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Expectations as a Source of Macroeconomic Persistence: An Exploration of Firms' and Households' Expectation Formation

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Abstract

This paper examines the expectations behavior of individual responses in the surveys of the Survey of Professional Forecasters and the University of Michigan's Survey Research Center. The paper finds that respondents consistently revise their forecasts of inflation, unemployment, and other key variables so as to move them closer to the lagged central tendency of expectations in the survey. This result is quantitatively and statistically significant, and is robust to the inclusion of essentially all of the real-time information available in these surveys. The paper shows that rational agents with full information have no motive to link their current forecast to lagged central tendencies. This may suggest that economic agents who do not know the true structure of the economy utilize a simple solution to a filtering problem, anchoring their forecasts to the most recently observed median forecast, which on average will contain important aggregated information about the variables they are attempting to forecast. This regularity bears important implications for macroeconomic dynamics, as illustrated in the last section of the paper. The regularity also provides a micro-based foundation for an earlier paper's finding that expectations persistence is an important source of the macroeconomic persistence (Fuhrer 2015).

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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, and likely more controversial.

The rational expectations paradigm has been used widely in macroeconomic models for decades, and has served the discipline well in 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 and on the economic circumstances. In tranquil times, many financial markets 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 works fairly well as a description of forward-looking behavior (although this too remains an empirical question).

But evidence is mounting that suggests that rational expectations may not be the best assumption to embed in macroeconomic models (see, for example, Fuhrer (2015), Fuster, Hebert and Laibson (2012), Adam and Padula (2011), Roberts (1997), and Trehan (2015)). The addition of many "bells and whistles" to 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 remains the valid assumption. Or it could be that the basic model structures are reasonable, but the expectations assumption causes the models to make strongly counterfactual predictions. A number of papers have explored alternative expectations assumptions and their implications for economic outcomes, in both theoretical and empirical settings (a leading example is learning: see Adam (2005), the many papers of Evans and Honkapohja and their 2001 book, Milani (2007), Orphanides and Williams (2005), and Slobodyan and Wouters (2012)). Milani

(2007) shows that the introduction of adaptive learning significantly reduces the dependence of a particular DSGE model on habit formation and price indexation to explain the persistence of macroeconomic time series. Slobodyan and Wouters (2012) find a notable reduction in the persistence of the estimated shocks that drive wages and prices; they also note that the expectations based on the "small forecasting models" in their paper bear a close resemblance to survey expectations.

It is striking that, in this context, relatively few authors have examined in detail the expectations behavior of individual economic agents (exceptions include empirical work by Paloviita and Viren (2013) and a vast theoretical literature that emphasizes the role of individual expectations [see especially Frydman and Phelps (2013) and the papers contained and cited therein]). Most of the papers cited above use aggregated measures of expectations from available surveys and (in fewer cases) from financial asset prices. Notable exceptions exist in behavioral economics, experimental economics, and a few other areas. But few have attempted to characterize the underlying behaviors in the micro-data from the oft-cited aggregate surveys from the Survey of Professional Forecasters (SPF), the University of Michigan's Survey Research Center, and others.

This paper examines a fairly rich set of micro-data evidence on the expectations behavior of firms and households. 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 2015). 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 independent persistence above and beyond 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 Survey of Professional Forecasters—one finds that the data prefer an estimated value for ω that is much smaller and typically not statistically significantly different from zero. In addition, the estimated autocorrelations of the error term ε_t, while sizable in rational expectations implementations of the equation, are much smaller and are also 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. To be clear, for inflation, the expectations add persistence above and beyond the persistence that inflation inherits from the marginal cost process. For habits, the expectations capture the sluggish adjustment of consumption growth to shocks that were previously proxied by lagged consumption.[1] While Fuhrer (2015) documents this finding with aggregate data, this paper aims to understand the underlying expectation behaviors that give rise to this kind of persistence in measures of expectations.

The paper uses the individual responses in the SPF 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

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

studied), while the Michigan survey contains over 500,000 observations on tens of thousands of households since 1978. The structures of the datasets differ: Whereas many firms in the SPF 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 is much richer in this dimension.

Although firms' and households' expectations differ in some respects, they share one key feature: Individual forecasters tend to adjust their own forecasts toward measures of the central tendency of forecasts from the previous period. The theoretical motivation for doing so will be discussed more fully later in the paper, but one can construe this as a solution to a filtering problem in which individual agents have partial information about the structure of the economy or (perhaps) the data that measure it. In such a limited-information environment, agents may improve the accuracy of their expectations by using the lagged central tendency of individual forecasts as an information-rich summary of many forecasters' recent views on the variable they wish to forecast. Thus, in the absence of perfect information, they use the lagged aggregate forecast as an input to their own forecasts of persistent aggregate variables. 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.

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 central tendency than to any of the lagged (real-time) actual data. It will also be shown that, from a filtering perspective in an imperfect-information environment, the lagged central tendency of the forecasts likely provides significantly more information than the lagged realization. The reasoning is simple: If the true model or data-generating process for a variable involves more than the lagged dependent variable, then the central tendency of forecasts will incorporate (on average) more than the information available in the lagged dependent variable, and thus will constitute a better variable onto which to anchor individual forecasts.

Importantly, it can be shown that this empirical finding is *not* a statistical artifact of reasonably well-informed forecasters using the known persistence of the data to forecast in a close-to-optimal fashion.[2] Simple simulation exercises demonstrate that the expected regression coefficient on the lagged central tendency of forecasts among a group of heterogeneous but approximately optimal forecasters should be very close to zero, if they possess unbiased information about the lagged actual values of the variable they are forecasting. ("Approximately optimal forecasters" here means forecasters who know the time-series features of the data they are forecasting, including its persistence.)

Of course, such anchoring of individual forecasts to lagged aggregate information imparts additional persistence to the expectations, beyond the persistence that would otherwise be a component of 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 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 validated by the empirical work in Fuhrer (2015), and explored further in 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.

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[2] Such an artifact would be akin to the well-known "Galton's Fallacy," which derives from an 1885 study by Sir Francis Galton (1885) called "Regression Toward Mediocrity in Hereditary Stature."

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 and inflation. To be sure, not all of the firms surveyed in the SPF 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.

Table 1 provides some summary statistics describing key features of the SPF sample. Figure 1 shows the duration and timing of each forecaster's participation in the survey from 1981:Q3 to the most recent survey in the sample.[3] 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 data, see the links to the sources in the appendix.[4]

Properties of individual SPF forecasts

The first set of results examines the correlations among individual inflation forecasts, the forecasters' idiosyncratic (real-time) estimates of lagged inflation, and measures of the previous period's central tendency of the SPF forecast for the same variable.[5] Table 2 presents results from the first set of test regressions, which take the general form

$$\pi_{t+1,t}^{i,SPF} = a\pi_{t-1}^{i} + bC(\pi_{t+k,t-1}^{SPF}) + dZ_t^i + \delta_i + \varepsilon_t^i \,, \tag{0.1}$$

where $\pi_{t+1,t}^{i,SPF}$ is the i^{th} forecaster's forecast of consumer price index (CPI) inflation for period *t+1* made in period *t*; π_{t-1}^{i} is the i^{th} forecaster's estimate of lagged inflation, $C(\pi_{t+k,t-1}^{SPF})$ is a measure of

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[3] 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.

[4] 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.

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

the central tendency of the forecasts for the same variable for period *t+k* (here *k= 0* or 1) using the previous period's information set, Z_t^i is a vector of other forecaster-specific variables, which includes forecasts of unemployment, output growth, and the Treasury bill rate, and δ_i denotes forecaster-specific fixed effects. Standard errors are corrected for heteroskedasticity, autocorrelation, and correlation among panels using the method set forth in Driscoll and Kraay (1998).[6]

Table 2 assesses the empirical performance of several candidates for the central tendency reference C(.) for these regressions. We consider four different candidates: (1) the median of all forecasts for period *t* made in period *t-1*; (2) the median of all forecasts for period *t+1* made in period *t-1*; (3) the average of forecasts for period *t+1* made in period *t-1* by the three forecasters with the lowest RMSE, computed real-time for the preceding 20 quarters; and (4) the forecasts for the same origin and horizon made by the forecasters who have been in the dataset longest, as a proxy for the largest and most-respected forecasters in the sample. The regression is estimated for the full sample from 1981:Q3 to 2014:Q2 as a panel regression, with standard errors corrected as noted above.[7] While anchoring to the most prominent or the highest-performing forecasters has some intuitive appeal, Table 2 suggests that these variables do not enter as consistently in the test regression, so the focus for the bulk of the paper is on the median forecast measure.[8]

Note that two different concepts of the central tendency are tested in options (1) and (2): The first looks at whether today's one-quarter-ahead forecast is anchored to last period's one-quarter-ahead forecast: do individual one-quarter-ahead forecasts today look like aggregate one-quarter-ahead forecasts from last quarter? The second looks at whether today's one-quarter-ahead forecast is anchored to the two-quarter-ahead forecast from last quarter: does the one-quarter-ahead forecast made today look like the aggregate forecast for the same period made last quarter? As we will see below, both types of anchoring add significant persistence, once aggregated, to price and output dynamics. But they are conceptually distinct: The first might suggest that *k*-period forecasts are correlated across time; the second might suggest that the forecast for period *j* is correlated across

[6] 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.

[7] 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.

[8] Including additional controls in the regressions shown in Table 2 does not alter the conclusion that the lagged median forecast strongly dominates the other central tendency measures.

expectation viewpoint dates. In almost all of the test regressions, the median forecast for period *t+1* dominates the median for period *t*.

Table 3 takes the results from Table 2 on board, and examines in more detail the correlations among individual and aggregate forecast variables. The regressions in Table 3 take the form

$$\pi_{t+1,t}^{i,SPF} = a\pi_{t-1}^{i} + b\pi_{t+1,t-1}^{i,SPF} + cC(\pi_{t+1,t-1}^{SPF}) + dZ_t^i + \delta_i + \varepsilon_t^i \ , \qquad (0.2)$$

where most of the variables are defined as in Table 2, and where we add $\pi_{t+1,t-1}^{i,SPF}$, the i^{th} forecaster's forecast for the same horizon *t+1* made last period (*t-1*). Including the lagged forecast for the same horizon might capture serial correlation in the individual forecasts that is not captured by other regressors in the test regressions, which might also be proxied by lagged central tendencies. As in Table 2, the regression is estimated for the full sample from 1981:Q4 to 2014:Q2 as a panel regression, with standard errors corrected as above. In these regressions, the strongest explanatory variables are the lagged central tendency of the distribution of forecasts, as well as the individual forecasters' own lagged forecasts. Of course, there are good reasons why the individual forecasts made today might be related to the forecasts for the same period made yesterday, especially for variables that are autocorrelated, and hence for which not all of the relevant information for any given period is contained in one period. But even in the presence of this additional control, the lagged central tendency enters with about the same magnitude, and with strong statistical significance.

Table 3 shows that the estimated coefficient on the median forecast for *t+1* made in period *t-1* ranges from 0.5 to 0.7, regardless of what other controls are included. The additional columns in the table show that this strong dependence on the 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.[9] Table 4 examines a somewhat simplified set of results for the next quarter's forecast (*t+2*), and develops essentially the same results. The bottom panel of Table 3 displays the same regressions for forecast horizons *t+2* to *t+4*, with and without the macro controls in the top panel of the table. Note that the forecast for period *t+4* made in period *t-1* is not in the dataset (this is a five-quarter-ahead forecast), so we use instead the forecast for the following calendar year made last quarter. This difference in horizon and forecast span may account for the reduction in the size of the coefficient.

[9] A number of other regression specifications, not reported, examine the sensitivity to other forecaster-specific variables in the SPF dataset, as well as other ways of combining aggregate information, such as the change in inflation implied by the median forecasts. None of these regressions alter the conclusion from Tables 2 and 3. Note that in some regressions, the later-dated median expectation takes on a negative sign, suggesting that a combination of the previous expectation and the implied change in inflation both enter the regression.

Nonetheless, the results in this panel are striking, as they suggest that individual forecasts out to four quarters ahead exhibit a strong link to the lagged central tendency of the forecast for the same horizon.[10]

Table 5 examines the subsample stability of the results, looking at estimates of the simplified regression that excludes other forecaster-specific controls and time dummies

$$\pi_{t+1,t}^{i,SPF} = a\pi_{t-1}^{i,SPF} + b\pi_{t+2,t-1}^{Median} + \delta_i + \varepsilon_t^i \tag{0.3}$$

over 5-year subsamples. Of particular interest is the change in the coefficient on $\pi_{t+1,t-1}^{Median}$. The coefficient is quite stable for many of the subsamples, but as suggested by the last few columns of the table, the effect, while significant in earlier data, was weaker in the earlier samples and has become *stronger* in more recent data.

