 (0.012)	0.04 (0.026)	0.03 (0.093)	0.05 (0.000)	0.06 (0.000)	0.04 (0.067)
$\pi^i_{t+k,t-1}$		0.57 (0.000)	0.43 (0.000)	0.45 (0.000)	0.48 (0.000)	0.41 (0.000)	0.33 (0.011)
$\pi^{Median}_{t+k,t-1}$			0.37 (0.000)	0.28 (0.012)	0.36 (0.000)	0.39 (0.000)	0.43 (0.000)
U^i_{t-1}				-0.01 (0.321)			
R^i_{t-1}				0.03 (0.324)			
ΔY^i_{t-1}				0.03 (0.020)			
Test: b+c=1, *p*-value			0.000	0.0023	0.000	0.000	0.000
Adjusted R-squared	0.046	0.292	0.324	0.326	0.435	0.423	0.313
Observations	5068	3988	3988	3659	3971	3883	3635
Unemployment forecast dependence on lagged forecast, central tendency							
	t+1 (*k=1*)				(*k=2*)	(*k=3*)	(*k=4*)
U^i_{t-1}	0.94 (0.000)	0.33 (0.000)	0.08 (0.428)	0.33 (0.009)	-0.03 (0.759)	-0.05 (0.570)	-0.21 (0.339)
$U^i_{t+k,t-1}$		0.65 (0.000)	0.32 (0.000)	0.22 (0.000)	0.60 (0.000)	0.56 (0.000)	0.45 (0.000)
$U^{Median}_{t+k,t-1}$			0.61 (0.000)	0.45 (0.001)	0.44 (0.000)	0.51 (0.000)	0.76 (0.002)
$U^i_{t,t-1}$				-0.00 (0.941)			
$\pi^{i,SPF}_{t-1}$				0.01 (0.194)			
$R^{i,SPF}_{t-1}$				-0.08 (0.000)			
Test: b+c=1, *p*-value			0.51	0.01	0.72	0.52	0.40
Adjusted R-squared	0.907	0.936	0.943	0.960	0.925	0.916	0.909
Observations	7658	5807	5807	3726	5784	5503	3945

Table 2a Test of revision efficiency, all variables, all horizons, 1981-2018:Q1 $x^i_{t+k,t} = ax^i_{t+k,t-1} + bMedian(x_{t+k,t-1}) + cx^i_{t-1}$								
	Inflation				**Unemployment**			
	k=1	*k=2*	*k=3*	*k=1*	*k=1*	*k=2*	*k=3*	*k=1*
$x^i_{t+k,t-1}$	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)
$Median(x^i_{t+k,t-1})$	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^i_{t-1}	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 variables				Y				Y
Test: a=1 (p-value)	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*
$x^i_{t+k,t-1}$	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)
$Median(x^i_{t+k,t-1})$	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^i_{t-1}	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 variables				Y				Y
Test: a=1 (p-value)	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

Table 3a

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

$$\pi^{i,SPF}_{t+k,t} - \pi^{i,SPF}_{t+k,t-1} = \delta[\pi^{i,SPF}_{t+k,t-1} - \pi^{Median}_{t+k,t-1}] + a\pi^{i}_{t-1} + cZ^{i}_{t} + \delta_i + \varepsilon^{i}_{t}$$

Inflation results, 1981:Q3-2018:Q1

Variable	*t+1 (k=1)*							*k=2*	*k=3*
$\pi^{i}_{t+k,t-1} - \pi^{Median}_{t+k\|t-1}$	-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)
$\pi^{i}_{t+k,t-1} - \pi^{Big}_{t+k\|t-1}$		-0.33 (0.000)	0.06 (0.279)						
π^{i}_{t-1}				0.02 (0.116)	0.04 (0.026)	0.04 (0.033)	-0.04 (0.001)	0.05 (0.000)	0.06 (0.000)
$\pi^{Median}_{t+k,t-1}$					-0.21 (0.000)	-0.29 (0.001)	-0.20 (0.001)	-0.16 (0.000)	-0.20 (0.000)
U^{i}_{t-1}						-0.01 (0.593)		-0.10 (0.263)	
R^{i}_{t-1}						0.04 (0.259)		0.01 (0.921)	
Kitchen sink							Y		
Adjusted R-squared	0.16	0.08	0.19	0.16	0.18	0.17	0.34	0.23	0.28
Observations	3999	2729	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

