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Households Forming Inflation Expectations: Who Are the 'Active' and 'Passive' Learners?

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Abstract. Recent research has established that households learn from professional forecasters as they form their inflation expectations. Professionals' forecasts are transmitted, or 'absorbed', throughout the population slowly but eventually. This provides the microfoundations for 'sticky information expectations'. The present paper considers whether absorption rates take place heterogeneously amongst households. We consider whether various segments of the population absorb the professional's forecasts at different rates. Using a unique survey-based dataset covering various segments of the UK population we identify 'active' and 'passive' learners in the population. 'Active' and 'passive' learners are identified and distinguished by their respective absorption rates. The present analyses also consider whether these absorption rates are non-linear.

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I: Introduction:

The role of households' expectations in determining aggregate outcomes, such as business cycles and inflation dynamics, is well established. However, how households form their expectations about the macroeconomy is less well studied. In a recent seminal study Carroll (2003 and 2006) addresses the issue of how households form expectations about the aggregate economy, especially inflation expectations. Carroll (2003 and 2006) put forward the idea of 'epidemiological expectations'. Households form their inflation expectations by observing the professionals' forecasts. However, they do not observe the professionals' perfectly and it is 'absorbed' over time and eventually transmitting throughout the entire population. This provides the microfoundations for rational inattentive behavior or 'sticky information expectations'. Recent papers have used such expectations to study inflation dynamics (Mankiw and Reis, 2002) and their implications for monetary policy (Ball et al, 2004).

In a related research Mankiw et al (2004) considered how disagreements may arises amongst different agents' inflation expectations. They conclude that any disagreements and heterogeneity found amongst various professionals' and households' inflation forecasts largely arise due to the varying rates these agents update their relevant information set.

So far empirical analyses have largely considered how households learn from the professionals' forecasts. Households are treated as a homogenous group where they absorb at same rate or, indeed, the estimates only establish the average rate by which households absorb. In the present paper, using a unique survey-based data for the UK, we consider whether different agents, or groups, that make up the population have different absorption rates. We identify agents who are 'active' and 'passive' learners. The distinction is made based on their respective absorption rates. There are some important implications for these results. In the first instance, it highlights and enables us to understand inflation expectations heterogeneity that clearly exists throughout the population. Distinguishing and identifying 'active' and 'passive' learners also has direct implications for inflation dynamics and the pursuit of monetary policy. So far inflation models that use ‘sticky information expectation’ suggests a single rate of absorption amongst households which reflects the average. If, for instances, the ‘active’ agent is someone who is crucial for the wage and price-setting process, such as trade union officials or financial directors, then their rate of absorption would be more important and the general public’s in determining inflation dynamics.

In subsequent section we outline a theoretical model which extends the Carroll (2003) analysis to account for different types of learning agents. Section 3 undertakes the empirical investigation based on the extended model and, finally, Section 4 draws the main points and concluding remarks.

II: Professional Forecasters, Active and Passive Learning Agents: The Model

In this section we outline the theoretical framework which is used as the basis for the ensuing empirical analysis. Carroll (2003 and 2006) establishes that the professional’s forecasts are absorbed by households and are transmitted throughout the entire population. Nevertheless, the absorption rate may vary between different groups that make-up the entire population. Thereby, indicating heterogeneity amongst the general public despite learning from a common source.

The model outlined here considers two types of stylized general public: the active and passive learner. They are simply distinguished by the rate they absorb the professional’s forecasts, where the active has a higher rate than the passive learner. We assume that both the active and passive general public (*GP,A* and *GP,P* respectively) may set their inflation expectations using the professional’s forecasts as an ‘anchor’ or a reference point. Hence, the active learner forms his expectations ($E_t^{HA*}(\pi_{t+1})$) as a ratio of the professional’s[1]:

$$\frac{E_t^{HA*}(\pi_{t+1})}{E_t^{P}(\pi_{t+1})} = \beta_{GP,A}$$

or $$E_t^{HA*}(\pi_{t+1}) = \beta_{GP,A} E_t^{P}(\pi_{t+1}) \qquad (1)$$

[1] For notational convenience we assume the expectations are demeaned; this assumption of zero-intercept is relaxed in the empirical analysis. The * character denotes that ratios are measured over large spans of data in which people learn from the professional forecaster, i.e. over the long run.

Likewise, the passive learner forms his expectations ($E_t^{HP*}(\pi_{t+1})$) as a ratio of the professional's:

$$\frac{E_t^{HP*}(\pi_{t+1})}{E_t^{P}(\pi_{t+1})} = \beta_{GP,P}$$

or
$$E_t^{HP*}(\pi_{t+1}) = \beta_{GP,P} E_t^{P}(\pi_{t+1}) \quad (2)$$

where $\beta_{GP,A};\beta_{GP,P} > 0$. Different segments of the population may set different ratios. They may target inflation obtained from varying notions of consumer prices, possibly due to different consumption baskets. For example, what media simply report as "inflation" is often measured on the basis of different price indexes, such as CPI (Consumer Price Index, whose inflation has been officially targeted by the Bank of England since December 2003), or the "traditional" RPIX (Retail Price Index, whose basket composition differs to that of CPI by about 10%). The learning agents observe the professional's forecasts imperfectly and are absorbed over time, albeit at different rates[2]:

$$E_t^{GP,A}(\pi_{t+1}) = \alpha_{GP,A}(\beta_{GP,A} E_t^{P}(\pi_{t+1})) + (1-\alpha_{GP,A})(E_{t-1}^{GP,A}(\pi_{t+1})) \quad (3)$$

$$E_t^{GP,P}(\pi_{t+1}) = \alpha_{GP,P}(\beta_{GP,P} E_t^{P}(\pi_{t+1})) + (1-\alpha_{GP,P})(E_{t-1}^{GP,P}(\pi_{t+1})) \quad (4)$$

The active learner absorbs faster that the passive and $\alpha_{GP,A} > \alpha_{GP,P} > 0$.

