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Understanding survey-based inflation expectations

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ABSTRACT

This paper examines the behavior of inflation expectations in the United States. After documenting deviations from rationality in survey-based inflation expectations, I apply a model selection algorithm, boosting, to the inflation expectations of households and professionals. The algorithm builds a regression-like model of expected inflation using a large panel of macroeconomic data as possible covariates. The algorithm achieves a very strong fit in-sample, and finds that the inflation expectations of households correlate with different macroeconomic variables from the expectations of professionals. However, it is difficult to exploit the predictability of inflation expectations in order to improve forecasts of the realized inflation.

1. Introduction

Inflation expectations are central to economic decisions such as how much to consume, save and invest. Yet despite their crucial role within macroeconomics, the mechanism underlying expectations formulation is not well understood. Measured expectations do not square with full-information rationality, as household inflation expectations are often biased and can be predicted by age cohort, sex, and recent price movements, for example.[1] Similarly, Coibion and Gorodnichenko (2012, 2015a) document that respondents to the Survey of Professional Forecasters systematically under-react to economic news when revising their expectations.

The aim of this paper is to gain a better understanding of survey-based inflation expectations in the United States. To do so, I model the expectations of households and professional forecasters empirically using a model selection algorithm, boosting, that produces regression-like models of inflation expectations. The algorithm searches over a large dataset of macroeconomic indicators, uncovering the variables that have the highest correlations with each survey measure. The final model is determined by minimizing an information criterion that penalizes model complexity, so that covariates with little or no correlation with expectations are excluded. The algorithm produces different models of the expectations of households from those of professional forecasters. Household inflation expectations co-move with particular subcomponents of the Consumer Price Index, especially food and energy prices. In contrast, the inflation expectations of professionals are correlated primarily with macroeconomic indicators, especially interest rates.

One reason why it is important to understand inflation expectations is that expectations affect the future realized inflation. Indeed, inflation dynamics during and following the Great Recession led to a reconsideration of the role of expectations in the Phillips curve.[2] Therefore, with an empirical model of expectations in hand, I explore the divergence of the inflation expectations of households from those of professional forecasters during and after the Great

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[1] Regarding the biasedness of survey-based inflation expectations, see Croushore (2010), Mehra (2002) and Thomas (1999). Binder (2016), Ehrmann, Pfajfar, and Santoro (2017), Johannsen (2014), Malmendier and Nagel (2016) and Schulhofer-Wohl and Kaplan (2016) all provide evidence relating to expectations formulation.

[2] Adam and Padula (2011) and Roberts (1995, 1998) use survey measures to identify the Phillips curve. Ball and Mazumder (2011) and Coibion and Gorodnichenko (2015b) discuss recent inflation dynamics and their implications for the Phillips curve.

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Recession. I do not find evidence of any large change in the behavior of expectations during this period. Neither the increase in households' inflation expectations during the recession nor the subsequent drift lower of both measures of expectations appear unusual, conditional on the evolution of macroeconomic data in this period.

Within the forecasting literature, survey-based inflation expectations have been found to forecast inflation more accurately than empirical models, at least in some of the samples evaluated (Ang, Bekaert, & Wei, 2007; Faust & Wright, 2013; Grothe & Meyler, 2015). When Groen, Paap, and Ravazzolo (2013) used Bayesian Model Selection to select inflation forecasting models, expectations were an important covariate, perhaps because inflation expectations proxy for the slow-moving trend in inflation (Clark & Doh, 2014; Kozicki & Tinsley, 2005, 2001). However, surveys are also informationally inefficient. For this reason, the final portion of the paper revisits the use of survey-based expectations for forecasting inflation. I compare inflation forecasts from a wide variety of models, including the raw surveys, bias-adjusted surveys, Phillips curve models, and univariate time series models. Household expectations are biased throughout the period that I consider, and a simple level-bias adjustment improves their average forecasting ability by 30%. However, the forecast performance of professionals does not improve when adjusted for bias, suggesting that the economic significance of the deviations from full-information rationality in professional forecasters is small, in terms of the loss of forecast accuracy. In any case, the surveys, whether used literally, bias-adjusted, or within a Phillips curve framework, do not outperform univariate time series models of inflation: over the period 1990 to 2015, on average, an ARMA(1,1) model produces the most accurate forecasts.