$$U^{i}_{t+k,t} - U^{i}_{t+k,t-1} = \delta[U^{i}_{t+k,t-1} - U^{Median}_{t+k,t-1}] + aU^{i}_{t-1} + cZ^{i}_{t} + \delta_i + \mu_t + \varepsilon^{i}_{t}$$

Variable	*t+1 (k=1)*						*k=2*	*k=3*
$U^{i}_{t+k,t-1} - U^{Median}_{t+1\|t-1}$	-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)
$U^{i}_{t+k,t-1} - U^{Big}_{t+1\|t-1}$		-0.45 (0.000)	0.09 (0.667)					
U^{i}_{t-1}				0.08 (0.428)	0.08 (0.707)	0.13 (0.000)	-0.03 (0.759)	-0.05 (0.570)
$U^{Median}_{t+k,t-1}$				-0.08 (0.508)	-0.07 (0.757)	-0.13 (0.000)	0.04 (0.717)	0.07 (0.524)
$\pi^{i}_{t-1,t}$					-0.01 (0.667)	-0.00 (0.754)		
$R^{i}_{t-1,t}$					0.02 (0.276)	0.05 (0.006)		
Additional controls						Y		
Adjusted R-squared	0.20	0.13	0.19	0.21	0.23	0.78	0.16	0.15
Observations	5817	4256	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*
$\Delta Y^{i}_{t+k,t-1} - \Delta Y^{Median}_{t+k\|t-1}$	-0.73 (0.000)	-0.73 (0.000)	-0.75 (0.000)	-0.73 (0.000)	-0.73 (0.000)
$\Delta Y^{Median}_{t+k\|t-1}$		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*
$R^{i}_{t+k,t-1} - R^{Median}_{t+k\|t-1}$	-0.68 (0.000)	-0.69 (0.000)	-0.69 (0.000)	-0.55 (0.000)	-0.51 (0.000)
$R^{Median}_{t+k\|t-1}$		-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*
$T10^{i}_{t+k,t-1} - T10^{Median}_{t+k\|t-1}$	-0.67 (0.000)	-0.68 (0.000)	-0.67 (0.000)	-0.59 (0.000)	-0.53 (0.000)
$T10^{Median}_{t+k\|t-1}$		-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*
$BAA^{i}_{t+k,t-1} - BAA^{Median}_{t+k\|t-1}$	-0.68 (0.000)	-0.66 (0.000)	-0.66 (0.000)	-0.56 (0.000)	-0.57 (0.000)
$BAA^{Median}_{t+k\|t-1}$		-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 3.g
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
$x^{i}_{t+k,t-1} - x^{Median}_{t+k\|t-1}$	-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)
$x^{Median}_{t+k\|t-1}$	-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
$x^{i}_{t+k,t-1} - x^{Median}_{t+k\|t-1}$	-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)
$x^{Median}_{t+k\|t-1}$	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
$x^{i}_{t+k,t-1} - x^{Median}_{t+k\|t-1}$	-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)
$x^{Median}_{t+k\|t-1}$	-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

Regression of change in k-period-ahead forecast ($x^i_{t+k,t} - x^i_{t+k-1,t-1}$) on lagged forecast and other controls, 1981-2018:Q1

