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HOW DO INDIVIDUAL FORECASTERS CHANGE THEIR VIEWS? AN ANALYSIS WITH MICRO PANEL DATA

Abstract. This paper scrutinizes the behavior of individual forecasters included in the Consensus Forecast inflation data for the US. More precisely, we try to determine whether individual forecasters deviate systematically from each other. We examine whether the ranking of forecasters is the same over time. The full micro data set includes 74 forecasters over the period 1989M10-2011M3. The results clearly indicate that the forecasters behave quite persistently so that, for instance, the ranking of forecasters does not change over time. Even so, we also find that the survey values imply reasonable values for the hybrid form of the New Keynesian Phillips curve and that forecaster's disagreement is positively related to the size of forecast errors.
Keywords: forecasting, survey data, expectations.

1. Introduction

In recent times, the use of survey data has become more widespread and frequent, reflecting the growing importance of expectation in analyzing inflation and other macroeconomic variables (see e.g. Canova and Gambetti 2010 for more on these developments). However, very little is known about what happens behind the mean values of forecasts. Thus, for instance, when mean values increase, does this mean that all forecasters change their opinions by the same amount, or do the low inflation forecasters generally become high-inflation forecasters, or what? In other words, micro data itself has not been analyzed even though micro data have been used increasingly to study firms' pricing behavior (Köberl and Lein 201) is a notable exception[1]). The main reason for

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[1] Köberl and Lein (2011) use survey data to derive a non-inflationary rate of capacity utilization (NIRCU) using the KOF Swiss Economic Institute's quarterly *Business Tendency Survey* in the manufacturing sector. See e.g. Kaufmann (2009) and Lein (2010) concerning micro data in analyzing firms' pricing behavior.

this lack of knowledge is perhaps the fact that most survey data are in the form of repeated cross-sections rather than genuine panel data. That is why it is difficult to analyze the dynamics of expectations formation at the micro level.

We have tried to solve the problem by using micro data from the Consensus Forecast. The data have the advantage that individual forecasters remain in the data for a fairly long time, some even for the whole period (24 years). The disadvantage is that the number of forecasters is relatively small, 25 on average (the minimum is 15 and the maximum 32). Altogether 74 forecasters appear in the data. Even so, we may derive some useful information from the data because the forecasters represent large companies (banks, in particular) and economic research organizations.

We arrange the data in panel form and use panel data estimation procedures to evaluate the behavioral patterns of the individual forecasters. The prime testing procedure makes use of a test for fixed (cross-section) effects. Thus, we test whether there are any significant individual patterns in the forecasts. The simplest possibility is that each forecaster has some fixed equilibrium inflation level in mind. If that is the case, we would expect that all forecasters change their forecasts by the same amount in response to new market information. Equally well, it could be that in each model used by an individual forecaster the coefficients are fixed but are not necessarily the same for all forecasters (in a sense, everybody has a different Phillips curve). Therefore, we might well expect to see a lot of persistence in the cross-section distribution of forecast values. One reflection of this expectation could be that the ranking of forecasters remains the same over time (somebody always produces the highest number). Another possibility is that everyone has the same model with the same parameters and the differences in the inflation forecasts are purely random (due e.g. to different inflows of information, different timing etc.). To examine the ranking pattern hypothesis, we use some conventional non-parametric tests: more precisely the Kendall Coefficient of Concordance which enables us to comparing multiple rankings (see Siegel 1956). Finally, to analyze the internal consistency of expectations and to estimate the Phillips curve, we also use micro data on output growth expectations. These data are handled in the same way as the data on inflation expectations.

2. Data

Our expectations data are from Consensus Forecast Inc and cover the period 1989M10-2011M3. Consensus Economics Inc collects data on a monthly basis from public and private economic institutions in all major economies; for the smaller countries, the number of participating institutions is very small (preventing e.g. analyses on forecast uncertainty). The data represent an incomplete panel of 74 forecasters, albeit on average there are only roughly 25 forecasters in the survey. Here we assume that the forecasters are independent. That is, they do not follow each others forecasts and thus there is no herding behavior, nor strategic forecasting (for instance, in terms of increased publicity). It is not all clear that these assumptions are true but an analysis of these issues would require quite a lot of additional effort and perhaps also a more extensive data.