Now we assume that the active and passive learners' two-step and one-step ahead expectations (based on their information set in *t-1*) evolve as follows:

$$E_{t-1}^{GP}(\pi_{t+1}) = E_{t-1}^{GP}(\pi_t) + u_{t+1}^{GP} \quad (5)$$

where u_{t+1}^{GP} is a zero-mean and constant variance idiosyncratic random error. This departs from the more restrictive assumption in Carroll (2003) where it was assumed $u_{t+1}^{GP} = 0$. Occasionally, in period *t-1* the individual learning agent may have relevant information about changes that could affect inflation in *t+1* (i.e. a further step ahead); for example pre-announced monetary

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[2] Carroll (2006) suggests that the professional's forecasts can be absorbed via the news media and/or social interaction. In the present scenario we assume that learning agents (or various segments of the population), for example trade union officials, may consult professional forecasters directly, albeit periodically.

and fiscal policy. It must also be assumed that u^{GP}_{t+1} are not related with professional's forecasts formed using the information set in *t*, $E^{P}_{t}(\pi_{t+1})$.

The professional's forecasts, on the other hand, are set independently. Following Carroll (2003) it is assumed that next-period inflation process is captured by two components: $\pi_{t+1} = \pi^{f}_{t+1} + \kappa_{t+1}$. The fundamental rate of inflation $\pi^{f}_{t+1} = \pi^{f}_{t} + \eta_{t+1}$ – whose changes are due to permanent innovations η_t – and the unforecastable transitory shock κ_{t+1}. Hence, the professional forecasts in *t* for *t+1* are $E^{P}_{t}(\pi_{t+1}) = E^{P}_{t}(\pi^{f}_{t+1}) + E^{P}_{t}(\kappa_{t+1}) = E^{P}_{t}(\pi^{f}_{t+1})$, and the professional forecaster updates his forecasts as follows:

$$E^{P}_{t}(\pi^{f}_{t+1}) = E^{P}_{t-1}(\pi^{f}_{t}) + E^{P}_{t}(\eta_{t+1}) \tag{6}$$

or

$$E^{P}_{t}(\pi_{t+1}) = E^{P}_{t-1}(\pi_{t}) + E^{P}_{t}(\eta_{t+1}) \tag{7}$$

where $E^{P}_{t}(\pi_{t+1})$ and $E^{P}_{t}(\eta_{t+1})$ denotes the professional's expectations of inflation and permanent innovation respectively. We assume the professional forecaster has some idea about how the one-step ahead fundamental rate may differ from the current rate by defining $E^{P}_{t}(\eta_{t+1})$ as a random variable with unconditional mean equal to zero and constant unconditional variance[3].

Previous assumptions can be summarized in the following system of interacting agents, that is active and passive learner and the professional forecaster:

$$E^{GP,A}_{t}(\pi_{t+1}) = \alpha_{GP,A}(\beta_{GP,A}[E^{P}_{t-1}(\pi_{t}) + E^{P}_{t}(\eta_{t+1})]) + (1-\alpha_{GP,A})(E^{GP,A}_{t-1}(\pi_{t}) + u^{GP,A}_{t+1})$$

$$E^{GP,P}_{t}(\pi_{t+1}) = \alpha_{GP,P}(\beta_{GP,P}[E^{P}_{t-1}(\pi_{t}) + E^{P}_{t}(\eta_{t+1})]) + (1-\alpha_{GP,P})(E^{GP.P}_{t-1}(\pi_{t}) + u^{GP.P}_{t+1})$$

$$E^{P}_{t}(\pi_{t+1}) = E^{P}_{t-1}(\pi_{t}) + E^{P}_{t}(\eta_{t+1})$$

The system of equations can be reparameterized in the following way in order to explain inflation forecasts changes from *t* to *t+1*:

[3] This follows from a similar assumption made in Carroll (2006) (see footnote 3).

$$\Delta E_t^{GP,A}(\pi_{t+1}) = \alpha_{GP,A}(\beta_{GP,A}[E_{t-1}^{P}(\pi_t) + E_t^{P}(\eta_{t+1})]) - \alpha_{GP,A}(E_{t-1}^{GP,A}(\pi_t)) + (1-\alpha_{GP,A})[u_{t+1}^{GP,A}]$$

$$\Delta E_t^{GP,P}(\pi_{t+1}) = \alpha_{GP,P}(\beta_{GP,P}[E_{t-1}^{P}(\pi_t) + E_t^{P}(\eta_{t+1})]) - \alpha_{GP,P}(E_{t-1}^{GP.P}(\pi_t)) + (1-\alpha_{GP,P})[u_{t+1}^{GP.P}]$$

$$\Delta E_t^{P}(\pi_{t+1}) = E_t^{P}(\eta_{t+1})$$

The dynamic relationship between the respective expectations changes can be represented as a matrix equation:

$$\begin{bmatrix} \Delta E_t^{GP,A}(\pi_{t+1}) \\ \Delta E_t^{GP,P}(\pi_{t+1}) \\ \Delta E_t^{P}(\pi_{t+1}) \end{bmatrix} = \begin{bmatrix} -\alpha_{GP,A} & 0 & \alpha_{GP,A}\beta_{GP,A} \\ 0 & -\alpha_{GP,P} & \alpha_{GP,P}\beta_{GP,P} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} E_{t-1}^{GP,A}(\pi_t) \\ E_{t-1}^{GP,P}(\pi_t) \\ E_{t-1}^{P}(\pi_t) \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{GP,A} \\ \varepsilon_t^{GP,P} \\ E_t^{P}(\eta_{t+1}) \end{bmatrix}$$

where the two random terms ε_t^{GP} are defined as a weighted average of both learners and professionals random terms:

$$\varepsilon_t^{GP} = \alpha_{GP}[\beta_{GP} E_t^{P}(\eta_{t+1})] + (1-\alpha_{GP})[u_{t+1}^{GP}]. \qquad (8)$$

The matrix notation above, can be better interpreted as a Vector Equilibrium-Correction Mechanism (VECM):

$$\begin{bmatrix} \Delta E_t^{GP,A}(\pi_{t+1}) \\ \Delta E_t^{GP,P}(\pi_{t+1}) \\ \Delta E_t^{P}(\pi_{t+1}) \end{bmatrix} = \begin{bmatrix} -\alpha_{GP,A} & 0 \\ 0 & -\alpha_{GP,P} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & -\beta_{GP,A} \\ 0 & 1 & -\beta_{GP,P} \end{bmatrix} \begin{bmatrix} E_{t-1}^{GP,A}(\pi_t) \\ E_{t-1}^{GP,P}(\pi_t) \\ E_{t-1}^{P}(\pi_t) \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{GP,A} \\ \varepsilon_t^{GP,P} \\ E_t^{P}(\eta_{t+1}) \end{bmatrix} \qquad (9)$$

The professional's forecasts evolve independently, while the learning agents form their expectations absorbing, or adjusting, to the professional's at different rates α_{GP} determining, as pointed out by equations (3)-(4), whether the respective learning agents are 'active' or 'passive' learners when forming their inflation expectations.

The model we outlined has some implications for the empirical behavior of the variables of interest. Firstly, as far as the unit root properties of the variables of interest is concerned, equation (7) implies that professional's inflation forecasts are first order integrated, i.e. I(1). Further, equations (1)-(2), together with (5), implies that the two active/passive learners forecasts are both

I(1) at univariate level, and both cointegrated with professional's forecasts, CI(1,1), at multivariate level.

Secondly, following the preceding implication, VECM (9) must be a valid depiction of the joint dynamic behavior of the variables of interest in view of the Granger representation theorem (see Engle and Granger, 1987). In the present context, the cointegrating rank of the system – i.e. the number of cointegrating relationships – is equal to the number of learning agents. After model estimation, the residuals $\hat{\varepsilon}_t^{GP}$ in VECM (9) are expected to be positively correlated with those of the professional's forecasts ($\hat{E}_t^P(\eta_{t+1})$).

Thirdly, the structure of the loading factor matrix of α parameters in VECM (9) implies that the professional's forecasts should be weakly exogenous for the cointegrating relations and their adjustment coefficients, see Johansen (1992, 1995). The weak exogeneity property allows for a simplification of VECM (9) structure in the partially-modelled two-variables VECM (10), which makes possible to exploit the simultaneous information embodied in $\Delta E_t^P(\pi_{t+1})$.

$$\Delta E_t^{GP,A}(\pi_{t+1}) = \eta_{GP,A}[\Delta E_t^P(\pi_{t+1})] - \alpha_{GP,A}[E_{t-1}^{GP,A}(\pi_t) - \beta_{GP,A}\, E_{t-1}^P(\pi_t)] + \nu_t^{GP,A} \tag{10}$$

$$\Delta E_t^{GP,P}(\pi_{t+1}) = \eta_{GP,P}[\Delta E_t^P(\pi_{t+1})] - \alpha_{GP,P}[E_{t-1}^{GP,P}(\pi_t) - \beta_{GP,A}\, E_{t-1}^P(\pi_t)] + \nu_t^{GP,P}$$

where η_{GP} are parameters which measure the impact of $E_t^P(\eta_{t+1})$ on learning individuals and, given the equation (8) for ε_t^{GP}, we have that $\eta_{GP} = \alpha_{GP}\beta_{GP}$. As a result, ν_t^{GP} are random terms which embody only the information about u_{t+1}^{GP} structural errors and, given equation (8), may be represented as $\nu_t^{GP} = (1-\alpha_{GP})\, u_{t+1}^{GP}$. In other terms, the estimate of in model (10) allows to make more efficient inferences about the learners' parameters of interest, as it does not require modelling professional's forecasts behavior. Note also that in the light of VECM (9) weak exogeneity also entails strong exogeneity, as in the short run the other forecasts cannot Granger-cause professional's forecasts.

Finally, though the whole structural model has been set up under linear assumptions, the absorption rates may also be non-linear, as the learning agent may absorb at varying rates and the absorption rate itself may take different forms. The issues pertaining nonlinearity will also be investigated in Section III.3.

III: Empirical Analysis and Results:

The remainder of the paper considers the empirical implications of the theoretical model outlined in the preceding section. The empirical investigation identifies which learning agents are 'active' and 'passive' based on their absorption rates. In addition, we also consider whether these absorption rates are non-linear.