	Inflation				Unemployment			
	k=1		*k=2*	*k=3*	*k=1*		*k=2*	*k=3*
x^i_{t-1}	0.03 (0.136)	0.08 (0.236)	0.09 (0.019)	0.17 (0.000)	0.09 (0.285)	-0.02 (0.940)	0.05 (0.821)	0.08 (0.737)
$x^i_{t+k-1,t-1}$	-0.84 (0.000)	-0.79 (0.000)	-0.79 (0.000)	-0.69 (0.000)	-0.97 (0.000)	-0.75 (0.000)	-0.58 (0.000)	-0.51 (0.000)
$x^{Median}_{t+k,t-1}$	0.61 (0.000)	0.90 (0.013)	0.61 (0.008)	0.21 (0.218)	0.88 (0.000)	2.07 (0.000)	0.43 (0.318)	0.41 (0.130)
Other controls	N	Y	Y	Y	N	Y	Y	Y
Adjusted R-sq.	0.33	0.35	0.30	0.32	0.27	0.50	0.42	0.37
Observations	3987	3596	3596	3575	5809	3662	3660	3639

Additional variables include “forecasts” of lagged unemployment, inflation, Treasury bill rates, and lagged median forecasts for unemployment, inflation, Treasury bill rates at the one- to three-quarter horizons.

Table 5
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

$$\pi^{i,SPF}_{t+1,t} - \pi^{i,SPF}_{t+1,t-1} = \gamma[\pi^{Median}_{t+1,t-2} - \pi^{Median}_{t+1|t-1}] + \delta[\pi^{i,SPF}_{t+1,t-1} - C(\pi_{t+1,t-1})] + a\pi^{i}_{t-1} + cZ^{i}_{t} + \delta_i + \mu_t + \varepsilon^{i}_{t}$$

Inflation results

Variable	Lagged revision				Contemporaneous revision			
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$	-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)
$\pi^{Median}_{t+1,t-1} - \pi^{Median}_{t+1\|t-2}$		0.11 (0.386)	0.16 (0.204)	0.19 (0.172)				
$\pi^{Median}_{t+1,t} - \pi^{Median}_{t+1\|t-1}$					0.91 (0.000)	0.88 (0.000)	0.87 (0.000)	0.62 (0.006)
π^{i}_{t-1}	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)	
$\pi^{Median}_{t+1,t-1}$			-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			
$U^{i}_{t+1,t-1} - U^{Median}_{t+1\|t-1}$	-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)
$U^{Median}_{t+1,t-1} - U^{Median}_{t+1\|t-2}$		0.44 (0.000)	0.53 (0.000)	0.61 (0.000)				
$U^{Median}_{t+1,t} - U^{Median}_{t+1\|t-1}$					0.96 (0.000)	0.96 (0.000)	0.99 (0.000)	0.99 (0.000)
U^{i}_{t-1}	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)	
$U^{i}_{t+1,t-1}$			-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 6
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										
	$\pi^i_{t+1,t} - \pi^i_{t+1,t-1}$					$U^i_{t+1,t} - U^i_{t+1,t-1}$				
Sample	Full sample	1990-	1995-	2000-	2005-	Full sample	1990-	1995-	2000-	2005-
$\pi^i_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$	-0.56 (0.000)	-0.50 (0.000)	-0.49 (0.000)	-0.49 (0.000)	-0.48 (0.000)					
$U^i_{t+1,t-1} - U^{Median}_{t+1\|t-1}$						-0.70 (0.000)	-0.70 (0.000)	-0.71 (0.000)	-0.72 (0.000)	-0.75 (0.000)
$\pi^{Median}_{t+1,t} - \pi^{Median}_{t+1,t-1}$	0.87 (0.000)	0.85 (0.000)	0.85 (0.000)	0.84 (0.000)	0.86 (0.000)					
$U^{Median}_{t+1,t} - U^{Median}_{t+1,t-1}$						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 π^i_{t-1}, $\pi^i_{t+1,t-1}$ for inflation, U^i_{t-1}, $U^i_{t+1,t-1}$ for unemployment										