The main analytical problem with the data is that the forecast horizon is not fixed; instead the forecasts are for fixed calendar periods, for the current and subsequent calendar years; thus the survey data comprise a series of *fixed event* forecasts (the terminology is from Dovern et al. 2012). However, we would prefer *fixed horizon* (e.g., one-year-ahead) forecasts to avoid the “seasonal” pattern of forecasts.

In practice, we use both fixed event and fixed period forecasts. For the former, we use original data but employ fixed time effects to control for the “seasonal” pattern of forecasts. In essence, this means that we treat forecasts made in, say, February differently from forecasts made in June.

To approximate fixed horizon forecasts as weighted averages of fixed event forecasts, we use the following calculation rule (see Gerlach 2007 and Dover et al. 2009 for details). Denote by $F[y_0,m,y_1(x)]$ the fixed event forecast of variable x for year y_1 made in month m of previous year, y_0 , and by $F[y_0,m,12(x)]$ the fixed horizon, twelve-month-ahead forecast made at the same time. We can then approximate the fixed horizon forecast for the next twelve months as the average of forecasts for the current and next calendar years weighted by their shares in the forecasting horizon:

$$F[\,y_0,m,12(x)] =((\,12 - m\,)/12)^*\,F[\,y_0,m,y_0(x)] + (m/12)^*\,F[\,y_0,m,y_1(x)]. \quad (1)$$

For example, the July 2010 twelve-month-ahead forecast of inflation rate Δp $F[2010,7,12(\Delta p)]$ is approximated by the sum of $F[2010,7,2010(\Delta p)]$ and $F[2010,7,2011(\Delta p)]$ weighted by 5/12 and 7/12 respectively.

As pointed out earlier, Consensus Forecasts contain forecast values for both the current year and the next year. Fixed period forecasts for the subsequent 12 months make use of forecasts for both years according to (1) whereas the fixed period assessment of current inflation employs forecasts for the current year and actual CPI inflation data which are assumed to be known to all forecasters.

In addition to inflation data, we also use data on output growth expectations. These data have been treated in the same way as the inflation data except that we do not have actual monthly output growth figures. That creates some problems, specifically in the estimation of the Phillips curve.