Tables 3–5 include quite an array of additional variables to check the robustness of the relationship between individual forecasts and the lagged central tendency. However, these regressions are simply summaries of sets of partial correlations, so they can tell us only so much. In particular, it is not surprising that the i^{th} forecaster's forecast of x_{t+k} made in period *t-1* is correlated with the same forecaster's forecast for the same variable made in period *t*. As long as the variable *x* is autocorrelated, a reasonable (and certainly an optimal) forecaster's sequence of forecasts for the same period will also be autocorrelated. Thus, while the addition of these variables serves as a check on the correlation with the lagged central tendency, in uncovering a mechanical correlation these variables detract from the main purpose of these regressions: to uncover behavioral aspects of expectation formation that are less commonly appreciated in the macro literature.

A stronger test may be found in regressions of the *revisions* in the forecasts on the lagged discrepancy between the individual and the median forecast. That is, the regression is designed to test whether an individual forecast for (say) inflation that is noticeably above the median forecast last period tends to get revised down toward that median; this is the mechanism by which the individual forecasts tend to track the median.[11] Of course, the presence of a levels relationship implies that the individual SPF forecasts must move toward the central tendency over time, and in fact the revision regressions below are restricted versions of a levels relationship that will be tested below.

[10] Although not reported here, regressions that include the median forecast for periods *t+1, t+2, t+3* made in period *t-1* are included for the forecasts for period *t+2, t+3* and *t+4* respectively, and are also estimated significantly, as is the case in the top panel of Table 3.

[11] 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.

The revision regressions constitute a stronger test of the influence of aggregate information, because this period's revision to an efficient forecast should not be correlated with information that was available to the forecaster in the previous period. In the levels regression, the correlation with lagged median forecasts could reflect the influence of common information that is not captured by other variables in the regression. While the determinants of the forecast may be manifold, and some may not be captured in the test regressions, the quarter-to-quarter revisions should be based on information that represents news to the forecaster.

Consistent with the levels regression results reported above, Table 6 shows that forecasters consistently revise their forecasts so as to bring them into closer conformity with the previously observed central tendency of forecasts. Table 6 parallels Table 2 in examining several candidates for the appropriate central tendency reference, presenting regressions of the form

$$\pi_{t+1,t}^{i,SPF} - \pi_{t+1,t-1}^{i,SPF} = \delta[\pi_{t+1,t-1}^{i,SPF} - C(\pi_{t+1,t-1})] + a\pi_{t-1}^{i} + cZ_t^i + \delta_i + \varepsilon_t^i \quad . \tag{0.4}$$

Just as in the levels regressions, the results show clearly that the lagged median of previous forecasts serves most reliably as the anchor for individual forecast revisions. All regressions develop negative and precise estimates of δ: 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 revise his next forecast for the same period toward the central tendency. As is the case for the regressions of forecast levels in Tables 2–5, this result appears quite robust across control variable sets and time periods. Figure 2 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 (1.4)), and the negative correlation is clear. Figure 3 displays a histogram of the coefficients for equation (1.4) estimated for each forecaster in the sample. While there is clearly some heterogeneity in the "speed of adjustment" to the deviation of an individual's forecast from the lagged central tendency, it is clear that the mass of estimates is solidly centered between zero and minus one, with a modest standard error. The aggregate regression is not the artifact of a few outliers.

The bottom panel of Table 6, like its counterpart in Table 2, shows the results of forecast revision regressions for additional forecast horizons. The results are uniformly strong, suggesting that individual forecasters revise *all* of their forecasts in response to deviations from previous median forecasts.[12]

Table 7 provides results from a variant of the revision regressions reported in Table 6. Here, the dependent variable is the change in the one-period-ahead forecast from quarter to quarter; that is, the $t+1$ forecast made in period t minus the t-period forecast made in period $t-1$. Interestingly, this regression shows very similar results: no matter the set of controls, the change in the one-period-ahead forecast responds strongly to the discrepancy between the one-period-ahead forecast last period and the median of all one-period-ahead forecasts last period. This similarly implies that forecasts are adjusted over time so that they do not deviate from the previously observed central tendency, but here it is not the revision in the forecast for a fixed forecast period that error-corrects, but the change in the one-quarter-ahead forecast for successive forecast periods.

Along the lines discussed above, it is possible that the revisions in the forecasts are correlated with the median forecast discrepancy simply because many forecasters share common information that may not be completely reflected in the available survey responses that are included in the preceding regressions. Most of that information should be contained in forecasters' lagged expectations, and in the other individual survey expectations that enter the regressions (for example, common information should be reflected to some extent in individual respondents' forecasts of unemployment, output, and interest rates as well). But if the regressions have not completely captured common information, all could revise their forecasts in response to the revisions in (uncaptured) common information. To control for this possibility, Table 8 presents regressions of the individual forecast revisions on the lagged discrepancies from Table 2, adding the revision in the median forecast, which could reflect revisions due to changes in commonly held information. The last observed revision is the change in the median forecast from viewpoint $t-2$ to viewpoint $t-1$; this is the 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 in response to the lagged discrepancy between their forecast and the median forecast. As a final check, I include the *contemporaneous* revision to the aggregate forecast, which cannot be observed by individual forecasters in real time. While the coefficients on this variable are larger and quite significant—magnitudes of 0.8 to 0.9 with near-zero p-values, as shown in the bottom panel of Table 8—the coefficients on the individual

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

forecast discrepancies are essentially the same as those using the lagged aggregate revision, and are qualitatively unchanged from the regressions that omit the aggregate revision.

A nested regression

The regressions of equations (1.1) and (1.4) may be nested in the overarching regression that describes the behavior of the forecast level for inflation or unemployment:

$$\pi^{i,SPF}_{t+k,t} = \omega_1 \pi^{i,SPF}_{t+k,t-1} + \omega_2 C(\pi^{SPF}_{t+k,t-1}) + a\pi^{i,SPF}_{t-1} + \beta U^{SPF}_{t+k,t-1} + \gamma U^{i,SPF}_{t+k,t} + \phi TB^{i,SPF}_{t,t} + \sum_{j=0}^{1} \tau_j \Delta y^{i,SPF}_{t+j,t} + cZ^i_t + \delta_i + \varepsilon^i_t, k = 0,1 \quad (0.5)$$

Regression (1.4) restricts $\omega_1 + \omega_2 = 1$; the test of this restriction is presented in Table 9 for each variant of the test regression. The additional regressors include the individual forecaster's estimate of lagged inflation, the median of all of last period's unemployment forecasts for period *t+1*, and the individual forecaster's forecast for the unemployment gap, Treasury bill rate, and output growth in the periods indicated.

The columns of Table 9 examine different versions of the test regression (1.5), but all include the lagged individual and lagged median forecasts. The inclusion of the lagged median of unemployment (inflation) for the inflation (unemployment) regression allows for the possibility that forecasters not only revise their forecast toward the central tendency of forecasts from last period, but that the effect of the driving variable on the forecast variable may also be influenced by the central tendency of the forecasts for the driving variable. The results are unambiguous. In all cases, one can reject the hypothesis $\omega_1 + \omega_2 = 1$, usually with a *p*-value that is smaller than 0.000. That is, the results in Tables 2–6 reflect not only the tendency of forecasters to revise their level forecasts toward last period's central tendency forecast for the level, as in equation (1.4); they also reflect a levels relationship by which forecasters anchor their current-period forecast to the central tendency of all forecasts from last period.

Other forecast variables

So far, we have focused on the properties of inflation forecasts, but the SPF includes forecasts for a number of other variables. Table 10 summarizes a subset of results from regressions like those of Tables 2–6, using the revisions to the one- to four-quarter-ahead forecasts for the unemployment rate. Once again, the influence of the lagged discrepancy between the individual and the median forecast is strong, and changes little with the addition of other forecaster-specific controls. The bottom panel displays results for other 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 gap between that forecast last period and 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.

Altogether, the results summarized in Tables 2–10 suggest that the current-period forecasts for all forecast horizons (or the revisions in those forecasts) for inflation, unemployment, and other forecasted variables depend significantly on

- The central tendency of all forecasts (or the discrepancy from the central tendency) for the same variable that were made last period;
- The forecaster's own forecasts of plausible determinants of inflation and unemployment;
- The forecaster's own estimate of the lagged value of the variable, although the size of this effect is not terribly large.

The dependence of forecast revisions on the forecaster's own estimates of lagged values is somewhat surprising. But the dependence on the deviations from the lagged central tendency suggests dynamics in expectations that are unlikely to be captured by simple rational expectations models. A richer information structure is likely required to motivate these findings, and a simple example is discussed in Section 5 below.

2. Evidence from households

Tables 11 and 12 provide evidence on both the levels and the revisions of forecasts from the University of Michigan's Survey Research Center Survey of Consumers. This monthly survey is largely a cross-sectional survey of about 500 randomly selected households per month. However, a subsample (about one-fifth) of respondents are 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 12).

Table 11 displays the results from the test regressions

$$\pi_{t+1y,t}^{i,Mich} = a\pi_{t-1,t} + bC(\pi_{t+1y,t-1}^{Mich}) + cZ_t^i + \delta_i + \varepsilon_t^i, \tag{0.6}$$

where $\pi_{t+1y,t}^{i,Mich}$ is the i^{th} forecaster's one-year-ahead inflation expectation made in period *t,* $\pi_{t-1,t}^{i}$ 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 central tendency of all forecasters' forecasts for the one-year-ahead inflation rate 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.[13] As Table 11 indicates, the Michigan survey respondents also exhibit a strong tendency to anchor their forecasts to the previous central tendency of forecasts. For a variety of controls, the coefficient on the lagged central tendency varies from 0.57 to 0.84, and is always significant at exceedingly high levels. Figure 4 displays the rolling-sample estimates for the coefficient on $C(\pi_{t+1y,t-1}^{Mich})$ in equation (2.1); the estimates remain remarkably stable across time (1978 to the present). The bottom panel of the figure displays a histogram of the estimated coefficients over time.

Table 12 provides the results from regressions of the revision of the one-year inflation forecast on the discrepancy between the first inflation forecast and the central tendency of forecasts at that time, as in equation (1.4) above for the SPF data. Additional variables control for the revisions in those questions that elicit numeric responses. Because the time dimension of the survey is limited, we examine in this table the extent to which the pooled-cross section results vary over time. With a sizable number of observations for each cross-section, we are also able to examine whether these revision regressions correspond only to times of economic tumult (recessions), or times of relative calm, or both. Again, there is little in the way of variation across any of these cases.

Here again, the results are strong and consistent across controls and time periods. The coefficient on the lagged discrepancy varies narrowly between -0.68 and -0.72 for all of the specifications presented in the table. On the one hand, 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.

[13] 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.

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.

3. "Anchoring" inflation expectations

While the regressions in Tables 2–5 suggest that both professional and household forecasters anchor their expectations to the previous central tendency of all forecasts, many economists also embrace the notion that expectations may be well anchored to the central bank's inflation goal, especially in the context of a credible inflation-targeting monetary regime. By this, economists often mean that long-run inflation expectations do not deviate far from the central bank's announced inflation goal. In addition, they often assert that such anchored expectations provide a firm anchor for realized inflation, perhaps explaining why the variation of inflation in the wake of the Great Recession has been relatively small.

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

If anchoring to long-run expectations is an important feature of inflation and inflation expectations, then the omission of this variable from the regressions above could bias the estimates presented in Tables 2–12. This dataset allows us to examine directly the extent to which short-run inflation expectations are anchored to long-run expectations. Figure 6 displays the median 10-year CPI inflation forecast from the SPF from the date it was first collected (1991:Q4) through mid-2014. Table 13 presents results from regressions that augment those in Section 2 with the median 10-year CPI inflation forecast, which enters with a lag, as it would not be observable to all forecasters contemporaneously.

The first columns in the top panel of Table 13 (full sample estimates) show the results of regressing short-run (1-quarter to 4-quarter) inflation forecasts on the lagged central tendency of the corresponding 1- to 4-quarter forecasts and the lagged median 10-year forecast (fixed effects for each forecaster ID are included; standard errors are corrected as above). These columns suggest at best a limited role for the long-run forecast, with the exception of the 4-quarter-ahead forecast. Generally, these regressions suggest that the primary anchor for short-run expectations remains the lagged central tendency of forecasts, which continues to develop a coefficient between 0.6 and 0.9. The next set of columns uses a fuller set of individual respondents' forecasts of key macro variables. The evidence for anchoring remains modest, with none at the short end, but with increasing significance for longer-horizon forecasts. Still, the anchoring to the lagged median forecast remains economically and statistically significant.