III.1: Data: Univariate unit roots and bivariate common trends and dynamics:

The data used in the present analysis are quarterly data complied by Barclays Basix based on surveys of various sections of the UK population. The period covered is from the fourth quarter of 1986 to the first quarter of 2005; this is the entire period of this dataset compiled by Barclay Basix. Since the 2005 Q1 they abandoned collecting the relevant information at a disaggregate level and just focused on the 'general public'. This unique dataset has the advantage of categorizing, or disaggregating, the agents surveyed. They can be divided into economists: business economists (*be*) and academic economists (*ae*), and non-economists: financial directors (*fd*), trade unionists (*tu*) and general public (*gp*). The surveyed are simply asked:

Can you tell me what you expect the rate of inflation to be over the next twelve months?

The compiled figures are the average of the respondents in each category. Inflation forecasts one year ahead of the surveyed groups of agents are depicted in the first five plots of Figure 1. Following the notation adopted in the previous section, each series may be denoted as $E_t^g(\pi_{t+1})$, where g = *be*, *ae*, *fd*, *tu* and *gp*. The time patterns appear to be the same for all forecasts: long waves and strong persistence suggesting the presence of stochastic trends (e.g. the first principal component of the five forecast levels explains almost 99 percent of the overall variance, and simple correlations are in the 0.91-0.99 range).

Figure 1 about here

Preliminary inspection of the inflation forecasts focuses on their univariate stochastic properties. The p-values of unit root tests for inflation forecasts levels $E_t^g(\pi_{t+1})$ (see Dickey and Fuller, 1979) and of autocorrelation LM test up to the 4^{th} order for inflation forecasts in first differences $\Delta E_t^g(\pi_{t+1})$ (see Godfrey, 1988) are reported respectively in the first two rows of Table 1. The results in the columns refer to each of the five surveyed groups of agents, *g*.

Table 1 about here

At the univariate level, $E_t^g(\pi_{t+1})$ series behave as random walks. In fact, the Dickey-Fuller test never rejects the null hypothesis, indicating that the forecasts are non stationary. The LM test of $\Delta E_t^g(\pi_{t+1})$ too is never rejected, suggesting that changes in inflation forecasts are not autocorrelated over time. Details of the test procedures are found in the footnotes of Table 1. These results are robust when different unit roots and/or stationarity tests, lag-selection criteria and higher-order autocorrelations are applied. As depicted in Figure 1, though the first differences indicate stochastic trends, random shock seem correlated simultaneously: the first principal component still explains about 78 percent of the overall variance of the five $\Delta E_t^g(\pi_{t+1})$ time series, and their correlation coefficients are in the 0.55 / 0.86 range. The univariate analysis verify the first empirical implication of the theoretical model discussed at the end of Section II: $E_t^g(\pi_{t+1})$ series are I(1) and their permanent innovations are not correlated over time, though can be correlated across agents.

The bivariate cointegration tests are reported in the lower part of Table 1. We assess whether any pair of forecasts has a common stochastic trend. We follow the suggestion of Gonzalo and Lee (1998) by comparing results from alternative methods; using both Engle and Granger (1987) two-step approach– looking for a unit root in the residuals of a first-stage static regression – and Johansen (1995) trace test based on the reduced rank analysis. Using the more efficient Johansen's approach, the results always reject the null hypothesis of no cointegration and, thereby, suggesting that any pair of inflation forecasts is a stationary linear combination, as predicted at theoretical level by equations (1)-(2). The same results are found, at least at the 10% level, using the Engle-Granger approach.

The estimates of the corresponding slopes β for each pair of bivariate relationships are reported in Table 2. Since all the bivariate long run relationships are normalized in the same way, we can compare the β estimates below the diagonal (using the Engle-Granger approach) with those symmetrically above the diagonal (using the Johansen approach). Estimates are remarkably similar for the different approaches and are always significantly different to both zero and one (test results that are not reported are available upon request). The latter result is consistent with learning agents setting their optimal expectations as a proportion of those of the professionals, see equations (1)-(2).

Table 2 about here

The Johansen's approach enables us to analyze the full dynamics of the bivariate systems where the VECM model (9) is simplified by dropping one variable and, without the imposition of an agent as the professional forecaster, can be represented as:

$$\begin{bmatrix} \Delta E_t^i(\pi_{t+1}) \\ \Delta E_t^j(\pi_{t+1}) \end{bmatrix} = \begin{bmatrix} -\alpha_i \\ -\alpha_j \end{bmatrix} \begin{bmatrix} 1 & -\beta \end{bmatrix} \begin{bmatrix} E_{t-1}^i(\pi_t) \\ E_{t-1}^j(\pi_t) \end{bmatrix} + \begin{bmatrix} \varepsilon_t^i \\ \varepsilon_t^j \end{bmatrix} \tag{11}$$

We can estimate the loading parameters α_i and α_j , and test for weak exogeneity of either $E_t^i(\pi_{t+1})$, i.e. α_i = 0, or $E_t^j(\pi_{t+1})$, i.e. α_j = 0. As highlighted in the theoretical model, the weak exogeneity property identifies which forecaster of the two in the VECM (11) acts as a professional by leading the other.