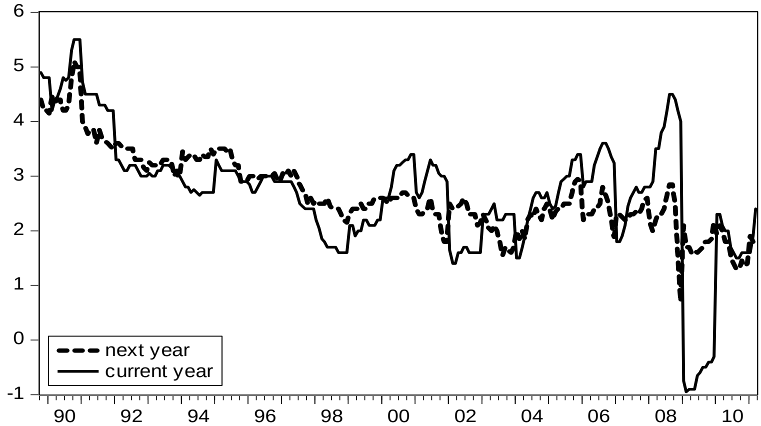

Figure 1. Forecasts of current and next calendar year's inflation

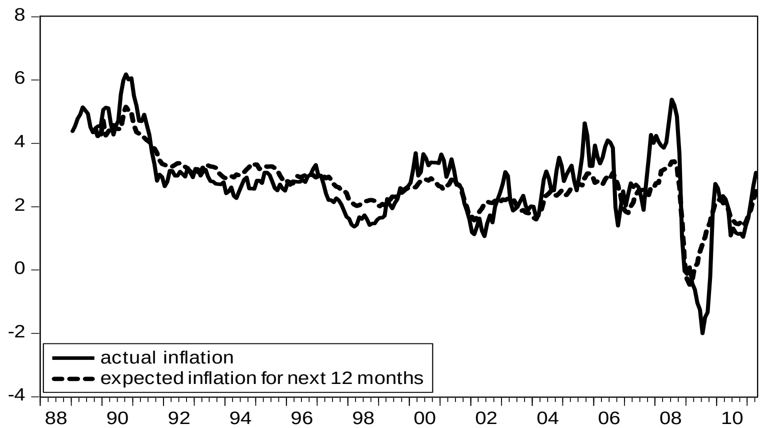

Figure 2. Actual and expected inflation

The mean values of Consensus forecasts are displayed in Figure 1. In Figure 2, the actual inflation data are contrasted with the expected fixed time-horizon inflation. In Figure 3, the mean and median values of Consensus forecasts for the next calendar year are compared and, finally, in Figure 4, the standard deviation of inflation forecasts for the next calendar year is displayed. Forecasts for output growth in current and next year are displayed in Figure 5. On the basis of these graphs, we readily conclude that mean values of expectations become smoother when the time horizon becomes longer and in general the time series of mean expectations is smoother than actual inflation. Dispersion of expectations has not been constant having been very small in early part of 2000 (as noted by Gamber et al. 2011) and very large during the recent financial crisis.[2]

Figure 3. Mean and median values of next year's inflation forecasts

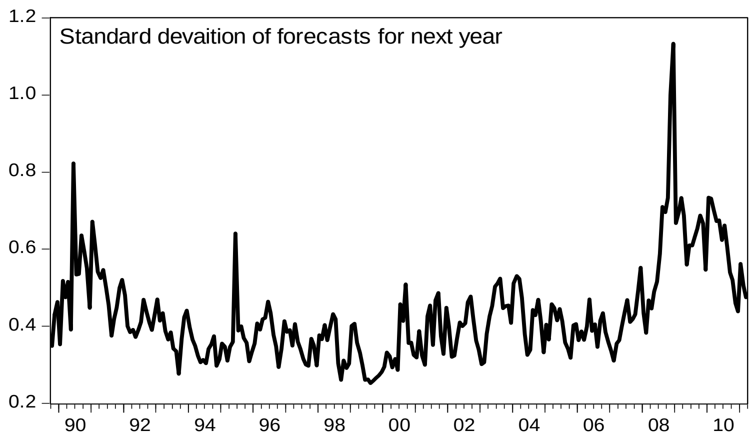

Figure 4. Standard deviation of next year's inflation forecasts

[2] Here we pay only little attention to forecast uncertainty (see, however, the first paragraph in section 3). See Mankiw et al. (2003), Döpke and Fritsche (2006) and Lahiri and Sheng (2010) for analyses of disagreement between forecasters and forecast uncertainty.