The middle panel of Table 13 limits the sample to the post-1999 period, the time during which most of the discussion of expectations anchoring has occurred. This also coincides with the time that the SPF long-run expectation measure has exhibited significant stability, although Figure 6 shows that there has been some variation over this period. As this panel indicates, however, while forecasts remain strongly anchored to the previous central tendency, we develop no evidence of a compelling link to the median long-run forecast. The sign of the coefficient is almost always counterintuitive, and the *p*-values are woefully high.

The bottom panel of Table 13 estimates forecast revision regressions, allowing for the revision in the10-year forecast to enter as well. The long-run forecast revision typically does not enter significantly, but regardless, it does not alter the strong reversion to the lagged discrepancies reported throughout.

The household data afford some opportunity to examine the question of anchoring as well. For most of the sample, a 5-year inflation forecast is collected by the SRC, so we use this as a proxy for the long-run forecast around which short-run expectations might be anchored. For expositional clarity, and because the 1- and 5-year expectations have a 20 percent overlap, we construct the years 2–5 expectation and use it as the long-run anchoring proxy.[14] As Table 12 shows, short-run expectations remain tied to the lagged central tendency regardless of which other regressors are included. There appears to be some linkage to the lagged median 2–5-year expectation, but the magnitude is modest. Whether this constitutes anchoring to the central bank's inflation goal or part of the solution to a filtering problem, in much the same way as the link to the 1-year expectation, is difficult to tell. Overall, then, while the evidence for anchoring to lagged expectations is strong, the evidence for anchoring to the long-run expectation is modest, at best.

4. **Could this be a statistical artifact?**

One might be tempted to conclude that the regressions that link individual forecasts to the central tendency of last period's forecasts must be a statistical artifact—of course, current idiosyncratic forecasts of a persistent variable look like last period's median forecast. This might be akin to the well-known Galton's fallacy. But a couple of simple exercises show that this is not at all what one should expect.

First, consider a set of N forecasters, each of whom has the correct model for a process that she is forecasting, but each of whom adds idiosyncratic information to her forecast, which we model as white noise. Assume the true process for the variable *x* is

$$x_t = (1-\rho)\mu + \rho x_{t-1} + e_t, \tag{1.1}$$

so that the optimal forecast of *x* at period *t-1* is $\mu + \rho x_{t-1}$, and each forecaster *i* observes x_{t-1} perfectly, knows μ, and makes her forecast according to

$$x_{t,t-1} = (1-\rho)\mu + \rho x_{t-1} + \phi_t^i \ , \tag{1.2}$$

so that each forecaster adds idiosyncratic (assumed white) noise ϕ_t^i. We simulate the underlying process and the set of idiosyncratic forecasts many times, estimating the simplified test regression of equation (1.2) for each draw. The regressors are the lagged realization and the lagged central tendency. Figure 6 displays the distribution of estimates for the coefficient on the lagged central tendency so obtained. As the figure clearly indicates, the odds on obtaining a sample estimate of

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

0.3–0.96, as in Table 2, are virtually nil. So the results do not arise as a statistical artifact of a set of rational forecasters who are forecasting a persistent series. The intuition is straightforward: once we condition on the perfectly observed lagged value of x, there is no information in the mean or median forecast from last period, as it simply averages over the optimal forecast plus the idiosyncratic noise, which averages zero.

The same exercise is performed for the revision regressions of Table 2 and equation (1.4), with the results displayed in Figure 7. Again, the estimates are solidly centered on zero, and the probability of obtaining an estimate in any sample as large as those in Table 6 (-0.3 to -0.96) is virtually nil. The intuition here is straightforward as well, and, of course, related to that above: if your forecast deviates from the optimal by white noise, there is no reason to systematically move that forecast toward the previous central tendency.

Could it be that, while not a trivial statistical artifact, the results in these regressions can be explained by some other linkage that is still consistent with standard theory? For example, individual inflation forecasters might base their forecasts on observations of salient lagged variables, such as the relative prices of oil or food. But these variables should be reflected in the idiosyncratic estimates of lagged overall inflation measures that are included in the regression. Perhaps other omitted variables that are used by individual forecasters are captured by lagged aggregate forecasts, but are not in the forecast database? This could certainly be, but in this case, it is hard to see why the revisions in forecasts would be tied to information that was observed by the forecasters in the previous period.

Because it is difficult to devise an explanation that removes all economic content from the empirical results, we turn to behavioral explanations that are consistent with the observed regularities. In the next section, we explore a simple model of incomplete information below to motivate the empirical results and to point toward a way in which one might augment standard macroeconomic models to reflect this feature of expectation formation.[15]

[15] Another avenue that might be consistent with the empirical results is "herding" behavior, such as that documented in Scharfstein and Stein (1990), in which investment managers and others stay close to the central tendency so as to "share the blame" for a particularly bad forecast outcome. This incentive runs counter to that of the forecaster who wishes to distance herself from the pack, taking advantage of the low probability that she will be the sole accurate forecaster for an unusual event, guaranteeing a stream of revenue from those who believe that her lucky forecast signals true acumen (see Batchelor and Dua (1990)).

5. A simple model of incomplete information and expectations formation

Suppose the economy is populated by a number of heterogeneous households and firms. Each household's decisions depend on its expectation of a key variable x. The households do not have access to the true model of the economy (who does?), and they are aware of this fact. In fact, no household or firm has the true model of the economy.[16]

In an effort to construct her forecast, forecaster i uses her own idiosyncratic modeling structure but, aware of her incomplete information, seeks an observable that can augment her forecast because it plausibly contains more information, and because that variable will, on average, use that information more efficiently than any one agent can. A natural candidate for such a variable is the central tendency of a group of forecasters who aim to forecast the same variable x.[17]

To formalize the intuition behind this setup, define a vector of observable variables that summarize the state of the macroeconomy

$$z_t \equiv [z_{1t}, z_{2t}, z_{3t}], \tag{1.3}$$

where the three elements of z might represent inflation, output, and the policy rate. These variables are assumed to evolve according to

$$z_t = \Phi z_{t-1} + [I - \Phi]\mu + \varepsilon_t. \tag{1.4}$$

There are J agents in the economy, and each j^{th} agent begins with an idiosyncratic model for z

$$z_t = \phi_j z_{t-1} + (I - \phi_j)\mu_j + e_{jt}. \tag{1.5}$$

If we allow elements of $[\phi_j, \mu_j]$ to be zero, then for linear models, equation (4.3) becomes quite general and allows both for differences in coefficients and for the exclusion of lags in z. The errors made by any agent j if she uses her idiosyncratic model (4.3) will be

$$a_{jt|,t-1} \equiv z_{jt,t-1} - z_t = (\phi_j - \Phi)z_{t-1} + (I - \varphi_j)\mu_j - (I - \Phi)\mu - \varepsilon_t. \tag{1.6}$$

The last term in (4.4) is unavoidable, and would be the same if the agents knew the true model for z. Agents do not know the true values of the coefficients in (4.2), and they are aware of their ignorance in a general sense. They wish to form a reasonable forecast of z knowing that they are ignorant of the true model. They also know that other forecasters are going through the same process and might use information differently—and perhaps more efficiently—than they do. But they cannot observe other forecasters' forecasts at the time they are making their own.

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[16] While there exist differences in the sophistication of professional forecasting firms, and perhaps of households, all that is required for this paper is that no individual or firm possesses knowledge of the true structure of the economy.

[17] A considerable literature demonstrates the superiority of the central tendency of private forecasters over that of any one forecaster, and in most cases even over the forecast of the most sophisticated forecaster in the distribution.

How can these agents augment their individual models, given their information and knowledge constraints, to improve their forecasts? One object they can observe is the central tendency of forecasts made in the previous period. In the case of the SPF, such a forecast is published and available without cost on the Philadelphia Federal Reserve Bank's website. But it is not necessary to construe this anchor quite so literally. One could consider the most recently published forecasts or assessments in newspapers and on the Web as essentially costless reference points for any agents making a forecast with enough self-knowledge to know that they have an incomplete understanding of the economy's structure.[18]

Under reasonable conditions, individual forecasters will do well to augment their idiosyncratic forecasts by putting some weight on the most recently observed aggregate forecast, as that forecast will average out the idiosyncratic errors made by individual forecasters. If the individual forecasters' parameters $[\phi_j, \mu_j]$ are distributed symmetrically around the true parameters $[\Phi, \mu]$, then a measure of the central tendency of the individual forecasts will average out the idiosyncratic variations around the true parameters and produce a more accurate forecast.[19]

This chain of logic suggests a forecast for z_{t+1} made in period t by one of these individuals that puts some weight on the lagged central tendency:

$$Fz^i_{t+1,t} = \alpha_i z^i_t + \beta_i Z_t + \gamma_i C(Fz_{t+1,t-1}) + \varepsilon^i_{t+1}, \tag{1.7}$$

where the notation indicates the forecast F of variable z in period $t+1$ given information in period t for individual i, which depends on the lagged realization of z (with superscript i to indicate the potential for individual assessments of lagged realizations), a vector of other observables Z that all forecasters can observe at the same time, and the central tendency of the forecasts for the same variable made last period, denoted $C(F(.))$. As above, each of the coefficients in equation (4.5) has a j subscript, indicating that all agents have different models for z, and that in this simple linear setup, allowing for some $\alpha_j = 0, \beta_j = 0$ also implies that different agents may incorporate different variables in their models for z.

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18 For some forecast sources, the individual forecasts are available with a lag; this is the case for the SPF. Sections 2–4 above examine the extent to which sophisticated forecasters might observe the forecasting prowess of individual forecasters and anchor their own forecasts to the best-performing forecasters from the group. While this strategy has intuitive appeal, it develops less-compelling evidence in the data for professional forecasters.

19 Given enough observations, forecasters could estimate the relationship among the central tendencies of forecasts and recover estimates of $[\Phi, \mu]$. If the model and the distribution of forecasters remained constant over time, individual forecasters could learn about the average model implied by the central tendency. By the same token, they could learn about the true model by regressing observations of all variables on all lags. Over time, they might converge on the true model. Of course, if it were this simple, most forecasters would be using the same model by now, and they would have forecast errors of irreducible size.

6. Implications for macroeconomic modeling

We begin by examining how such expectations behavior might influence the properties of variables in a very stylized depiction of a macroeconomy. Consider a model for inflation and output in which output *x* is generated by a "true" but unknown process

$$x_t = \rho_x x_{t-1} + \xi_t \tag{2.1}$$

that is not explicitly a function of individual expectations. Inflation follows the form of many expectations-augmented Phillips curves

$$\pi_t = C(\pi_{jt+1,t}) + \beta x_{t-1} + e_t\,. \tag{2.2}$$

For simplicity, expected inflation in equation (5.2) is the median of a set of individual inflation expectations (denoted $C(\pi_{jt+1,t})$), each of which is formed according to[20]

$$\pi_{jt+1,t} = bC(\pi_{jt+1,t-1}) + c\pi_{t-1} + dx_{t-1} + \upsilon_{jt}\,. \tag{2.3}$$

Thus, individual agents forecast inflation with reference to the previous central tendency of forecasts, the lagged inflation rate, and lagged output, as in the true model. Their expectations feed back into the economy through their influence on the lagged central tendency. This simple example abstracts from many important interactions in more fully articulated models of the economy, but it will allow us to demonstrate some simple results that will motivate the presence of the lagged central tendency in the survey regressions presented above.

Key parameters in this simple setup matter in determining how inflation will behave. To be sure, the more persistent is output (indexed by ρ_x), the more persistence inflation will inherit from output, as is evident from inspection of equations (5.1) and (5.2). The larger the weight placed by individual agents on the lagged central tendency (*b*), the more this lagged forecast of inflation will feed into aggregate inflation. Importantly, the larger is the variance of the shock term to aggregate inflation (the variance of *e* in equation (5.2)), the less the persistence of output will matter in aggregate inflation, a feature of expectations-augmented Phillips curves that is emphasized in Fuhrer (2011).

Figures 8 and 9 present the autocorrelations of inflation that arise from a simulation of this simple model for three different values of ρ and for an array of values of *b,* the weight that

[20] Note that this differs from some of the results in Tables 2–10, as it feeds the lagged expectation for the period *t*, rather than the lagged expectation for period *t+1*. Accounting for these differences in expectation horizon and viewpoint date will be taken up more carefully in the next section.

individual forecasters place on the lagged central tendency. For values of *b* like those estimated in Sections 2–4 above, the implied autocorrelation of the aggregate inflation rate varies from 0.5 to 0.95. Even when the persistence of output is quite modest, the presence of expectations that refer backward to the lagged central tendency adds markedly to the persistence of inflation. For more persistent output processes ($\rho = 0.9$), the autocorrelation of inflation rises from 0.5 to above 0.95 as the weight on the lagged central tendency rises from 0 to values near those estimated above.