Table 7
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, INFLATION Results, Euro SPF, 1999-2018

	Dependent variable (forecast revisions)					
Regressor	*k*=1	*k*=2	*k*=1	*k*=2	*k*=1	*k*=2
$\pi^i_{yk,t-1} - \pi^{Median}_{yk,t-1}$	-0.56 (0.000)	-0.48 (0.000)	-0.59 (0.000)	-0.49 (0.000)	-0.52 (0.000)	-0.51 (0.000)
$\pi^{Median}_{yk,t-1}$	-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						
$\pi^{Median}_{yk,t-1}$			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 8 **Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, UNEMPLOYMENT Results, Euro SPF, 1999-2018**						
	Dependent variable (forecast revisions)					
Regressor	*k=1*	*k=2*	*k=1*	*k=2*	*k=1*	*k=2*
$U^{i}_{yk,t-1} - U^{Median}_{yk,t-1}$	-0.36 (0.000)	-0.32 (0.000)	-0.23 (0.000)	-0.08 (0.504)	-0.38 (0.000)	0.06 (0.518)
$U^{Median}_{yk,t-1}$	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						
$U^{Median}_{yk,t-1}$			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 9 **Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, OUTPUT GROWTH Results, Euro SPF, 1999-2018**						
	Dependent variable (forecast revisions)					
Regressor	*k=1*	*k=2*	*k=1*	*k=2*	*k=1*	*k=2*
$\Delta y^{i}_{yk,t-1} - \Delta y^{Median}_{yk,t-1}$	-0.68 (0.000)	-0.52 (0.000)	-0.73 (0.000)	-0.52 (0.000)	-0.77 (0.000)	-0.55 (0.000)
$\Delta y^{Median}_{yk,t-1}$	-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						
$\Delta y^{Median}_{yk,t-1}$			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 10
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

	Dependent variable (forecast revisions)					
	π		U		Δy	
Regressor	*k=1*	*k=2*	*k=1*	*k=2*	*k=1*	*k=2*
$X^{i}_{y1,t-1} - X^{Median}_{yk,t-1}$	-0.54 (0.000)	-0.48 (0.000)	-0.51 (0.000)	-0.38 (0.000)	-0.66 (0.000)	-0.54 (0.000)
$X^{Median}_{yk,t} - X^{Median}_{yk,t-1}$	0.94 (0.000)	0.66 (0.000)	0.96 (0.000)	0.96 (0.000)	0.98 (0.000)	0.96 (0.000)
$X^{Median}_{yk,t-1}$	-0.02 (0.464)	-0.14 (0.009)	0.03 (0.171)	0.06 (0.021)	-0.02 (0.145)	0.00 (0.865)
$X^{i}_{k,t-1}$	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 11
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. con-trols	Add aggre-gate revs.	Drop round resp.'s	1985-forward	1995-forward	2000-forward	2005-forward	Recess. only	Non-recess.
$\pi^{Mich}_{1Y,t-1}$ - $Median(\pi^{Mich}_{1Y,t-1})$	-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)
$Median(\pi^{Mich}_{1Y,t-1})$		-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

$$\pi^{Mich}_{kY,t} = a\pi^{Mich}_{kY,t-1} + bMedian(\pi^{Mich}_{kY,t-1}); k = 1,5$$

Test: $a = 1$

	One-year forecast		
	Coefficient		*p*-value of test $a = 1$
$\pi^{Mich}_{1Y,t-1}$ (a)	0.29 (0.000)	0.28 (0.000)	0.000
$Median(\pi^{Mich}_{1Y,t-1})$ (b)		0.60 (0.000)	0.000
	Five-year forecast		
	Coefficient		*p*-value of test $a = 1$
$\pi^{Mich}_{5Y,t-1}$ (a)	0.33 (0.000)	0.30 (0.000)	0.000
$Median(\pi^{Mich}_{5Y,t-1})$ (b)		0.76 (0.000)	0.000