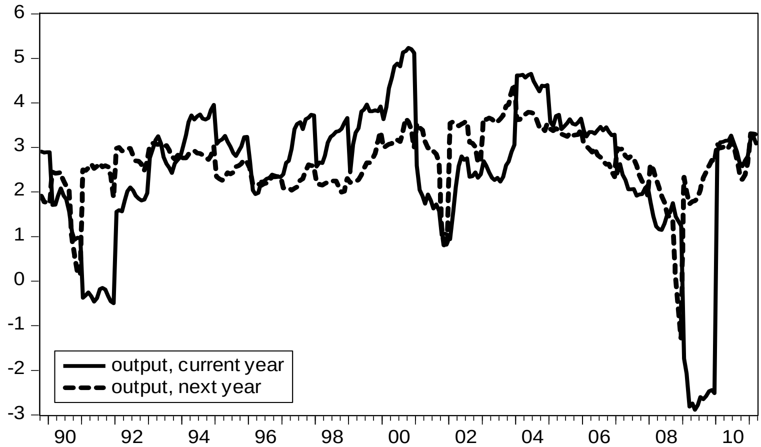

Figure 5. Forecasts of current and next year's output growth

3. Analysis

We start by scrutinizing the basic features of the data, specifically looking at the errors in expectations. A scrutiny of expectation errors (Table 1) confirms the facts which are visible already on the basis of Figure 2: (1) expected inflation is much more persistent than actual inflation, (2) expected inflation is higher than actual inflation and (3) expectation errors depend positively on current inflation. In other words, expectations are not unbiased and the bias seems to depend on the current inflation environment. Current inflation peaks translate to higher expected inflation for the future periods. Thus there are noticeable backward-looking features in the formation of (micro) inflation expectations. From the point of view of conventional interpretation of the rational expectations hypothesis, this of course is somewhat puzzling. One may also notice that inflation uncertainty (standard deviation of forecasts over respondents) seems to predict forecast errors; the more the forecasters disagree today, the more the forecasts will exceed actual values and the larger the absolute forecast errors.

Table 1. Nature of inflation expectation errors

$$\Delta p^{e}_{it+12} - 0.145\Delta p_{t+12} = 0.080$$
$$t = 4.59,\ R^2 = 0.00,\ SEE = 1.364$$

$$\Delta p^{e}_{it+12} = 2.328 + 0.145\Delta p_{t+12}$$
$$t_1 = 83.49,\ t_2 = 15.01,\ R^2 = 0.036m\ SEE = 0.902,\ F = 3946.1.$$

$$\Delta p^{e}_{it+12} = 2.627 + 0.032\Delta p_{t+12} + \text{fixed effects}$$
$$t_1 = 106.5,\ t_2 = 3.63,\ R^2 = 0.323,\ SEE = 0.761,\ F = 35.31.$$

$$\Delta p^{e}_{it+12}-\Delta p_{t+12} = 0.109\Delta p_t$$
$$t = 16.92,\ R^2 = 0.055,\ SEE = 1.326$$

$$\Delta p^{e}_{it+12}-\Delta p_{t+12} = 0.221 sd_t$$
$$t = 4.70,\ R^2 = 0.002,\ SEE = 1.363$$

$$|\Delta p^{e}_{it+12}-\Delta p_{t+12}| = 2.379 sd_t$$
$$t = 76.92,\ R^2 = 0.086,\ SEE = 0.876$$

$$\Delta p^{e}_{it+12}-\Delta p_{t+12} = -.319\Delta p_t + .117\Delta p_t^2$$
$$t_1 = 19.02,\ t_2 = 23.75,\ R^2 = 0.154,\ SEE = 0.255$$

$$\Delta p^{e}_{it+12}-\Delta p_{t+12} = -.241\Delta p_t|\Delta p_t<2 + 0.129\Delta p_t|\Delta p_t>2$$
$$t_1 = 13.34,\ t_2 = 19.35,\ R^2 = 0.088,\ SEE = 1.302$$

The expected values represent fixed 12 month time horizon computed using formula (1). Δp denotes inflation and sd the (seasonally adjusted) standard deviation of forecasts for the next year. In the second equation, F denotes the conventional F test for bias in expectations, in the third equation F denotes the test for cross-section fixed effects supported by respective corrected t-ratios. The last equation represents a simple threshold model where the actual rate rate of inflation is the threshold variable. In the sixth equation, the dependent variable is the absolute expectation error.

To answer the question of whether there are persistent differences in the forecasted levels of inflation we use the tests for fixed effects in the panel regressions. For that purpose, we first employ some very simple "models" for inflation forecasting derived from the Consensus Forecasts. To start with, we estimate the following equation:

$$\Delta p^e_{it,T+1} = c + c_i + c_t + u_{it} \quad (2)$$

where $\Delta p^e_{it,T+1}$ denotes expected inflation for period (year) T+1 made in period (month) t . Here T denotes the current calendar year and T+1 the next calendar year[3], i denotes an individual forecaster where i = 1 ….74 and u is an error term which is assumed to be uncorrelated with constant variance. c_i denotes the cross-section fixed effect and c_t the period fixed effect (t=1989M10-2011M3). The same equation is estimated for the current period (year) expectations, $\Delta p^e_{it,T}$. In addition to this very simple model, we estimate equations (3) and (4) to deal with the relationship between expectations for the next and current-year inflation and equation (5) to deal with the relationship between consecutive forecasts for the next year's inflation. In equation (3), the fixed effects are allowed whereas in equation (4) the slopes are allowed to differ. Equation (5) basically tests the differences in the persistence of forecast values (forecast made in this month compared with forecast made in previous month).