Table 3 presents the twenty loading parameter estimates of the ten VECM (11) that delivered the β estimates reported in the upper diagonal part of Table 2. In particular, each estimate of Table 3 below the diagonal refers to the loading parameter -α_j of the group of agents indicated in the row from a bivariate VECM (11) whose long run relationship is normalized for the i^{th} group of agents indicated in the column; the symmetrical estimate above the diagonal refers to the -α_i loading parameter in the same VECM (11). Given the similarity of the long run estimates in Table

2, the more restrictive Engle-Granger approach would produce similar results to those discussed here.

Table 3 about here

In each bivariate VECM, insignificant estimates of the loading parameters suggest the weak exogeneity of the forecast group indicated in the row. If all the estimates in one row are never significant, the group in that row always acts as a professional forecaster who leads the other group, regardless of who is it in the bivariate VECM.

Results in Table 3 suggest that in each of our VECM there is always one leader, as both loading estimates of the same VECM are never significant simultaneously. When the business economist forecasts (*be*) enter any bivariate VECM it always leads. Conversely, the general public forecasts (*gp*), is never weakly exogenous in any VECM they are part of. The other three groups of agents show mixed and sometime inconsistent results because the assessment is made in pair, and not by putting together all the five forecasts. Since β estimates are significantly different to one, the extension of the bivariate VECMs to a system modelling together all the five forecast groups avoids that the identification of the long run and of the loading parameters only depends on arbitrary normalization restrictions. Therefore, bivariate findings have to be further verified in the multivariate context.

III.2: Multivariate linear VECMs

The multivariate analysis starts with a first-order unrestricted VAR where the five inflation forecasts are jointly modelled. The choice of one-lag order (from five max-lags) is robust to a number of alternative methods: sequential testing-down LR test statistic and alternative Akaike, Schwarz and Hannan-Quinn information criteria. As the Johansen's approach assumes vector white noise errors, panel [A] of Table 4 reports the *P*-values of the VAR residuals misspecification tests, both at single equation and at system level (respectively in the first five and in the last column). Overall the diagnostic tests suggest that first-order VAR representation of the dynamic relationships among the variables of interest is data congruent and as such, it can be used as the starting point of the cointegration analysis.

Table 4 about here

Panel [B] of Table 4 reports the trace and maximum eigenvalues of the cointegration rank tests. The results suggest four cointegrating relationships among the five inflation forecast groups. This outcome is not surprising, given the evidence of the pairwise cointegration results reported in Table 1. Cointegrating vectors possess an invariance property: because a cointegrating vector for a subsystem is also a cointegrating vector for a larger system, multiple cointegrating vectors in a large system may be identified by finding single cointegrating vectors in subsystems. Therefore, if we assume that the same long run relationship previously detected are still valid at multivariate level – i.e. that all pairs of forecasts cointegrate – we can impose twelve just-identifying restrictions, as we exclude three variables from each of the four long run relationships.[4] There are two possible ways to undertake this: *(a)* forecasts of all groups but one are pairwise cointegrated with that group;[5] *(b)* all forecasts groups are sequentially cointegrated. The choice of scheme *(a)* or *(b)* implies the same number of exact identification restrictions and, as such, cannot be tested.

In the bivariate analysis, we note that business economist forecasts (*be*) are always weakly exogenous. So there is no point in assuming *ex ante* a given sequence in which the different forecasts are linked to each other, as would be needed with scheme *(b)*. Therefore, we implement the scheme *(a)* and report the corresponding long run β parameters in panel [A] of Table 5. Results are remarkably similar to those obtained in the bivariate subsystems involving *be* (see the last column of Table 2).

Table 5 about here

[4] Exact identification of r cointegrating vectors (here $r=4$) requires the imposition of $r-1$ independent restrictions on each vector (here, twelve restrictions). Only overidentifying restrictions – i.e. those exceeding $(r-1)\times r$ – can be tested.
[5] In literature, applications of “in pair” identification schemes range from modelling the spreads cointegration among Treasury bill yields (see e.g. Hall et al, 1992), to the analysis of the macroeconomic fluctuations (see e.g. King et al, 1991), and to the study of data revisions through cointegrated vintages (see e.g. Patterson, 2000 and 2003).

The identification scheme *(a)* for the long run gives specific[6] estimates of the loading parameters whose significance indicates that it is the *be*'s forecasts that lead the others. The followers learn directly from the leader, and independently of the other learning agents. This can be verified by testing for *be* weak exogeneity restrictions together with the independence of the other adjustment mechanisms, i.e. each learning agent only accounts for the disequilibria between her forecasts and those of the leader and not for the other unbalances. The independence of learning hypothesis imposes 16 overidentifying zero restrictions on the loading parameters matrix, i.e. the 4 implied by the *be* exogeneity plus further 12 restrictions on the off-diagonal parameters of the loading factors matrix.

The estimated results of the restricted VECM are reported in panel [B] of Table 5. As the restrictions are largely not rejected (the p-value is 0.7363), efficiency is improved without substantial changes in long run parameter estimates (see panel [A] and Table2). Overall, estimates in panel [B] of Table 5 depict learning dynamics consistent the theoretical VECM (9) representation of Section II. In fact, weakly exogenous *be* agents behave as professional forecasters and two groups of agents (*gp* and *ae*) can be classified as passive learners, given that their loading factors are significantly lower than those of *fd* and *tu* which, for this, can be classified as active learners.

The residuals series of the VECM model estimated in panel [B] of Table 5 also corroborate the prediction of positively correlated errors we made on the basis of the theoretical model in Section II: cross-correlations coefficients for each group of agents with respect to the professional *be* are always positive and quite large (well above 0.5). This fact, together with *be* forecasts weak exogeneity, suggest the relevance of conditioning on *be* time series the learning agents dynamics in order to improve efficiency. This will be undertaken in the next section, while also relaxing the linearity assumption.