To motivate the empirical approach, the next section introduces survey-based inflation expectations and revisits the evidence that they conform to full-information rationality. Section 3 then describes the boosting algorithm and applies it to the surveys. Section 4 of the paper presents the forecast experiment, and the final section concludes.

2. Revisiting the informational inefficiencies of survey-based inflation expectations

Fig. 1 shows three primary measures of inflation expectations: the Michigan Survey of Consumers' year-ahead expectation (MSC), the year-ahead CPI forecast from the Livingston Survey (Liv), and the year-ahead CPI forecast from the Survey of Professional Forecasters (SPF). The surveys measure broadly the same thing, namely expectations of average inflation for the next year, but differ in their respondents, coverage and frequency.[3] Table 1 provides summary statistics. The table shows statistics covering three periods: each survey's full sample, and the first and second halves of the post-1984 period, chosen to exclude the disinflation of the early 1980s. The average behaviors of the three surveys are quite similar, especially for the 1984–1999 period, when each survey has a mean of about 3% and is quite stable. However, the behavior of the surveys diverges in the last 15 years. Whereas the average expected rate of inflation for professionals is 1½ percentage points lower, with one-half the standard deviation of the 1984–1999 period, the behavior of household inflation expectations are about unchanged.

Table 2 explores this divergence further by presenting simple empirical tests of the behavior of the surveys' forecast *errors* over these periods.[4] As the first panel shows, the surveys have mean absolute errors of about one percentage point. Notably, the average error from MSC since 2000 is double that from the 1984–1999 period: households have been overestimating the realized inflation by nearly one percentage point since 2000. In contrast, the professional forecasters over-predicted inflation between 1984 and 1999 but have had about mean-zero forecast errors since then.

The remainder of the table tests for deviations from rational expectations. The second panel of the table presents two measures of the persistence of forecast errors, namely the estimated coefficient from an AR(1) process and the sum of the autoregressive coefficients (SARC).[5] Under the null of rational expectations, forecast errors should not be predictable, and the final two panels show regression-based tests of this kind of predictability. Panel 3 presents a version of the Mincer and Zarnowitz (1969) regression, regressing the forecast errors on the forecast itself. The final panel presents Nordhaus (1987) regressions, which regress forecast errors onto forecast revisions. The sets of regressions include two important and widely-known macroeconomic variables as covariates, namely the unemployment rate and the yield on the 10-year Treasury Bond.

It is difficult to reconcile Tables 1 and 2 with fully rational expectations formulation. Depending on the sample, the survey expectations are biased. The forecast errors also appear to be predictable. When Coibion and Gorodnichenko (2015a) used regressions of the types presented in the third and fourth panels of Table 2 to discern between sticky information models (Mankiw & Reis, 2002) and noisy information models (Sims, 2003), they found that macroeconomic variables enter significantly in their Mincer–Zarnowitz regressions, but not in the Nordhaus regressions. They interpret these results as supporting models of informational rigidities: conditional on the forecast revision, macroeconomic data do not predict forecast errors. The results here are less clear cut, but nevertheless strongly indicate deviations from efficiency. The coefficient on forecast revisions is usually positive, if not always statistically significant. While not shown, tests of the null hypothesis that all regression coefficients are zero are rejected strongly. Overall, the results conform to the prior literature, which has concluded typically that expectations are not informationally efficient (Fuhrer, 2015; Mehra, 2002; Thomas, 1999).

[3] See Table A1 in the appendix for survey details.

[4] The quarterly annualized rate of inflation is $\pi_t = 400 \times log(P_t/P_{t-1})$ throughout, where P_t denotes the quarterly value of the price index. The superscript on π indicates that it is an average rate of inflation over several quarters; the year-ahead inflation is denoted π^4_{t+4}, where $\pi^4_{t+4} = \frac{1}{4}\sum_{i=1}^{4}\pi_{t+i-1}$. The forecast errors are then e_t, where $e_{t+4} = \pi^4_{t+4} - S_{j,t}\pi^4_{t+4}$ and $S_{j,t}$ denotes the 'survey operator,' the median forecast from survey j at time t.

[5] The lag length of the autoregressive process in SARC is determined by the AIC.