$$\Delta p^e_{it,T+1} = c + \alpha \Delta p^e_{it,T} + c_i + c_t + u_{it} \quad (3)$$

$$\Delta p^e_{it,T+1} = c + \gamma_i \Delta p^e_{it,T} + c_t + u_{it} \quad (4)$$

$$\Delta p^e_{it,T+1} = c + \beta_i \Delta p^e_{it-1,T+1} + c_t + u_{it} \quad (5)$$

Again, all error terms are assumed to be uncorrelated and with constant variance. In all cases, we simply test for the hypothesis that the cross-section specific coefficients (either c_i, α_i, β_i or γ_i) are the same. These parameter restriction tests constitute the core of the analysis of heterogeneity of individual forecasts. The sample period is 1989M10–2011M3, which produces 6396 data points in the final estimation[4]. The estimation results for equation (2) to (5) are reported in Table 2. To illustrate the differences in cross-section coefficients, the cross-plot of coefficients β_i and γ_i is presented in Figure 6.

The estimation results clearly indicate that the individual coefficients are not the same for individual forecasters for whichever way we look at them (in the tests, the null hypothesis is the assumption that the coefficients are the same). Thus forecasters persistently deviate from each other. The different models produce somewhat different cross-section terms but for instance for coefficients β_i and γ_i (Figure 6) the correlation is 0.91 (correlation between γ_i and different c_i's

[3] When we use the original "fixed event" Consensus forecasts for the current and next calendar years, we also used period fixed effects in the panel estimation to account for this "seasonal" pattern in forecasts.

[4] Had we data for all forecasters for all periods, we would have had 20868 data points (thus more than three times the number of data points we actually have).

are roughly the same), which suggests that the basic nature of differences between individual forecasters is the same.

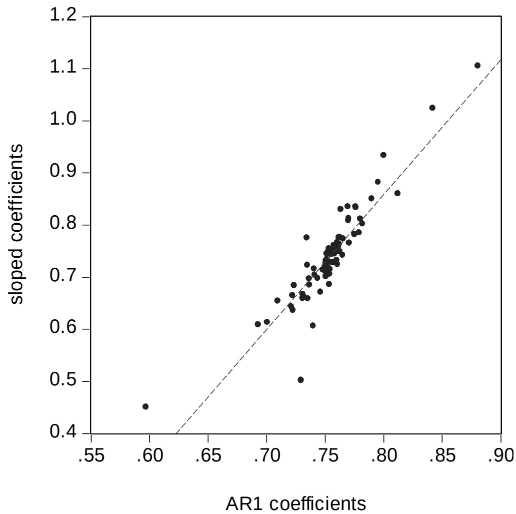

Figure 6. Comparison of individual coefficients

Table 2. Panel data estimates of simple inflation forecast equations

	1	2	3	4	5
Constant	2.695 (989.45)	2.700 (588.28)	.812 (10.31)	.645 (13.80)	.684 (8.56)
$\Delta p^e_{t,T}$			.699 (24.01)		
fixed cross section terms	X	X	X		
individual coefficients of lagged p^e_{T+1}				X	
individual coefficients of p^e_T					X
dependent variable	$\Delta p^e_{t,T}$	$\Delta p^e_{t,T+1}$	$\Delta p^e_{t,T+1}$	$\Delta p^e_{t,T+1}$	$\Delta p^e_{t,T+1}$
SEE	0.222	0.367	0.334	0.243	0.345
R^2	0.964	0.828	0.854	0.922	0.844
χ^2 test statistic for equality of individual cross-section coefficients	782.15 (0.00)	2576.06 (0.00)	2152.25 (0.00)	274.40 (0.00)	1744.27 (0.00)

Inside parentheses corrected t-ratios; x indicates that cross-section terms are included. The models always include period fixed effects. In all cases, we can reject the hypothesis that the coefficients (or fixed cross-section terms) are equal across forecasters.