III.3: Nesting models with alternative nonlinear speeds of adjustment:

[6] In fact, choosing one scheme of identification results in different estimates and significance of the loading parameters which can be better interpreted under one scheme than the other; see e.g. Patterson (2003) for further explanations on this point.

So far we have assumed that the learning agents' absorption rates are linear but Carroll (2003) also suggests the absorption, or adjustment, rates are likely to be non-linear. Nonlinear adjustments may take different forms. For example, asymmetric threshold autoregressive (TAR) and momentum threshold autoregressive (MTAR) models are analyzed, among the others, in Enders and Granger (1998) and in Enders and Siklos (2001); smooth transition autoregressive (STAR) models are e.g. used in Kapetanios et al (2003).

Following Enders and Siklos (2001), we consider a TAR alternative specification of the error-correction model, in which the residual $\hat{u}_{i,j,t}$ of any bivariate static Engle-Granger's cointegrating regression of the i^{th} against j^{th} inflation forecast group (see the results below the diagonal in Table 1) follows a TAR dynamics: $\Delta\hat{u}_{i,j,t} = I_{i,j,t}\ \alpha^{+}_{i,j}\ \hat{u}_{i,j,t-1} + (1 - I_{i,j,t})\ \alpha^{-}_{i,j}\ \hat{u}_{i,t-1} + \varepsilon_{i,t}$; where subscripts i and j = 1, 2, ..., 5 identify any pair of forecaster groups, subscript t is time, $I_{i,j,t}$ is the Heaviside indicator such that: $I_{i,j,t}$ = 1 if $\hat{u}_{i,j,t-1} \geq \tau_{i,j}$ and $I_{i,j,t}$ = 0 if $\hat{u}_{i,j,t-1} < \tau_{i,j}$, and $\tau_{i,j}$ is the threshold for the bivariate relationship between the i^{th} forecast group against the j^{th} forecast group. Of course, the Engle-Granger (linear) cointegration approach is a special case in which $\alpha^{+}_{i,j} = \alpha^{-}_{i,j}$. The figures below the diagonal in Table 6 are the $\phi_{i,j}$ (non-standard F) statistic for the joint hypothesis $\alpha^{+}_{i,j} = \alpha^{-}_{i,j} = 0$ (i.e. of no cointegration). Under the alternative hypothesis of TAR cointegration, we test for symmetry, i.e.: $\alpha^{+}_{i,j} = \alpha^{-}_{i,j}$ reporting the corresponding p-values of the standard F distribution above the diagonal in Table 6.

Table 6 about here

Overall, results in Table 6 support the view that in the bivariate context the adjustment process of the inflation forecasts towards the target follows an asymmetric dynamics with respect to an estimated threshold quite close to (but not) zero.[7] In fact, $\phi_{i,j}$ test statistics always reject the null

[7] We also tested for nonlinear cointegration using STAR models (see Kapetanios *et al.* 2003), where the (smoothed) speed of the adjustment process is slower when the EG cointegrating residual is close to zero. Results were inconclusive, suggesting that such dynamics is not appropriate in the present context.

of no cointegration (only at 10% in just one case in ten), and with very few exceptions the symmetry F test p-values detect significantly different adjustment parameters below/above the threshold. Thresholds super-consistent estimates are in the -0.235 / 0.335 range, and are obtained by searching for the $\tau_{i,j}$ value (over the 20% trimmed $\hat{u}_{i,j,t}$ data) which minimizes the sum of squared errors from the fitted model, see Chan (1993).

The multivariate extension of the bivariate nonlinear approach would imply a threshold VECM in which the threshold variable itself is determined by the cointegrating vectors that, in turn, must be estimated. This data-intensive approach cannot be tackled in our small sample of data which prevents us from obtaining reliable "full information" estimates of the nonlinear model. Therefore, we follow the two-step procedure recommended of Balke and Fomby (1997) and supported by the findings of Enders and Siklos (2001). In the first step, the cointegration rank and the long run parameters of the model are estimated with Johansen's approach (results are summarized in Tables 4 and 5 of Section III.2). In the second step, both threshold and asymmetric adjustment parameters are efficiently estimated in a partial system of four equations (one for each *gp, ae, fd* and *tu* groups of agents) conditioned on *be* forecast changes $\Delta E_t^{be}(\pi_{t+1})$ without loss of relevant information.

The model FIML estimated at the second step may be seen as the nonlinear extension of the theoretical model (10), where each equation for the i^{th} learning agent forecast changes $\Delta E_t^{i}(\pi_{t+1})$ is explained by an asymmetric equilibrium-correction mechanism (*ecm*) based on the parameters $\hat{\beta}_i$ and $\hat{c}_i$ (see Table 5, panel [B] "long run parameters") which lead to the equilibrium correction series:

$$e\hat{c}m_{t-1}^{i} = [\, E_{t-1}^{i}(\pi_t) - \hat{\beta}_i E_{t-1}^{be}(\pi_t) - \hat{c}_i \,] \quad i = gp, ae, fd, tu \tag{12}$$