Table 12 "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*
$\pi^{i}_{t,t-1} - \pi^{Median}_{t\|t-1}$	-0.59 (0.000)				-0.64 (0.000)			
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$		-0.47 (0.000)				-0.48 (0.000)		
$\pi^{i}_{t+2,t-1} - \pi^{Median}_{t+2\|t-1}$			-0.43 (0.000)				-0.43 (0.000)	
$\pi^{i}_{t+3,t-1} - \pi^{Median}_{t+3\|t-1}$				-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*
$\pi^{i}_{t,t-1} - \pi^{Median}_{t\|t-1}$	-0.60 (0.000)				-0.65 (0.000)			
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$		-0.47 (0.000)				-0.47 (0.000)		
$\pi^{i}_{t+2,t-1} - \pi^{Median}_{t+2\|t-1}$			-0.42 (0.000)				-0.42 (0.000)	
$\pi^{i}_{t+3,t-1} - \pi^{Median}_{t+3\|t-1}$				-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 13 **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 14 **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 15
Test regressions for sticky information models

$$Error^i_{t+k} \equiv x_{t+k} - x^i_{t+k,t} = \alpha x^{Median}_{t+k,t-1} + \beta R^i_{t+k,t} + \gamma x^i_{t+k,t-1} \mid R^i_{t+k,t} \neq 0$$

$$R^i_{t+k,t} \equiv x^i_{t+k,t} - x^i_{t+k,t-1}$$

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*
$R^i_{t+k,t}[\beta]$	-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)
$x^i_{t+k,t-1}[\gamma]$	-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)
$Median(x^i_{t+k,t-1})$ $[\alpha]$	-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*
$R^i_{t+k,t}[\beta]$	-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)
$x^i_{t+k,t-1}[\gamma]$	-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)
$Median(x^i_{t+k,t-1})$ $[\alpha]$	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)	
$Median(x^i_{t+k,t-1})[\beta]$	-0.20 (0.000)	0.08 (0.102)
$R^i_{t+k,t}[\gamma]$	-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 16

Test regressions for noisy information models

$$Error^i_{t+k} \equiv x_{t+k} - x^i_{t+k,t} = \alpha Z_t + \beta R^i_{t+k,t} + \gamma x^i_{t+k,t-1}$$

$$R^i_{t+k,t} \equiv x^i_{t+k,t} - x^i_{t+k,t-1}$$

$$Z_t = [x^{Median}_{t+k,t-1}, y^i_{t+k,t-1}, y^i_{t+k,t}]$$

	Inflation errors							
	k=0	*k=0*	*k=1*	*k=1*	*k=1*	*k=1*	*k=2*	*k=3*
$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.32 (0.023)		-0.81 (0.000)	-0.80 (0.000)	-0.82 (0.000)	-0.91 (0.000)	-0.91 (0.000)
$Median(x^i_{t+k,t-1})$		-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*
$R^i_{t+k,t}$	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)
$x^i_{t+k,t-1}$		-0.13 (0.163)		-0.23 (0.064)	-0.40 (0.000)	0.01 (0.917)	-0.22 (0.149)	-0.29 (0.022)
$Median(x^i_{t+k,t-1})$		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*
$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.51 (0.000)		-0.64 (0.000)	-0.80 (0.000)	-0.74 (0.000)	-0.83 (0.000)	-1.04 (0.000)
$Median(x^i_{t+k,t-1})$		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*
$R^i_{t+k,t}$	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)
$x^i_{t+k,t-1}$		-0.01 (0.905)		-0.29 (0.000)	-0.17 (0.060)	-0.17 (0.085)	-0.41 (0.000)	-0.50 (0.000)
$Median(x^i_{t+k,t-1})$		-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*
$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.74 (0.000)		-0.72 (0.000)	-0.97 (0.000)	-0.90 (0.000)		-0.85 (0.000)		-0.85 (0.000)
$Median(x^i_{t+k,t-1})$		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=2*	*k=2*	*k=3*	*k=3*
$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.49 (0.000)		-0.56 (0.000)	-0.93 (0.000)	-0.59 (0.000)		-0.50 (0.013)		-0.63 (0.000)
$Median(x^i_{t+k,t-1})$		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*
$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.76 (0.000)		-0.84 (0.000)	-1.01 (0.000)	-0.93 (0.000)		-0.81 (0.000)		-0.91 (0.000)
$Median(x^i_{t+k,t-1})$		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*
$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.65 (0.000)		-0.69 (0.000)	-0.94 (0.000)	-0.87 (0.000)		-0.70 (0.000)		-0.87 (0.000)
$Median(x^i_{t+k,t-1})$		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*