A comparison of mean and median values (Figure 3) also suggests that – except for the culmination of the recent financial crisis – there is very little difference which suggests that the distribution of forecast values has not changed very much. At least it seems unlikely that the distribution would be utterly skewed from time to time.

To characterize these persistent differences in a more concrete and intuitive way, we compute the Kendall Coefficients of Concordance, denoted by W (Siegel 1956). Unfortunately, we cannot compute them over the whole sample because there is so much turnover (and eventual missing observations) within the set of forecasters. Hence we compute the coefficients with some (partially overlapping) subsets of data. Figure 7 reports the coefficient values for these cases, with sample periods of 12 and 24 months and for forecasts of the current and next year's inflation.

The results clearly point to the same direction as the panel data estimates. Thus, the ranking seems to remain invariant over time (in fact, the same pattern comes out with all other subsamples of the data).

It is interesting to observe that the rankings do not change during the turbulent periods of the financial crisis in 2007-2010 even though the dispersion of forecasts quite clearly increases (Figure 3). Only in 2000-2002 does there seem to be a shake-up of rankings, with very little persistence in consecutive forecasts. One may speculate that the uncertainty over the future developments in inflation and the stance of monetary policy could have caused the low correlations (at that time, the possibility of deflation was considered a realistic one) but we have to acknowledge that the dispersion of forecasts was also extraordinary small (Figure 4).

Why do some forecasters systematically forecast high inflation and some other low inflation? Could the reason be that high-inflation forecasters consider the overall economic prospects more favorable than the others? To consider this possibility, we collected data on GDP growth and scrutinized the relationship between inflation and GDP growth (Table 3). We also estimated the hybrid New Keynesian Phillips curve of the form (6) to see whether the expected values reflect this basic relationship in the same way as the actual data (see, e.g., Kortelainen et al. 2011).

$$\Delta p^e_{it,T} = \alpha\Delta p^e_{it-1,T} + \beta\Delta p^e_{it,T+1} + \gamma\Delta y^e_{it,T} + \sum Seas_t + u_{it} \quad (6)$$

where $\Delta y^e_{it,T}$ denotes the expected growth rate of output for the current calendar year (expected in period t by forecaster i). "$Seas_i$" with i =1,2,…,12 denotes a seasonal dummy for month i. The equation has also been estimated using fixed 12-month time-horizon data.[5]

[5] As pointed out earlier, we have no monthly data on actual GDP growth which is needed in estimation of the Phillips curve. Hence, we have to use some sort of "real time" proxy for output. That is done by computing a 12-month moving average of expectations for current-year output growth (the results are reported as equation 5 in Table 3).

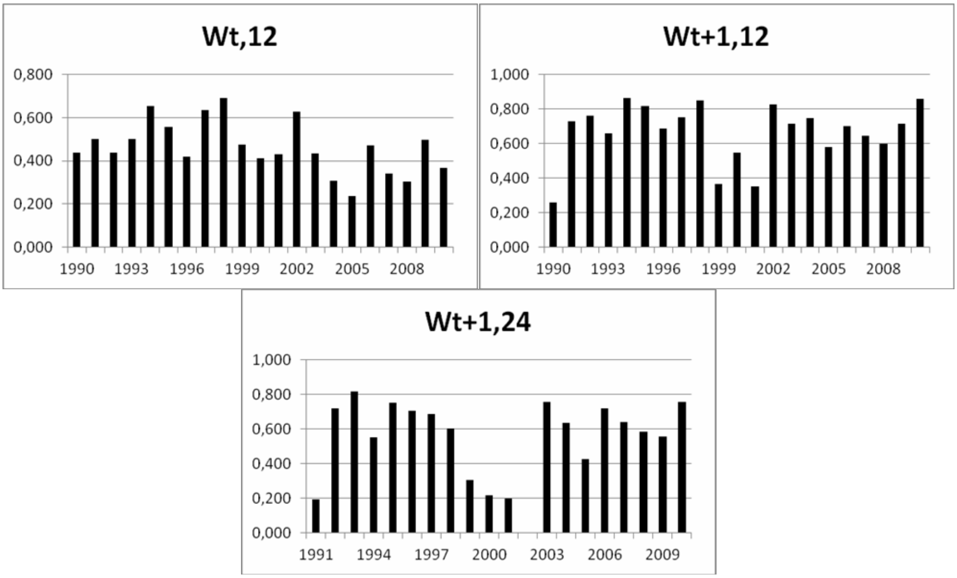

Figure 7. Coefficients of concordance for different data sets
Wn, *m* denotes the coefficient for current year's ($n = t$) or next year's ($n = t + 1$) forecast and
n the number of consecutive months included in the sample.