The resulting four-equation conditional VECM with TAR dynamics is fully specifies as:

$$\begin{aligned} \Delta E_t^{gp}(\pi_{t+1}) &= \eta_{gp}[\,\Delta E_t^{be}(\pi_{t+1})] - \alpha_{gp}^{+}\; I_{gp,t}[\,ecm_{t-1}^{gp}] - \alpha_{gp}^{-}(1 - I_{gp,t})[\,ecm_{t-1}^{gp}] + \xi_t^{gp} \\ \Delta E_t^{ae}(\pi_{t+1}) &= \eta_{ae}[\,\Delta E_t^{be}(\pi_{t+1})] - \alpha_{ae}^{+}\; I_{ae,t}[\,ecm_{t-1}^{ae}] - \alpha_{ae}^{-}(1 - I_{ae,t})[\,ecm_{t-1}^{ae}] + \xi_t^{ae} \end{aligned} \tag{13}$$

$$\Delta E_t^{fd}(\pi_{t+1}) = \eta_{fd}[\Delta E_t^{be}(\pi_{t+1})] - \alpha_{fd}^{+} \; I_{fd,t}[ecm_{t-1}^{fd}] - \alpha_{fd}^{-}(1 - I_{fd,t})[ecm_{t-1}^{fd}] + \xi_t^{fd}$$
$$\Delta E_t^{tu}(\pi_{t+1}) = \eta_{tu}[\Delta E_t^{be}(\pi_{t+1})] - \alpha_{tu}^{+} \; I_{tu,t}[ecm_{t-1}^{tu}] - \alpha_{tu}^{-}(1 - I_{tu,t})[ecm_{t-1}^{tu}] + \xi_t^{tu}$$

where for i = *gp, ae, fd, tu* we define: $I_{i,t}$ = 1 if $e\hat{c}m_{t-1}^{i} \geq \tau_i$; and group-specific parameters $\tau_i, \eta_i, \; \alpha_i^{+}, \alpha_i^{-}$ are to be estimated. Results are reported in column (1) of Table 7. As in the univariate context, τ_i estimates are grid-searched over the 20% trimmed values of the long run disequilibria $e\hat{c}m_{t-1}^{i}$; the retained values are those which maximize the level of the likelihood of the whole system of equations.

Table 7 about here

The asymmetric adjustment towards the long run of each learning agent depicts the two-category stylized behavior discussed in Section II: the passive and the active groups of agents. The first category includes general public (*gp*) and academic economists (*ae*) whose forecasts show slow speeds of adjustment towards the professional/leader target (*be*). Asymmetry entails that speeds of adjustment are even slower when the forecasts of the passive agents are above the *be* target by a positive wedge τ (0.486% for *gp* and 0.114% for *ae*).

The second category includes finance directors (*fd*) and trade unionist (*tu*) who are probably more keen to update their inflation expectations to inform their wage and price-setting and bargaining activity. However, the active learning agents' asymmetries are considerably more heterogeneous than those of the passive agents. In fact, finance directors asymmetries are not significant, while trade unionists maximize their asymmetric behavior: they update very quickly their forecasts towards those of professional/leader *be* only when their inflation forecasts are below those of *be*, while barely behave as passive agents when their inflation forecasts are above those of *be* by more than 0.189%.

Following the general-to-specific approach, the VECM model (13) with TAR dynamics is the general unrestricted model in which a number of specific linear models with alternative speeds of adjustment are nested. Therefore, we can assess the overall significance of the asymmetric behavior by comparing the likelihood of the VECM model (13) estimates in column (1) of Table 7 with that of the “4-speed linear” model in column (2) which is nested in model (13) under four joint restrictions H_0: $\alpha_i^+ = \alpha_i^- = \alpha_i$ ($i = gp, ae, fd, tu$), which are a sort of asymmetry test in the context of a multivariate system. It is worth noting that the conditional model estimated in column (2) corresponds to the linear model (10) of Section II and that, the speed of adjustment estimates in column (2) are equal to those of VECM (9) reported in panel [B] of Table 5 (“loading parameters”), while the standard errors in brackets are slightly lower because the valid conditioning of VECM (9) entails efficiency.

The likelihood ratio (LR) test statistic in the lower part of column (2) rejects the null hypothesis of four (agent-specific) speeds of adjustment identified by the linear model (10). Therefore, as discussed at the end of Section II, nonlinearities matter to better explain the dynamic behavior of the whole system of learning agents.

Columns (3) and (4) in Table 7 report the estimates of additional restrictions to the assumption of linear absorption rates and, thereby, further assess the learning dynamics. In particular the linear model estimated in column (3) assumes that the active/passive learning process entails only two speeds of adjustment: one for the passive agents (*gp* and *ae*) and the other for the active *fd* and *tu*. Finally, the linear model estimated in column (4) collapses the learning process in a single speed of adjustment and, in this way, abandons the assumption of agents learning at different speeds.

Results are unequivocal and can be summarized as follows. Firstly, nonlinearities matter to the learning dynamics (see LR test outcomes in column 2): both passive and active agents behave in a significantly different way depending on the state of their inflation expectations with respect to that of the professional’s in the previous period. Secondly, assuming a linear dynamics the four-groups of learning agents identified by our analyses can be split in only two categories (see LR test outcomes in column 3): active and passive the learning. The clear rejection of the LR test in the lower part of column (4) supports strongly the view that, even in the very restrictive linear framework, learning agents are differently active when accounting for professional forecasts.