Figure 10 displays the response of this model to an "aggregate demand" shock—that is, a unit shock to the *x* process in equation (5.1). When *b*=0.0, the effect of the lagged central tendency on expectations and on inflation is shut down and the response to the AD shock is relatively brief and less than half the magnitude of the response in the red line. Here, *b*=0.8, in line with the empirical estimates presented above. The response is twice as large and much more persistent, extending out dozens of quarters, as is typical in VAR estimates of shock responses in less-identified models. Of course, these impulse response results are completely consistent with the autocorrelation functions presented in Figures 8 and 9.

A more fully articulated macro model

Equations (5.1) to (5.3) constitute a highly stylized representation of a model with expectations that conforms loosely to the results presented above. Here, we examine the macroeconomic implications of expectations that are anchored to past central tendencies in a model that conforms more closely to the results from the micro survey data.

Specifically, we allow one-quarter-ahead expectations to anchor to the lagged aggregate one-quarter-ahead expectation, and/or to the expectation for quarter *t+1* made from expectation viewpoint *t-1*. The empirical results in Tables 2–10 provide evidence of both types of anchoring, and, as suggested above, there is a conceptual difference between the two central tendencies.

We examine a simple DSGE model that embeds these expectations throughout. The model includes a Phillips curve

$$\pi_t = (1-b)\pi_{t+1,t}^{Agg} + b\pi_{t-1} - \gamma \tilde{U}_t \,, \tag{2.4}$$

where $\pi_{t+1,t}^{Agg}$ is the aggregate 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). We add an "IS" curve of similar form

$$\tilde{U}_t = (1-b)U_{t+1,t}^{Agg} + bU_{t-1} - \sigma(f_t - \pi_{t+1,t}^{Agg} - \overline{\rho}) \,, \tag{2.5}$$

where the aggregate expectation for the driving variable appears in parallel fashion to (5.4), 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 (potentially inertial) policy rule

$$f_t = af_{t-1} + (1-a)[\bar{\rho} + \bar{\pi} + a_\pi(\pi_t - \bar{\pi}) - a_u\tilde{U}_t] \ . \tag{2.6}$$

We can envision a set of N economic agents who form expectations as suggested by the empirical results in the paper,

$$\pi^i_{t+1,t} = \omega\pi^{Agg}_{t,t-1} + \omega_E\pi^{Agg}_{t+1,t-1} - c\tilde{U}_{t-1} + d\pi_{t-1} + \varepsilon_{it}, i = 1, \ldots, N \tag{2.7}$$

and similarly for individual expectations of the unemployment/output gap

$$U^i_{t+1,t} = \omega U^{Agg}_{t,t-1} + \omega_E U^{Agg}_{t+1,t-1} + c(f_t - \pi^i_{t+1,t} - \bar{\rho}) + d\tilde{U}_{t-1} + \eta_{it}, i = 1, \ldots, N \ . \tag{2.8}$$

The aggregate expectations $[\pi^{Agg}_{t,t-1}, \pi^{Agg}_{t+1,t-1}]$ and $[\tilde{U}^{Agg}_{t,t-1}, \tilde{U}^{Agg}_{t+1,t-1}]$ are the expectations for the current and next period's inflation and unemployment gap, respectively, as of viewpoint date *t-1*, and are defined as the averages of the individual expectations in equation (5.7). The shocks ε_{it} and η_{it} reflect the idiosyncratic component of the i^{th} forecaster's forecasts, although in principle that component could also be modeled as idiosyncratic variations in the coefficients ω, ω_E, *c,* and *d*. Equations (5.7) and (5.8) are very close analogues of the expectations regressions in Sections 2–4 above, in which individual expectations for period *t+1* depend on lagged central tendencies of period *t* and period *t+1* forecasts made in period *t-1*.

Importantly, none of the individual agents 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.

As written, with all agents identical, idiosyncratic differences in expectations (the ε_{it}) will average out, and the macroeconomic thrust of the model can be captured in aggregate expectations equations

$$\pi^{Agg}_{t+1,t} = \omega\pi^{Agg}_{t,t-1} + \omega_E\pi^{Agg}_{t+1,t-1} - c\tilde{U}_{t-1} + d\pi_{t-1}, \tag{2.9}$$

with a parallel equation for the aggregate unemployment/output gap variable that follows equation (5.8). [21] Equation (5.9) allows expectations to be formed inertially, as the weights ω and ω_E increase in size, or according to rational expectations, as ω and ω_E go to zero.

[21] Allowing for greater and perhaps systematic heterogeneity in expectations, as might be suggested by Figure 2, could impart additional dynamics to the system, but those enhancements lie beyond the scope of this paper.

To compare the outcome of this model to a rational expectations version of the same model, we examine cases in which (5.4) and (5.5) are instead determined by

$$\begin{aligned}\pi_t &= (1-b)E_t\pi_{t+1} + b\pi_{t-1} - \gamma\tilde{U}_t \\ \tilde{U}_t &= (1-b)E_tU_{t+1,t} + bU_{t-1} - \sigma(f_t - \pi^{Agg}_{t+1,t} - \bar{\rho})\end{aligned}.$$

Figure 11 examines the properties of this simple model (equations (5.4), (5.5), (5.6), and (5.9)) by simulating a disinflation shock, beginning from the model's steady state, for various values of the parameters ω and ω_E. Inspection of equation (5.9) (and its unemployment gap cousin) suggests that, for values of ω and ω_E, like those estimated in the empirical section, this backward-referential expectations behavior will impart additional persistence to output, inflation, and the policy rate. Figure 11 displays the quantitative implications of this intuition. The black line, which assumes rational expectations with a modest weight on lagged inflation and unemployment ($b = 0.3$ in equation (5.9)), exhibits very little persistence. The red and green lines, which employ different weights on lagged *t* and *t+1* aggregate expectations (ω and ω_E, respectively), exhibit considerable persistence in response to a disinflation shock. For these cases, the weight on lagged inflation and unemployment is set to 0.1.[22]

The conclusion from this simple exercise is that if expectations are formed in a manner consistent with the micro evidence, aggregate expectations that arise from individual forecasters' "looking over their shoulders" at previous aggregate expectations 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.

7. 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 (2015) showed that empirical estimates of a standard DSGE model preferred inertia in expectations over price indexation or habit formation as a mechanism to explain the persistence of aggregate time series for

[22] The weight of 0.3 in the rational expectations case is close to the estimates found in Galí and Gertler (1999).

output, inflation, and interest rates. A question left open in that paper was 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: Individuals who do not possess full information about the economy link their own expectations to previous aggregate expectations, perhaps as a way of solving a filtering problem. In doing so, they build inertia into the expectations process. The last sections of this paper show that building such expectations into relatively standard (but admittedly simple) macroeconomic models can generate the kinds of impulse responses that are commonly found in macroeconomic VARs, without resorting to the bells and whistles that have been added to DSGE models in recent years—price indexation, habit formation, and autocorrelated structural shocks.

While the micro-data results appear quite robust, their implications for macroeconomic dynamics no doubt merit further investigation; this paper provides only simple examples of the possible implications of such expectations behavior in macro models. However, coupled with the results in Fuhrer (2015), this paper suggests that micro data-based expectations behavior in which agents "look over their shoulders," using lagged aggregate expectations as an anchor for their own individual expectations, might go far in explaining the persistence observed in macro data.