Estimation results in Table 3 indicate that inflation and output forecasts are indeed positively correlated although allowing for both cross-section and period time effects produces rather low t-ratios. When the cross-section fixed effects are eliminated, the t-values increase substantially (being 3.42 in the case of equation 1 and 7.41 in the case of equation 2 in Table 3). This finding is consistent with evidence on Dutch households (see Christensen et al. 2006), although the relationship seems to be much stronger in the Dutch data. Recent cross-country evidence with Consensus Economics micro data on professional economists (Fendel et al. 2011) also point to the same direction. The interesting point of this study is strong support to nonlinear form of the Phillips curve.

If inflation expectations only partially reflect output growth expectations we should consider other sources of differences in inflation expectations. The most obvious explanation is a difference in the Phillips curve. Thus, we estimate equation (5) with equal slopes for all forecasters and, alternatively, allowing for different (forecaster-specific) slopes. The results are reported in Table 3.

We see that the slopes are indeed different (although only "marginally" in the hybrid specification), suggesting that the "forecasting model" may indeed also produce differences in inflation forecasts. Thus, it is not simply a question of optimism versus pessimism.

Table 3. Panel data estimates of inflation-output growth equations

	1	2	3	4	5	6
Constant	2.617 (57.12)	2.601 (65.16)				1.597 (16.09)
$\Delta y^e_{t,T}$	.032 (1.74)		.149 (12.71)	.053 (7.63)	.062 (11.73)	.430 (10.91)
$\Delta y^e_{t,T+1}$		.038 (2.25)				
$\Delta p^e_{t,T+1}$			.855 (51.08)	.138 (8.86)	.258 (23.66)	
$\Delta p^e_{t-1,T}$				.851 (63.51)		
Δp_{t-1}					.696 (68.47)	
fixed cross section terms	X	X				X
seasonal dummies			X	X		
dependent variable	$\Delta p^e_{t,T}$	$\Delta p^e_{t,T+1}$	$\Delta p^e_{t,T}$	$\Delta p^e_{t,T}$	$\Delta p^e_{t,T}$	$\Delta y^e_{t,T+1}$
SEE	0.222	0.366	0.835	0.389	0.445	0.400
R^2	0.963	0.828	0.464	0.828	0.858	0.792
χ^2 test statistic for equality of individual cross-section coefficients	784.4 (0.00)	2495 (0.00)	599.17[a] (0.00)	130.08[a] (0.001)	166.60[a] (0.00)	1200 (0.00)

Notation is the same as in Table 2. Superscript a denotes the case where the alternative is a model with forecaster-specific coefficients of the output growth variable. For equation 5, expectations are expressed as 12 month fixed time horizon and actual past inflation is assumed to be known to all forecasters. No time-effects are used with the Phillips curves.

Finally, note that the estimates of the Phillips curve (columns 3, 4 and 5 in Table 3) generally make sense – to some extent the results make more sense that those obtained by using actual data as to imposing the REH orthogonality conditions via the GMM estimator, see e.g. Adam and Padula (2011). Thus, the coefficient of output is always positive and the coefficients for both the forward and backward-looking inflation terms are of reasonable magnitude and the coefficients can be estimated quite precisely. This in turn confirms that the use of survey data is indeed useful in recovering the basic relationships from empirical observations.