$R^i_{t+k,t}$	-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)
$x^i_{t+k,t-1}$		-0.88 (0.000)		-0.74 (0.000)	-1.00 (0.000)	-1.06 (0.000)		-0.78 (0.000)		-1.08 (0.000)
$Median(x^i_{t+k,t-1})$				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 17

Shleifer *et al* test (2017)

Regress forecast errors on components of revision from *t-1* to *t* (allow forecasts to enter separately)

$$x_{t+h} - x^i_{t+h,t} = ax^i_{t+h,t} + bx^i_{t+h,t-1} + \varepsilon^i_{t+h}$$

	Inflation				Unemployment			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$x^i_{t+k,t}$ (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)
$x^i_{t+k,t-1}$(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
$x^i_{t+k,t}$ (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)
$x^i_{t+k,t-1}$(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
$x^i_{t+k,t}$ (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)
$x^i_{t+k,t-1}$(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
$x^i_{t+k,t}$ (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)
$x^i_{t+k,t-1}$(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
$x^i_{t+k,t}$ (a)	-0.78 (0.000)	-0.41 (0.003)	-0.54 (0.000)	-0.74 (0.000)
$x^i_{t+k,t-1}$ (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?harcsda+sca.

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** $\pi^{i,SPF}_{t+1,t} - \pi^{i,SPF}_{t+1,t-1} = \gamma[\pi^{Median}_{t+1,t-2} - \pi^{Median}_{t+1\|t-1}] + \delta[\pi^{i,SPF}_{t+1,t-1} - C(\pi_{t+1,t-1})] + a\pi^{i}_{t-1} + cZ^{i}_{t} + \delta_i + \mu_t + \varepsilon^{i}_{t}$						
	$\pi^i_{t+1,t} - \pi^i_{t+1,t-1}$	$\pi^i_{t+2,t} - \pi^i_{t+2,t-1}$	$\pi^i_{t+3,t} - \pi^i_{t+3,t-1}$	$U^i_{t+1,t} - U^i_{t+1,t-1}$	$U^i_{t+2,t} - U^i_{t+2,t-1}$	$U^i_{t+3,t} - U^i_{t+3,t-1}$
$\pi^i_{t+k,t-1} - \pi^{Median}_{t+k\|t-1}$	-0.35 (0.000)	-0.36 (0.000)	-0.43 (0.000)	-0.40 (0.000)	-0.35 (0.000)	-0.37 (0.000)
$\pi^{Median}_{t+k,t-1} - \pi^{Median}_{t+k,t-2}$	-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						
$\pi^i_{t+k,t-1} - \pi^{Median}_{t+k\|t-1}$	-0.58 (0.000)	-0.54 (0.000)	-0.55 (0.000)	-0.64 (0.000)	-0.57 (0.000)	-0.51 (0.000)
$\pi^{Median}_{t+1,t} - \pi^{Median}_{t+1,t-1}$	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
$x^i_{t+k,t-1}$	-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)
$x^{Median}_{t+k,t-1}$	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
$x^i_{t+k,t-1}$	-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)
$x^{Median}_{t+k,t-1}$	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									