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Figure 1

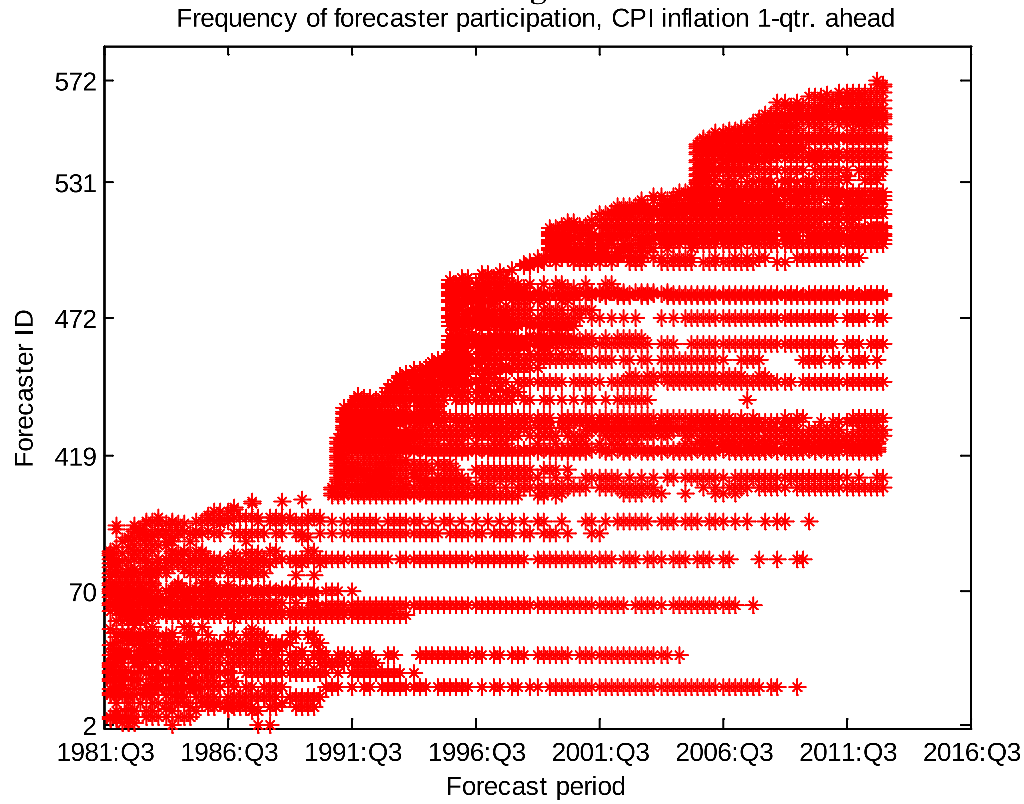


Figure 2

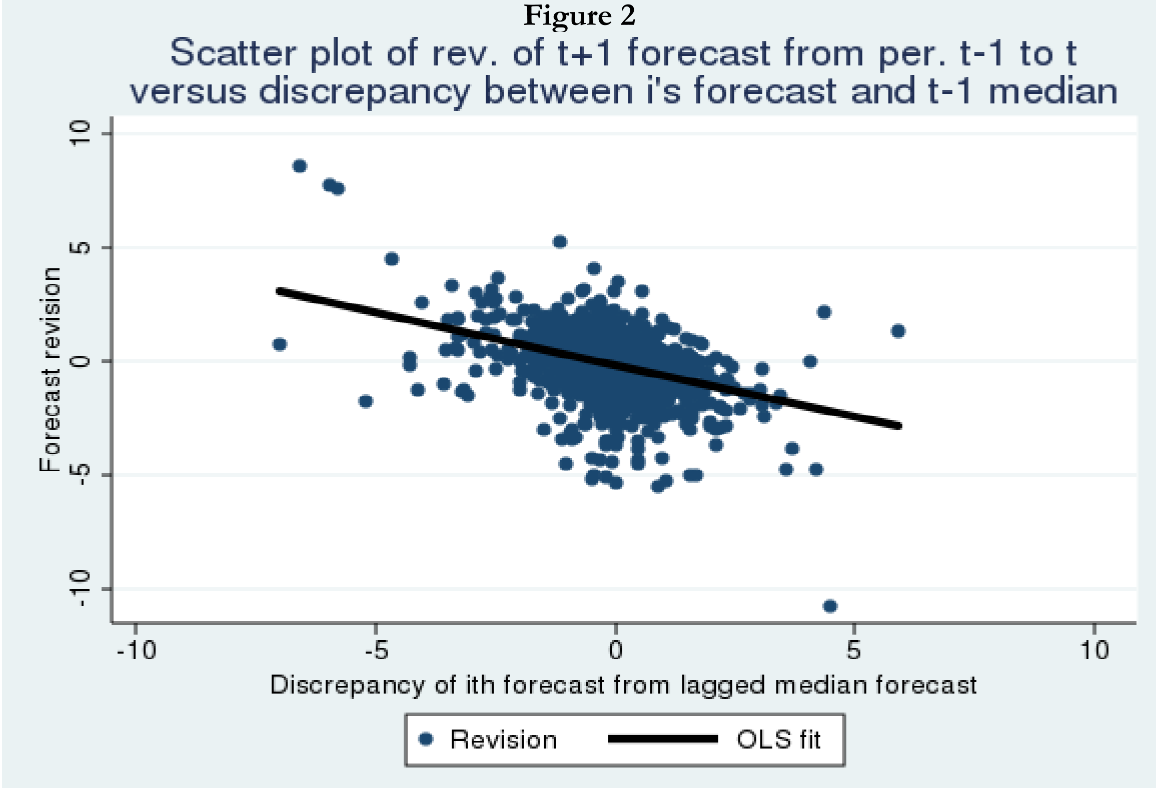


Figure 3
Distribution of individual forecaster revision coefficients

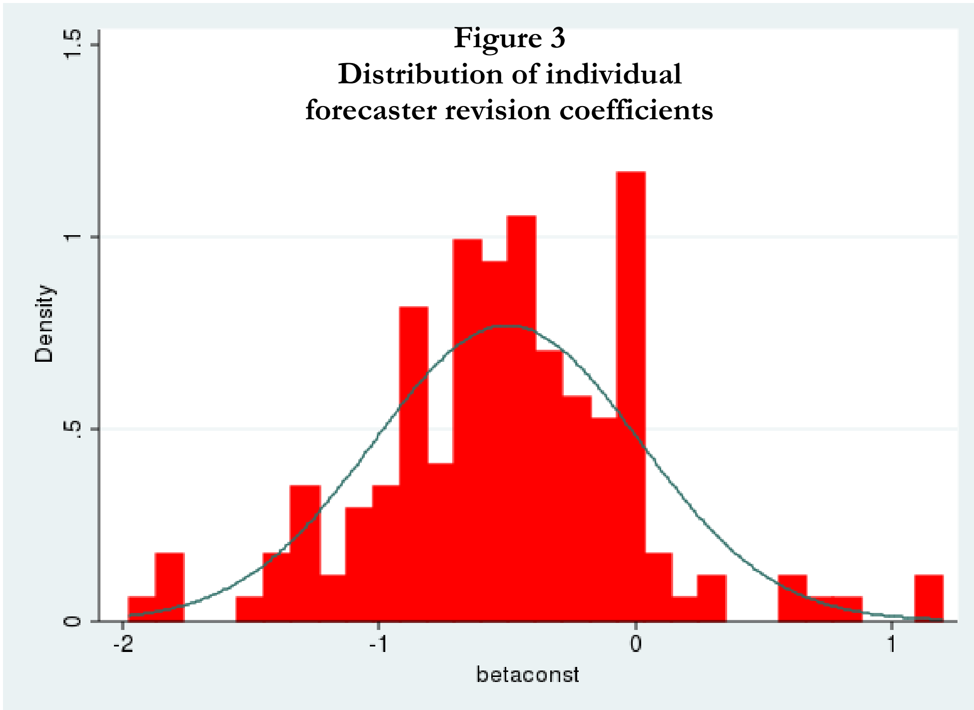


Figure 4
Michigan Survey, inflation expectations

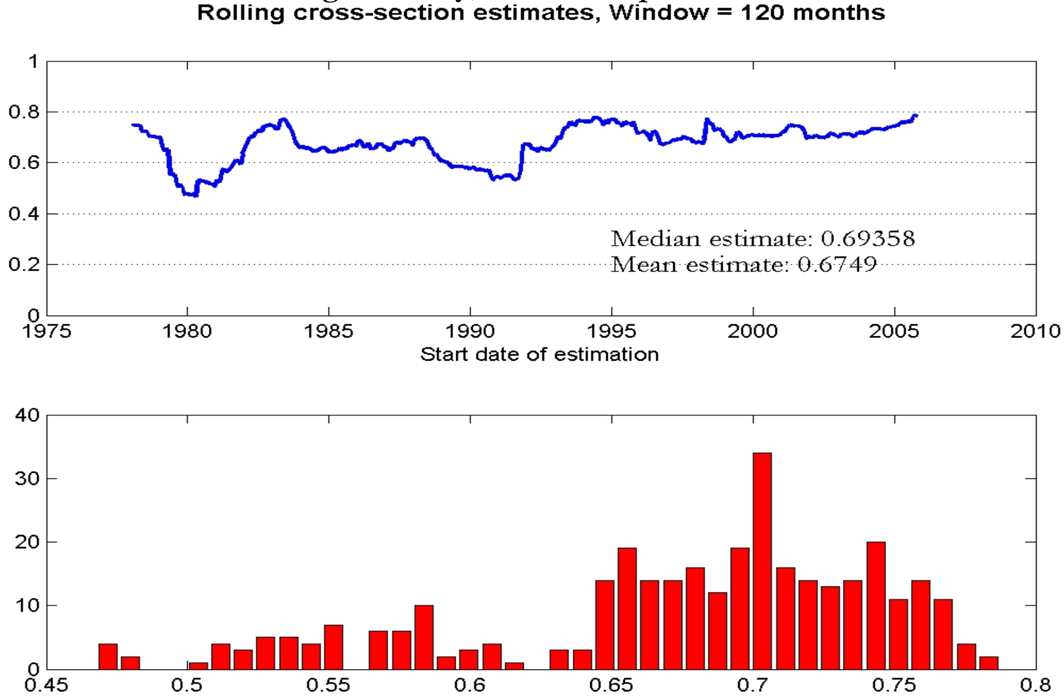


Figure 5

Figure 6

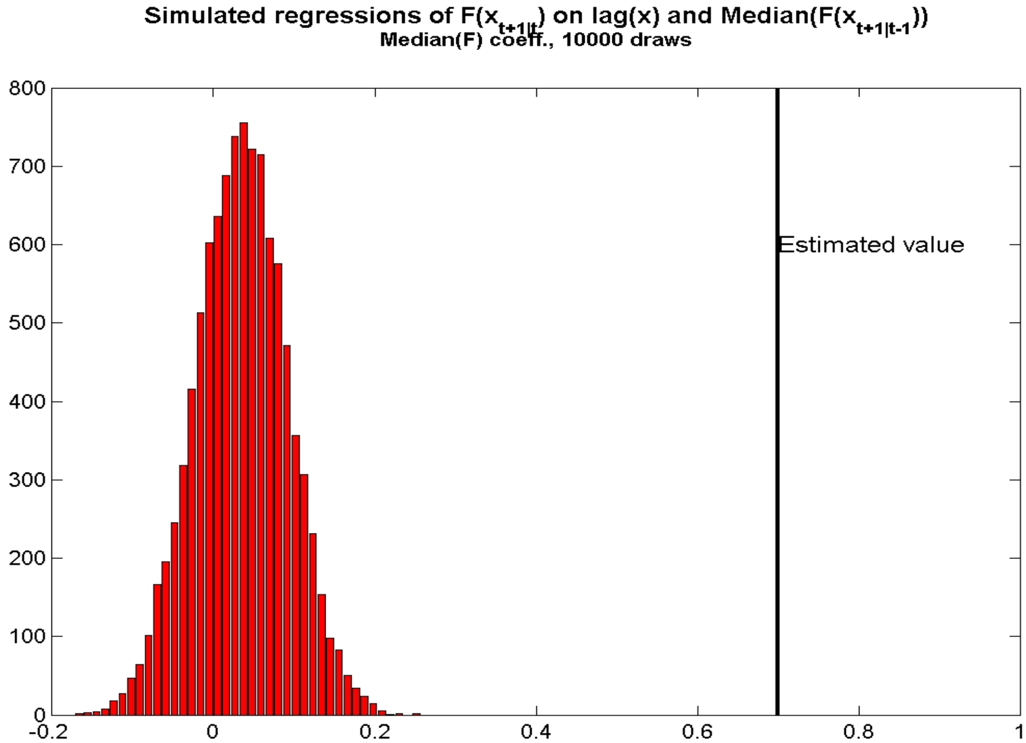


Figure 7

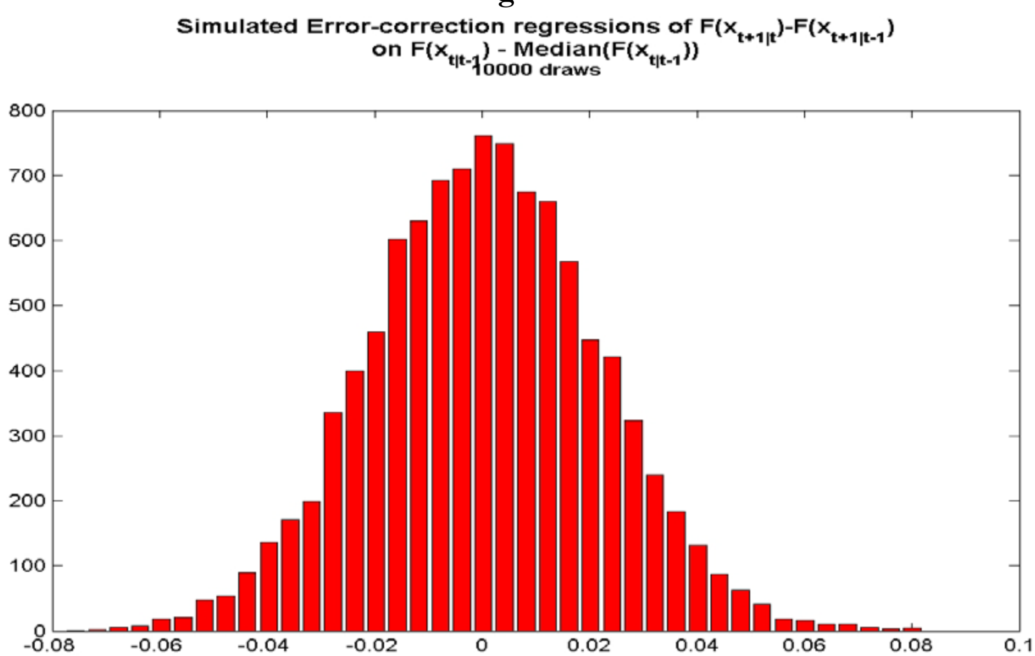


Figure 8

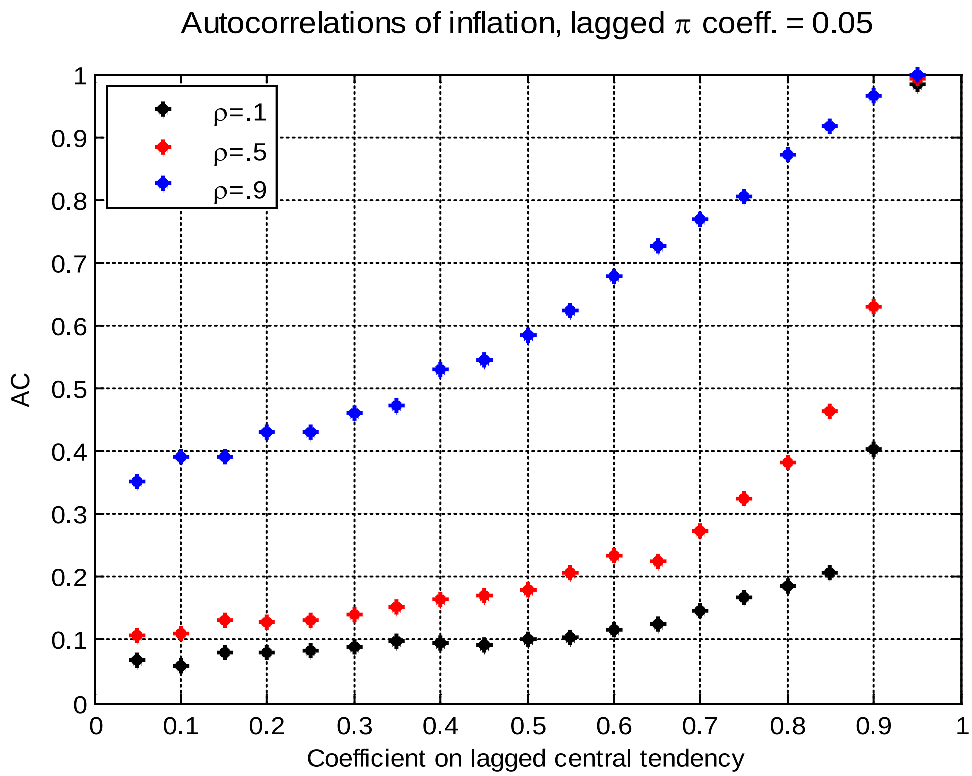


Figure 9

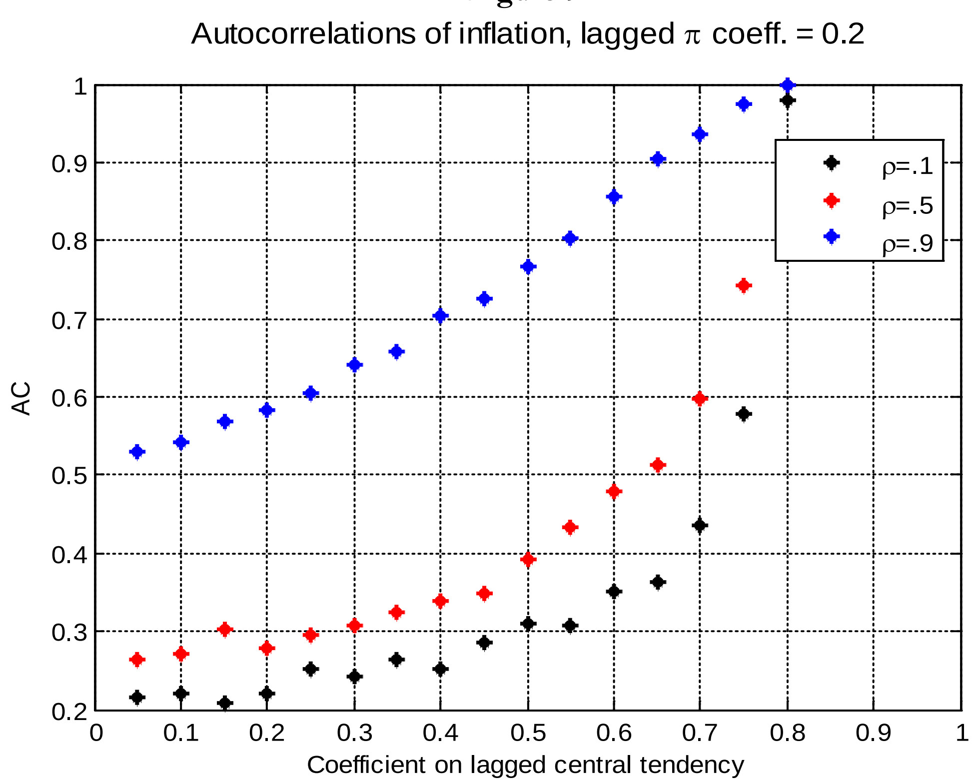
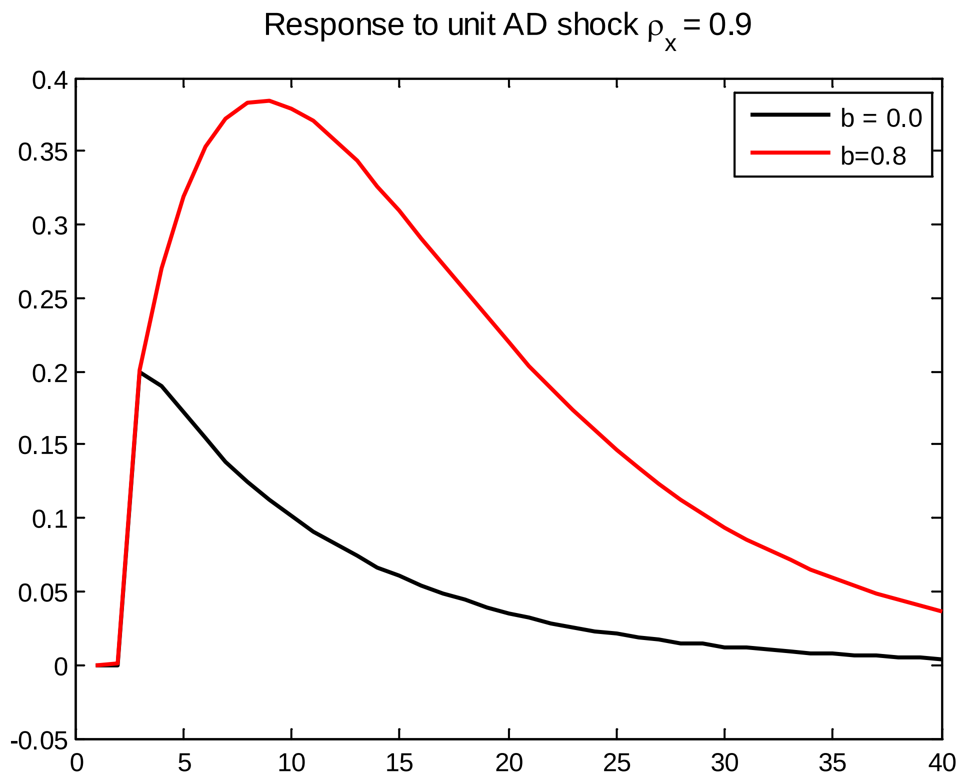


Figure 10



Response to unit AD shock ρx = 0.9
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
0
5
10
15
20
25
30
35
40
b = 0.0
b=0.8

Figure 11

Disinflation simulations with different expectations assumptions

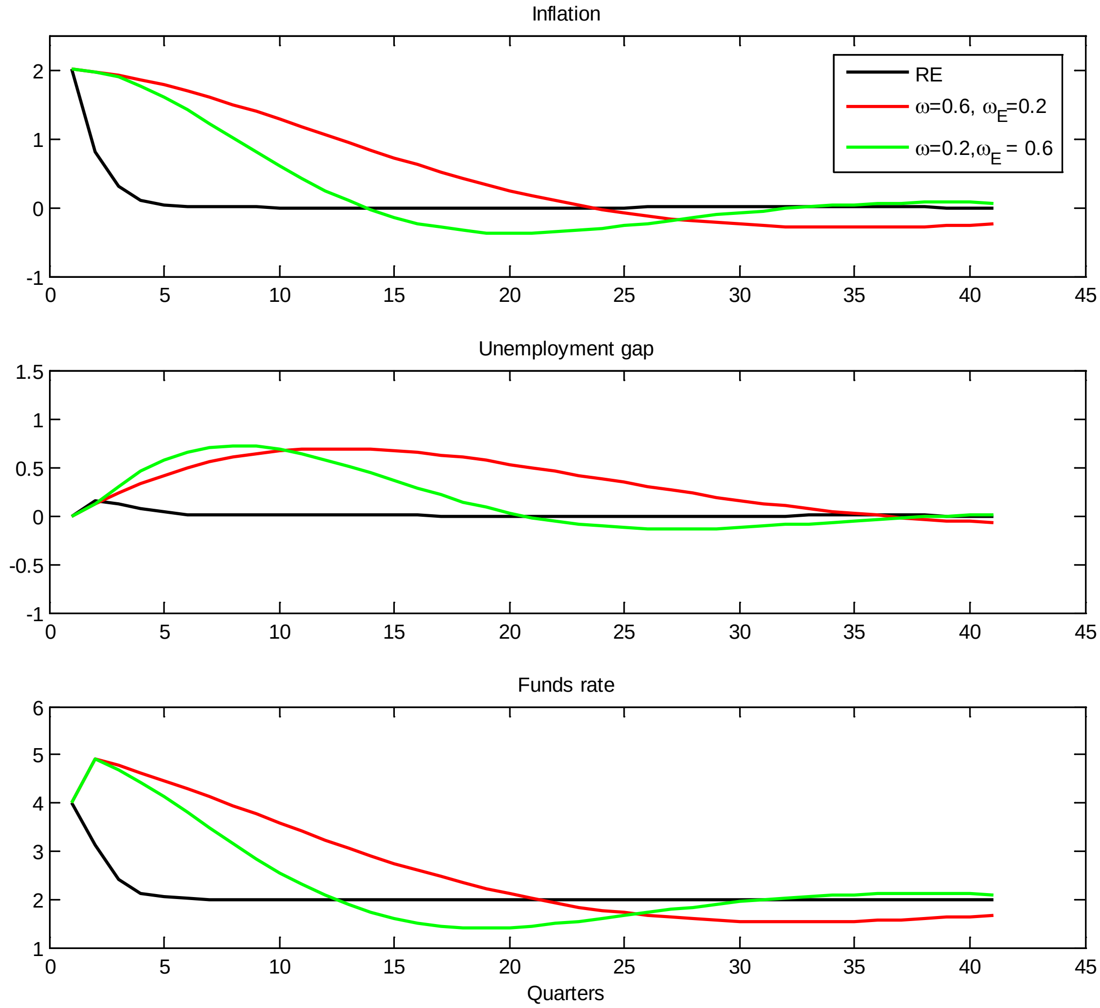


Table 1
Characteristics of SPF sample

Forecaster participation (percent of forecasts submitted, 1968-2013)		Central tendency of forecast (1-qtr. Ahead)					
Inflation, CPI							
N_t=126		1968:Q4		1981:Q3		2012:Q3	
Mean	15.0	Mean	Med.	Mean	Med.	Mean	Med.
Median	8.7	-		7.9	8.0	2.0	2.1
Min, max	1, 70						
Inflation, GDP deflator							
N = 177		1968:Q4		1981:Q3		2012:Q3	
Mean	9.5	Mean	Med.	Mean	Med.	Mean	Med.
Median	5.1	3.0	3.3	7.4	8.5	1.7	1.8
Min, max	1, 71						
Unemployment							
N = 177		1968:Q4		1981:Q3		2012:Q3	
Mean	9.4	Mean	Med.	Mean	Med.	Mean	Med.
Median	4.5	3.8	3.8	7.5	7.5	7.9	7.9
Min, max	1, 71						
Firm type (percentage, N_f=154)[1]							
Financial	45.8						
Nonfinancial	46.4						
Unknown	7.7						

[1] Firm type available only beginning in 1990:Q2 survey

Table 2
Inflation forecast dependence on lagged central tendency:
Which central tendency reference?

$$\pi_{t+1,t}^{i,SPF} = a\pi_{t-1}^{i,SPF} + bC(\pi_{t+k,t-1}^{SPF}) + dZ_t^i + \delta_i + \mu_t + \varepsilon_t^i$$

$\pi_{t,t-1}^{Median}$	0.62 (0.000)				-0.19 (0.325)	
$\pi_{t+1,t-1}^{Median}$		0.72 (0.000)			0.96 (0.000)	0.70 (0.000)