4. Concluding remarks

The Consensus Forecast data for individual forecasters quite clearly favors the interpretation that differences between different forecasters' projections are quite persistent up to the point where the ranking of forecasts remain the same over time. It would surely be interesting to know what causes these differences – are they some sort of "taste parameters" or permanent differences in information sets, for instance different cost pressures. The limited amount of data that we have does not enable us to analyze the effects of different sectoral or other structural factors, such as the difference between "service sector" and "manufacturing sector" companies' assessment of inflation, but that would be a useful avenue for further research. When scrutinizing the relationship between inflation and output growth forecasts, it turns out that they are internally consistent. Moreover, at least part of the differences of inflation forecasts can be explained by differences in output growth forecasts, which means that inflation differences reflect some overall optimism/pessimism in both inflation and/or growth prospects. Still, a lot remains unexplained which implies that there are important "permanent" differences in ways in forming inflation forecasts. To some extent this shows up in differences in perceived slopes of the Phillips curve.

References

Adam K. and Padula M. (2009), Inflation Dynamics and Subjective Expectations in the United States, *Economic Inquiry*, 49 (1), 13–25.

Canova F. and Gambetti L. (2010), Do Expectations Matter? The Great Moderation Revisited, *American Economic Journal, American Economic Association*, 2(3), 183–205.

Christensen C., van Els P. and van Rooij M. (2006), Dutch Households' Perceptions of Economic Growth and Inflation, *De Economist*, vol. 154(2), 277–294.

Dovern J., Fritsche U. and Slacalek J. (2012), Disagreement Among Forecaster in G7 Countries, *The Review of Economics and Statistics*, vol. 94(4), 1081–1096.

Döpke J. and Fritsche U. (2006), When Do Forecasters Disagree? An Assessment of German Growth and Inflation Forecast Dispersion, *International Journal of Forecasting*, 22, 125–135.

Fendel R., Lis E. and Rülke J.C. (2011), Do professional forecasters believe in the Phillips curve? Evidence from G7 countries, *Journal of Forecasting*, 30, 268–287.

Gamber E., Smith J. and Weiss M. (2011), Forecast errors before and during Great Moderation, *Journal of Economics and Business*, vol. 63(4), 278–289.

Gerlach S. (2007), Interest Rate Setting by the ECB, 1999–2006: Words and Deeds, *International Journal of Central Banking, September*, 1–42, 389–439.

Kaufmann D. (2009), Price-setting behaviour in Switzerland: evidence from CPI micro data, *Swiss Journal of Economics and Statistics*, 145, 293–349.

Kortelainen M., Paloviita M. and Viren M. (2011), Observed Inflation Forecasts and the New Keynesian macro Model, *Economics Letters*, 112(1), 88–90.

Köberl E. and Lein S. (2011), The NIRCU and the Phillips curve: an approach based on micro data, *Canadian Journal of Economics*, 44(2), 673–694.

Lahiri K. and Sheng X. (2010), Measuring Forecast Uncertainty by Disagreement: The Missing Link, *Journal of Applied Econometrics*, vol. 25(4), 514–538.

Lein S. (2010), When do firms adjust prices? Evidence from micro panel data, *Journal of Monetary Economics*, 57, 696–715.

Mankiw N. G., Reis R. and Wolfers J. (2003), Disagreement about Inflation Expectations, *NBER Working Paper 9796.*

Siegel J. (1956), *Nonparametric Statistics for the Behavioral Sciences*, McGraw-Hill, 2. Edition, New York.

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W JAKI SPOSÓB PROGNOSTYCY ZMIENIAJĄ POGLĄDY? ANALIZA NA PODSTAWIE MIKRODANYCH PANELOWYCH

Streszczenie

Przeanalizowano zachowanie się poszczególnych ośrodków prognostycznych ujętych w prognozach Consensus Forecast dla inflacji w USA. Starano się określić, czy poszczególne prognozy systematycznie odbiegają od siebie. W szczególności zbadano, czy ranking ośrodków jest taki sam w czasie. Pełny zestaw danych obejmuje 74 prognostyków w okresie 1989M10–2011M3. Wyniki wyraźnie wskazują, że prognostycy zachowują się bardzo konsekwentnie tak, że na przykład, ranking ośrodków nie zmienia się w czasie. Ponadto pokazano, że prognostycy są zgodni co do hybrydowej postaci neokeynesowskiej krzywej Phillipsa oraz że różnice pomiędzy nimi są dodatnio skorelowane z wielkością błędów prognozy.