$\pi_{t+1,t-1}^{Big}$			0.32 (0.000)		-0.06 (0.170)	
$\pi_{t+1,t-1}^{RMSE}$				0.12 (0.275)		
π_{t-1}^{i}	0.03 (0.446)	0.06 (0.063)	0.11 (0.157)	0.16 (0.041)	0.08 (0.194)	0.04 (0.209)
Z included?	N	N	N	N	N	Y
Adjusted R-squared	0.247	0.285	0.164	0.114	0.303	0.305
Observations	4205	4205	3556	2416	3556	3899

Table 3
Inflation forecast dependence on lagged central tendency: Additional controls

$$\pi^{i,SPF}_{t+1,t} = a\pi^{i}_{t-1} + b\pi^{i,SPF}_{t+j,t-k} + cC(\pi^{SPF}_{t+1,t-1}) + dZ^{i}_{t} + \delta_i + \mu_t + \varepsilon^{i}_{t}$$

π^{i}_{t-1}	0.16 (0.011)	0.06 (0.071)	0.06 (0.024)	0.06 (0.185)	0.03 (0.446)	0.06 (0.063)	0.14 (0.000)	0.13 (0.000)
$\pi^{i,SPF}_{t,t-1}$		0.36 (0.000)					-0.02 (0.712)	
$\pi^{i,SPF}_{t+1,t-1}$			0.56 (0.000)				0.42 (0.000)	0.44 (0.000)
$\pi^{Median}_{t-1,t-1}$				0.17 (0.003)			-0.24 (0.000)	-0.24 (0.000)
$\pi^{Median}_{t,t-1}$					0.62 (0.000)		0.06 (0.703)	
$\pi^{Median}_{t+1,t-1}$						0.72 (0.000)	0.52 (0.001)	0.56 (0.000)
$U^{i,SPF}_{t+1,t}$								-0.06 (0.774)
$U^{i,SPF}_{t,t}$								-0.08 (0.741)
$U^{i,SPF}_{t-1,t}$								0.10 (0.215)
$\Delta Y^{i,SPF}_{t,t}$								0.04 (0.004)
$R^{i,SPF}_{t,t}$								0.00 (0.967)
Adjusted R-squared	0.101	0.200	0.328	0.109	0.247	0.285	0.384	0.405
Observations	4233	3262	3263	4205	4205	4205	3261	3027
Tests								$\Delta Y^{i,SPF}_{t,t}$, $R^{i,SPF}_{t,t}$ = 0, *p=0.025;* $U^{i,SPF}_{t+k,t}$ = *0, p*=0.012

Inflation dependence on lagged central tendency: Other forecast horizons

Dep. Vble.	$\pi^{i,SPF}_{t+2,t}$	$\pi^{i,SPF}_{t+3,t}$	$\pi^{i,SPF}_{t+4,t}$	$\pi^{i,SPF}_{t+2,t}$	$\pi^{i,SPF}_{t+3,t}$	$\pi^{i,SPF}_{t+4,t}$
π^{i}_{t-1}	0.06 (0.024)	0.09 (0.000)	0.05 (0.130)	0.05 (0.065)	0.08 (0.000)	0.05 (0.063)
$\pi^{Median}_{t+2,t-1}$	0.76 (0.000)			0.76 (0.000)		
$\pi^{Median}_{t+3,t-1}$		0.70 (0.000)			0.69 (0.000)	
$\pi^{Median}_{Y1,t-1}$			0.50 (0.000)			0.41 (0.001)
Macro controls?	N	N	N	Y	Y	Y
Adjusted R-sq.	0.327	0.335	0.299	0.360	0.363	0.330
Observations	4205	4184	2928	3872	3855	2752

Table 4
Inflation forecast dependence on lagged central tendency: *t+2* forecast, more controls

$$\pi^{i,SPF}_{t+2,t} = a\pi^{i,SPF}_{t-1} + bC(\pi^{SPF}_{t+2,t-1}) + dZ^i_t + \delta_i + \mu_t + \varepsilon^i_t$$

π^i_{t-1}	0.14 (0.017)	0.01 (0.818)	0.04 (0.128)	0.06 (0.024)	0.06 (0.036)	0.05 (0.045)	0.05 (0.062)
$\pi^{Median}_{t,t-1}$		0.64 (0.000)			-0.09 (0.480)		
$\pi^{Median}_{t+1,t-1}$			0.72 (0.000)		0.27 (0.204)		
$\pi^{Median}_{t+2,t-1}$				0.76 (0.000)	0.57 (0.014)	0.74 (0.000)	0.76 (0.000)
$U^{i,SPF}_{t+1,t}$							-0.32 (0.173)
$U^{i,SPF}_{t,t}$							0.39 (0.131)
$U^{i,SPF}_{t-1,t}$							-0.09 (0.336)
$\Delta Y^{i,SPF}_{t,t}$						0.03 (0.025)	0.02 (0.354)
$R^{i,SPF}_{t,t}$						0.03 (0.069)	0.02 (0.491)
Adjusted R-squared	0.097	0.291	0.321	0.327	0.328	0.356	0.359
Observations	4233	4205	4205	4205	4205	3897	3869

Table 5
Time-varying estimates of simple regression, with subsamples as indicated

$$\pi^{i,SPF}_{t+1,t} = a\pi^{i,SPF}_{t-1} + b\pi^{Median}_{t+2,t-1} + \delta_i + \mu_t + \varepsilon^i_t$$

	Full sample	Post-1989	Post-1994	Post-1999	Post-2004	Pre-2000	Pre-1996	Pre-1990	Pre-1986
π^i_{t-1}	0.06 (0.063)	0.02 (0.384)	0.02 (0.368)	0.01 (0.537)	0.00 (0.959)	0.19 (0.000)	0.21 (0.000)	0.27 (0.000)	0.28 (0.000)
$\pi^{Median}_{t+1,t-1}$	0.72 (0.000)	0.82 (0.000)	0.79 (0.000)	0.80 (0.000)	0.84 (0.000)	0.55 (0.000)	0.48 (0.000)	0.40 (0.000)	0.34 (0.000)
Adjusted R-squared	0.285	0.207	0.131	0.086	0.079	0.415	0.382	0.435	0.435
Observations	4205	3400	2788	2046	1409	2159	1590	805	501

Table 6
Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures

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

Inflation results

Variable								
$\pi^{i}_{t,t-1} - \pi^{Median}_{t\|t-1}$	-0.30 (0.002)				0.08 (0.193)			
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$		-0.58 (0.000)			-0.68 (0.000)	-0.47 (0.000)	-0.56 (0.000)	-0.56 (0.000)
$\pi^{i}_{t+1,t-1} - \pi^{RMSE}_{t+1\|t-1}$			-0.11 (0.000)		-0.08 (0.010)	-0.02 (0.312)		
$\pi^{i}_{t+1,t-1} - \pi^{Big}_{t+1\|t-1}$				-0.33 (0.000)	0.02 (0.772)			
π^{i}_{t-1}							0.01 (0.648)	-0.03 (0.011)
$U^{i,SPF}_{t+1,t}$							0.04 (0.883)	0.33 (0.178)
$U^{i,SPF}_{t+2,t}$							-0.10 (0.690)	-0.02 (0.904)
$\Delta Y^{i}_{t,t}$							0.06 (0.000)	0.03 (0.030)
$\Delta Y^{i}_{t+1,t}$							0.01 (0.640)	0.01 (0.465)
$R^{i}_{t+1,t}$							-0.05 (0.019)	0.04 (0.703)
All controls*								Yes
Adjusted R-squared	0.069	0.206	0.025	0.102	0.251	0.172	0.224	0.473
Observations	3272	3274	1926	2729	1591	1926	3029	2945

* "All controls" includes real-time estimates of lagged inflation, unemployment, Treasury bill rate, current period, *t*+1, *t*+2, *t*+3 forecasts of inflation, unemployment, Treasury bill rate, output growth.

Additional forecast horizons

	Revision from *t-1* to *t* for forecast period					
	t+1	t+2	t+3	t+1	t+2	t+3
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$	-0.58 (0.000)			-0.56 (0.000)		
$\pi^{i}_{t+2,t-1} - \pi^{Median}_{t+2\|t-1}$		-0.54 (0.000)			-0.53 (0.000)	
$\pi^{i}_{t+3,t-1} - \pi^{Median}_{t+3\|t-1}$			-0.61 (0.000)			-0.61 (0.000)
π^{i}_{t-1}				0.01 (0.648)	0.03 (0.019)	0.05 (0.000)
Other forecast controls	N	N	N	Y	Y	Y
Observations	3274	3257	3180	3029	3017	2960

Table 7 **Regression of change in one-period-ahead forecast ($\pi^{i}_{t+,t} - \pi^{i}_{t\|t-1}$) on lagged discrepancy**					
$\pi^{i}_{t,t-1} - \pi^{Median}_{t\|t-1}$	-0.80 (0.000)	-0.79 (0.000)	-0.90 (0.000)	-0.81 (0.000)	-0.90 (0.000)
$\pi^{i,SPF}_{t-1}$		-0.06 (0.001)	-0.12 (0.000)	0.30 (0.010)	-0.12 (0.000)
$U^{i,SPF}_{t+1,t}$		0.14 (0.515)	0.31 (0.434)	0.22 (0.495)	0.31 (0.434)
$U^{i,SPF}_{t+2,t}$		-0.19 (0.401)	-0.04 (0.862)	-0.29 (0.233)	-0.04 (0.862)
$\Delta Y^{i,SPF}_{t,t}$		0.05 (0.022)	0.04 (0.068)	0.01 (0.520)	0.04 (0.068)
$\Delta Y^{i,SPF}_{t+1,t}$		0.05 (0.082)	0.06 (0.021)	0.03 (0.180)	0.06 (0.021)
$R^{i,SPF}_{t,t}$		-0.04 (0.003)	0.10 (0.504)	0.07 (0.408)	0.10 (0.504)
Additional controls			Y		Y
Adjusted R-squared	0.344	0.367	0.523	0.520	0.523
Observations	3273	3029	2946	3029	2946
Additional controls include additional inflation, unemployment, GDP growth and T-bill forecasts (horizons *t*+2, 3, 4)					

Table 8

Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, controlling for revision in aggregate forecast

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

Inflation results

Variable								
$\pi_{t+1,t-1}^{Median} - \pi_{t+1\|t-2}^{Median}$	0.08 (0.202)	0.10 (0.140)	0.20 (0.000)	-0.20 (0.083)	0.38 (0.000)	0.31 (0.000)	-0.07 (0.328)	-0.12 (0.153)
$\pi_{t,t-1}^{i} - \pi_{t\|t-1}^{Median}$	-0.27 (0.001)				0.05 (0.428)			
$\pi_{t+1,t-1}^{i} - \pi_{t+1\|t-1}^{Median}$		-0.57 (0.000)			-0.71 (0.000)	-0.49 (0.000)	-0.54 (0.000)	-0.55 (0.000)
$\pi_{t+1,t-1}^{i} - \pi_{t+1\|t-1}^{RMSE}$			-0.09 (0.001)		-0.04 (0.176)	0.01 (0.847)		
$\pi_{t+1,t-1}^{i} - \pi_{t+1\|t-1}^{Big}$				-0.33 (0.000)	0.05 (0.529)			
π_{t-1}^{i}							0.01 (0.654)	-0.02 (0.029)
Additional forecast variables	N	N	N	N	N	N	Y	Y
All controls*	N	N	N	N	N	N	N	Y
Adjusted R-squared	0.069	0.206	0.025	0.102	0.251	0.172	0.224	0.363
Observations	3272	3274	1926	2729	1591	1926	3029	3029

Results for the revision to the *t*-period forecast are essentially the same.
* "All controls" includes real-time estimates of lagged inflation, unemployment, Treasury bill rate, current period, *t*+1, *t*+2, *t*+3 forecasts of inflation, unemployment, Treasury bill rate, output growth.

Add contemporaneous revision in median forecast

$\pi_{t+1,t}^{Median} - \pi_{t+1\|t-1}^{Median}$	0.90 (0.000)	0.92 (0.000)	0.78 (0.000)	1.01 (0.000)	0.96 (0.000)	0.84 (0.000)	0.88 (0.000)	0.49 (0.000)
$\pi_{t,t-1}^{i} - \pi_{t\|t-1}^{Median}$	-0.30 (0.001)				0.08 (0.146)			
$\pi_{t+1,t-1}^{i} - \pi_{t+1\|t-1}^{Median}$		-0.60 (0.000)			-0.64 (0.000)	-0.49 (0.000)	-0.57 (0.000)	-0.57 (0.000)
$\pi_{t+1,t-1}^{i} - \pi_{t+1\|t-1}^{RMSE}$			-0.10 (0.001)		-0.07 (0.000)	-0.01 (0.770)		
$\pi_{t+1,t-1}^{i} - \pi_{t+1\|t-1}^{Big}$				-0.36 (0.000)	-0.02 (0.541)			
π_{t-1}^{i}							-0.01 (0.598)	-0.03 (0.000)
Additional forecast variables	N	N	N	N	N	N	Y	Y
All controls	N	N	N	N	N	N	N	Y
Observations	3272	3274	1926	2729	1591	1926	3029	2945

Table 9
***t*+1-period forecast, test restriction implied by EC regression, various specs**

$\pi_{t+1,t-1}^{i,SPF}$	0.40 (0.000)	0.48 (0.000)	0.71 (0.000)	0.43 (0.000)
$\pi_{t+1,t-1}^{Median}$	0.44 (0.000)			0.34 (0.004)
$\pi_{t+1,t-1}^{RMSE}$		0.15 (0.009)		
$\pi_{t+1,t-1}^{Big}$			0.01 (0.894)	
$\pi_{t-1}^{i,SPF}$				0.03 (0.315)
$U_{t+1,t}^{i,SPF}$				0.16 (0.524)
$U_{t+2,t}^{i,SPF}$				-0.18 (0.455)
$\Delta Y_{t,t}^{i,SPF}$				0.04 (0.009)
$\Delta Y_{t+1,t}^{i,SPF}$				0.00 (0.871)
$R_{t,t}^{i,SPF}$				0.02 (0.497)
Test of restriction $\omega_1 + \omega_2 = 1$	0.000	0.000	0.000	0.0040
Adjusted R-squared	0.359	0.282	0.412	0.383
Observations	3274	2729	1888	3029

Table 10

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

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

Variable						
$U^{i}_{t+1,t-1} - U^{Median}_{t+1\|t-1}$	-0.67 (0.000)	-0.74 (0.000)		-0.68 (0.000)	-0.89 (0.000)	-0.85 (0.000)
$U^{i}_{t+1,t-1} - U^{RMSE}_{t+1\|t-1}$		0.01 (0.432)				
$U^{i}_{t+1,t-1} - U^{Big}_{t+1\|t-1}$			-0.39 (0.000)	0.04 (0.760)		
U^{i}_{t-1}					-0.48 (0.000)	-0.72 (0.000)
$U^{i,SPF}_{t+2,t}$					0.53 (0.000)	0.31 (0.000)
$\Delta Y^{i}_{t,t}$					-0.01 (0.015)	-0.00 (0.663)
$\Delta Y^{i}_{t+1,t}$					0.01 (0.188)	0.00 (0.816)
$R^{i}_{t+1,t}$					-0.00 (0.648)	-0.06 (0.183)
All controls*						Yes
$U^{i}_{t+1,t-1} - U^{RMSE}_{t+1\|t-1}$	-0.66 (0.000)	-0.94 (0.000)		-0.71 (0.000)	-0.76 (0.000)	-0.75 (0.000)
Adjusted R-squared	0.210	0.216	0.110	0.201	0.705	0.756
Observations	5086	1997	4497	4497	3210	3007

* "All controls" includes real-time estimates of lagged inflation, unemployment, Treasury bill rate, plus current period, *t*+1, *t*+2, *t*+3 forecasts of inflation, unemployment, Treasury bill rate, output growth.

All forecast horizons

	t	*t+1*	*t+2*	*t+3*	*t*	*t+1*	*t+2*	*t+3*
$U^{i}_{t,t-1} - U^{Median}_{t\|t-1}$	-0.86 (0.000)				-0.89 (0.000)			
$U^{i}_{t+1,t-1} - U^{Median}_{t+1\|t-1}$		-0.67 (0.000)				-0.78 (0.000)		
$U^{i}_{t+2,t-1} - U^{Median}_{t+2\|t-1}$			-0.56 (0.000)				-0.70 (0.000)	
$U^{i}_{t+3,t-1} - U^{Median}_{t+3\|t-1}$				-0.49 (0.000)				-0.62 (0.000)
U^{i}_{t-1}					0.01 (0.624)	0.01 (0.661)	0.00 (0.801)	0.01 (0.520)
$\pi^{i,SPF}_{t+1,t}$					-0.01 (0.598)	0.00 (0.857)	-0.00 (0.883)	-0.01 (0.748)
$\pi^{i,SPF}_{t+2,t}$					0.01 (0.557)	0.00 (0.941)	0.00 (0.821)	0.01 (0.517)
$\Delta Y^{i}_{t,t}$					-0.06 (0.000)	-0.07 (0.000)	-0.08 (0.000)	-0.08 (0.000)
$\Delta Y^{i}_{t+1,t}$					-0.02 (0.036)	-0.04 (0.001)	-0.06 (0.000)	-0.08 (0.000)
$R^{i}_{t+1,t}$					-0.01 (0.344)	-0.02 (0.117)	-0.02 (0.059)	-0.02 (0.104)
Observations	5088	5086	5064	4784	3097	3096	3084	3017

Table 11
Pooled cross-section regressions of Michigan 1-year-ahead inflation expectation on lagged mean of 1-year expectations, lagged actual, and various controls, 1978:Jan–2013:Jun

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged median expectation	0.75 (0.000)	0.74 (0.000)	0.62 (0.000)	0.60 (0.000)	0.60 (0.000)		0.57 (0.000)	0.10 (0.002)	0.14 (0.000)
Lagged mean expectation						0.76 (0.000)		0.74 (0.000)	0.50 (0.000)
Lagged real-time actual inflation	0.18 (0.000)	0.16 (0.000)	0.19 (0.000)	0.19 (0.000)	0.19 (0.000)	0.07 (0.000)	0.20 (0.000)	0.09 (0.000)	-0.03 (0.017)
Unemp. Controls	N	Y	Y	Y	Y	Y	Y	Y	Y
Financ., real income,	N	N	Y	Y	Y	Y	Y	Y	Y
Dummy, in survey 6 mos. ago				Y	Y	Y	Y	N	Y
General macro conditions controls							Y	Y	Y
Interaction terms I								Y	Y
Interaction terms II									Y
Adjusted R-squared	0.094	0.103	0.094	0.094	0.094	0.097	0.106	0.109	0.277
Observations	219330	219330	196091	196091	196091	196091	185664	185664	133306

Table 12
Pooled cross-section regressions of Michigan 1-year-ahead inflation expectation
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 (including lagged inflation, revisions to continuous variables)

	Full sample		(all discrepancies relative to lagged median)					
	With lagged mean	With lagged median	Obs 1985-forward	1995-forward	2000-forward	2005-forward	Recessions only	Non-recessions
Discrepancy between last forecast and corresponding median (6-mos. ago)	-0.70 (0.000)	-0.70 (0.000)	-0.70 (0.000)	-0.71 (0.000)	-0.72 (0.000)	-0.72 (0.000)	-0.68 (0.000)	-0.70 (0.000)
Revision to family income, 1-yr. expec.	-0.00 (0.923)	-0.00 (0.923)	-0.00 (0.958)	0.00 (0.044)	0.00 (0.037)	0.00 (0.343)	0.00 (0.867)	-0.00 (0.697)
Revision to 5-year inflation expec.	0.19 (0.000)	0.19 (0.000)	0.20 (0.000)	0.26 (0.000)	0.28 (0.000)	0.28 (0.000)	0.21 (0.000)	0.19 (0.000)
Adjusted R-squared	0.465	0.465	0.464	0.459	0.426	0.431	0.406	0.482
Observations	50345	50345	44997	33711	24267	15631	7117	43228
p-values in parentheses								

Table 13
"Anchoring" regressions
SPF forecasts, varying horizons

Levels regressions, full sample								
	Forecast horizon							
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Lagged median forecast (2-qtr.)	0.76 (0.000)				0.54 (0.003)			
Lagged median forecast (3-qtr.)		0.83 (0.000)				0.46 (0.000)		
Lagged median forecast (4-qtr.)			0.72 (0.000)				0.40 (0.000)	
Lagged median forecast (one-year)				0.49 (0.000)				0.47 (0.000)
Lagged median 10-year forecast	0.05 (0.755)	0.07 (0.603)	0.19 (0.039)	0.49 (0.000)	0.13 (0.373)	0.24 (0.041)	0.31 (0.005)	0.38 (0.000)
$\pi_{t-1}^{i,SPF}$	0.02 (0.338)	0.03 (0.037)	0.06 (0.000)	0.01 (0.034)	-0.01 (0.741)	0.01 (0.291)	0.06 (0.000)	0.01 (0.004)
Macro controls (GDP, T-bill, unemp., inflation)	N	N	N	N	Y	Y	Y	Y
Adjusted R-squared	0.164	0.226	0.255	0.349	0.207	0.269	0.286	0.366
Observations	3188	3186	3170	2307	2965	2946	2946	2185
	Post-1999 sample							
	t+1	t+2	t+3	t+4	t+1	t+2	t+3	t+4
Lagged median forecast (2-qtr.)	0.83 (0.000)				0.55 (0.025)			
Lagged median forecast (3-qtr.)		0.92 (0.000)				0.47 (0.005)		
Lagged median forecast (4-qtr.)			0.74 (0.000)				0.24 (0.117)	
Lagged median forecast (one-year)				0.47 (0.000)				0.44 (0.000)
Lagged median 10-year forecast	-0.28 (0.614)	-0.06 (0.902)	-0.06 (0.873)	0.02 (0.926)	-0.25 (0.534)	-0.10 (0.791)	0.10 (0.749)	-0.26 (0.415)
$\pi_{t-1}^{i,SPF}$	0.01 (0.627)	0.02 (0.115)	0.06 (0.000)	0.01 (0.034)	-0.02 (0.388)	0.01 (0.657)	0.05 (0.000)	0.01 (0.016)
Macro controls (GDP, T-bill, unemp., inflation)	N	N	N	N	Y	Y	Y	Y
Adjusted R-squared	0.086	0.099	0.096	0.151	0.137	0.143	0.128	0.172
Observations	2046	2047	2037	1502	1881	1872	1871	1418

Table 13 (continued) "Anchoring" regressions SPF forecasts, varying horizons Revision regressions with the revision in the long-term (10-year) forecast, full 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)				-0.68 (0.000)			
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$		-0.48 (0.000)				-0.49 (0.000)		
$\pi^{i}_{t+2,t-1} - \pi^{Median}_{t+2\|t-1}$			-0.44 (0.000)				-0.44 (0.000)	
$\pi^{i}_{t+3,t-1} - \pi^{Median}_{t+3\|t-1}$				-0.55 (0.000)				-0.56 (0.000)
Lagged revision in 10-year aggregate forecast	-0.32 (0.585)	0.41 (0.027)	0.20 (0.293)	0.09 (0.682)	-0.54 (0.308)	0.37 (0.041)	0.14 (0.400)	0.02 (0.920)
Other controls	N	N	N	N	Y	Y	Y	Y
Adjusted R-squared	0.034	0.096	0.137	0.206	0.195	0.133	0.174	0.242
Observations	2543	2542	2530	2469	2371	2370	2363	2321

Table 14 Michigan survey, one-year ahead inflation expectations Test for "anchoring" to long-run (2- to 5-year) median expectations					
	(1)	(2)	(3)	(4)	(6)
Lagged median 1-yr. expec.	0.85 (0.000)	0.80 (0.000)	0.74 (0.000)	0.73 (0.000)	0.72 (0.000)
Lagged median 2-5-yr. expec.	0.29 (0.000)	0.32 (0.000)	0.31 (0.000)	0.31 (0.000)	0.34 (0.000)
Unemp. controls		Y	Y	Y	Y
Income, financial controls			Y	Y	Y
In prev. survey?				Y	Y
Interaction terms					Y
Adjusted R-squared	0.041	0.053	0.057	0.058	0.070
Observations	152263	152263	144530	144530	137425

Appendix

SPF 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 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 A1

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

Driscoll-Kraay standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
π_{t-1}^{i}	0.16 (0.011)	0.06 (0.071)	0.06 (0.024)	0.06 (0.185)	0.03 (0.446)	0.06 (0.063)	0.14 (0.000)	0.13 (0.000)	0.13 (0.000)	0.31 (0.000)
$\pi_{t,t-1}^{i,SPF}$		0.36 (0.000)					-0.02 (0.712)			
$\pi_{t+1,t-1}^{i,SPF}$			0.56 (0.000)				0.42 (0.000)	0.44 (0.000)	0.44 (0.000)	0.43 (0.000)
$\pi_{t-1,t-1}^{Median}$				0.17 (0.003)			-0.24 (0.000)	-0.24 (0.000)	-0.24 (0.000)	-0.79 (0.109)
$\pi_{t,t-1}^{Median}$					0.62 (0.000)		0.06 (0.703)			
$\pi_{t+1,t-1}^{Median}$						0.72 (0.000)	0.52 (0.001)	0.56 (0.000)	0.56 (0.000)	0.62 (0.008)
$U_{t+1,t}^{i,SPF}$								-0.06 (0.774)	-0.06 (0.774)	-0.12 (0.448)
$U_{t,t}^{i,SPF}$								-0.08 (0.741)	-0.08 (0.741)	-0.11 (0.538)
$U_{t-1,t}^{i,SPF}$								0.10 (0.215)	0.10 (0.215)	0.32 (0.684)
$\Delta Y_{t,t}^{i,SPF}$								0.04 (0.004)	0.04 (0.004)	0.02 (0.081)
$R_{t,t}^{i,SPF}$								0.00 (0.967)	0.00 (0.967)	-0.02 (0.818)
Adjusted R-squared	0.101	0.200	0.328	0.109	0.247	0.285	0.384	0.405	Adjusted R-squared	0.101
Observations	4233	3262	3263	4205	4205	4205	3261	3027	3027	3027

Table A2 **Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures** $\pi^{i,SPF}_{t+1,t} - \pi^{i,SPF}_{t+1,t-1} = \delta[\pi^{i,SPF}_{t+1,t-1} - \pi^{Median}_{t+1,t-1}] + a\pi^{i}_{t-1} + cZ^{i}_{t} + \delta_i + \mu_t + \varepsilon^{i}_{t}$ **Inflation results, Driscoll-Kraay standard errors**									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Revis., t+1	Revis., t+1	Revis., t+1	Revis., t+1	Revis., t+1	Revis., t+1	Revis., t+1	Revis., t+1	Revis., t+1
$\pi^{i}_{t,t-1} - \pi^{Median}_{t\|t-1}$	-0.30 (0.002)				0.08 (0.193)				
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$		-0.58 (0.000)			-0.68 (0.000)	-0.47 (0.000)	-0.56 (0.000)	-0.57 (0.000)	-0.56 (0.000)
$\pi^{i}_{t+1,t-1} - \pi^{RMSE}_{t+1\|t-1}$			-0.11 (0.000)		-0.08 (0.010)	-0.02 (0.312)			
$\pi^{i}_{t+1,t-1} - \pi^{Big}_{t+1\|t-1}$				-0.33 (0.000)	0.02 (0.772)				
π^{i}_{t-1}							0.01 (0.648)	0.31 (0.000)	-0.03 (0.011)
$U^{i,SPF}_{t+1,t}$							0.04 (0.883)	0.01 (0.945)	0.33 (0.178)
$U^{i,SPF}_{t+2,t}$							-0.10 (0.690)	-0.15 (0.378)	-0.02 (0.904)
$\Delta Y^{i}_{t,t}$							0.06 (0.000)	0.02 (0.128)	0.03 (0.030)
$\Delta Y^{i}_{t+1,t}$							0.01 (0.640)	0.01 (0.713)	0.01 (0.465)
$R^{i}_{t+1,t}$							-0.05 (0.019)	0.03 (0.384)	0.04 (0.703)
All controls									-0.21 (0.000)
Constant	-0.14 (0.000)	-0.13 (0.000)	-0.03 (0.366)	-0.19 (0.000)	-0.04 (0.205)	-0.06 (0.068)	0.25 (0.168)	3.47 (0.000)	-0.19 (0.227)
Adjusted R-squared	0.069	0.206	0.025	0.102	0.251	0.172	0.224	0.363	0.473
Observations	3272	3274	1926	2729	1591	1926	3029	3029	2945