In addition, the adjustment mechanism, in the short run the conditioning effect of the simultaneous changes in *be* inflation forecasts are always close (and never significantly different) to one: followers tend to move the direction of their inflation forecasts immediately and of a very similar amount of that of professionals. This is robust for all the alternative linear/nonlinear and equal/different speeds of adjustment models. The conditioning *be* effect should proxy for the short-run reactivity of learning agents to the permanent innovations in the inflationary process expected by professional forecasters.

If this is the case, residuals' correlation coefficients of the conditional models in Table 7 measure the correlation between the learning agents' idiosyncratic shocks to inflation forecasts. Though smaller than the correlations discussed at the VECM estimation stage (in Table 5) because here the permanent innovations in the inflationary process expected by professional forecasters have been extracted through conditioning, they are still quite high (in the 0.4-0.5 range) denoting a sort of consensus of the learning agents in assessing future inflation shocks, e.g. due to pre-announced monetary and fiscal policies (not reported results are available upon request to the authors).

III.4: Discussion of results:

The bivariate and multivariate analyses indicate clearly that the business economists evolve independently. It establishes the business economists unequivocally as the professional forecaster from whom others base their inflation expectations. Though the multivariate analysis suggests that learning agents form their expectations by observing the business economists directly, the bivariate analysis suggests that learning agents may also partly observe the professional's forecasts via other learning agents. It latter is unsurprising as Carroll (2006) argues that households not only observe the professional's forecasts via the news media but also through social interaction with other households. On the one hand, the general public's expectations adjust to all the other learning agents' expectations while the academic economists only adjust to the business economists. Trade unionists adjust to both financial directors and academic economists and the financial directors adjust to the academic economists.

The empirical analyses also indicate that there is a slightly greater than one-to-one long-run relationship between professional's and the learning agents' forecasts. The learning agent may not be entirely clear the type of inflation the professional is forecasting. For example, is it Retail Price Index (RPI) or Consumer Price Index (CPI)? Indeed, different segments of the population may be affected by raising prices differently due to their consumption patterns. Hence, they may prefer to simply use the professional's forecasts as a reference point and erring slightly on the caution by setting a slightly greater than one ratio.

An important purpose of the present analysis is to identify and distinguish between 'active' and 'passive' agents as defined by their respective absorption rate. We identify trade unions and financial directors as the 'active' learners with absorption rates around 0.64 and 0.66 respectively. It is unsurprising that both these agents have relatively high absorption rates. Trade union officials are frequently involved in wage negotiations on behalf of their members, while financial directors may be engaged in both wage and price-setting on behalf of their firm and also they would be interested in their firm's relative prices (the firm's price relative to aggregate price). Hence, they need to form inflation expectations readily and frequently.

The general public and academic economist, on the other hand, constitute the passive learners. The general public may choose to update their expectations less frequently due to the costs of acquiring the relevant information. In the case of academic economists, it may seem perplexing in the first instances that they adjust their expectations to the business economists. On further reflection it may be less surprising. Most academic economists, even though they may have the expertise, may not develop formal models or, more importantly, update constantly the relevant information required to forecasts inflation. They too may rely on the forecasts of business economists whose very job is to undertake this.

The non-linear analyses try to establish whether the learning agent absorb asymmetrically. We find that the learning agents, with one exception, follow a TAR adjustment process. In the case of the passive learners, they absorb faster when their expectations are below the ‘anchored’ value of the business economists. The estimated threshold is positive, albeit small. This is consistent with the arguments purported in Akerlof et al (1996 and 2000). They argue that ignorance would be more costly for households during periods of high inflation. These periods have greater adverse effect on households’ real wages than low inflation periods. Hence, they would update their expectations more readily during these periods with the view of adjusting their behavior. Amongst the active learners, the trade union officials display a similar asymmetric behavior. The trade unions, for reasons similar to the general public, would be more concerned to update their inflation expectations during periods of high inflation. Conversely, financial directors absorb the professional’s forecasts symmetrically. Financial directors should be equally concerned about high and low inflation rates. During periods of high inflation rates they would be concerned with rising costs, while during periods of low inflation they would be concerned about rising relative prices.

IV: Summary and Concluding Remarks:

An important recent theory explaining how households form inflation expectations is the ‘sticky information expectations’ model. The underlining inattentive behavior of learning agents has been used to explain inflation dynamics and the implications for the pursuit of disinflationary has also been considered. The purpose of the present paper is to extend the microfoundations of how households form inflation expectations. We consider how different agents learning agents representing different segments of the population may update their inflation expectations. We consider two stylized learning agents – ‘active’ and ‘passive’ learners, as defined by their absorption rate as they observe the professional’s forecasts.

We outline a theoretical model which accounts for learning agents with different absorption rates which extends the microfoundations of ‘sticky information expectations’ and motive the ensuing empirical analysis. The empirical investigation uses a unique dataset complied by Barclays

Basix based on surveys of various sections of the UK population. The results identify the business economists as the professional forecaster as their forecasts evolve independently. The four learning agents update their inflation expectations by absorbing the business economist's forecasts. The results also suggest that some of them may observe the professional's forecasts via fellow learning agents. Hence, learning via social interaction may also take place. The results showed that the absorption rates, with one exception, are asymmetric. It suggests that higher inflation expectations would increase the rate of absorption.

The different absorption rates of different segments of the population explain the heterogeneity found amongst different agents. Disagreements amongst different agents' expectations simply reflect the different rates by which various agents may observe relevant information and update their expectations rather than any underlying theory of inflation dynamics. Undoubtedly, this also raises a question about inflation dynamics: are absorption rates of active learners (trade unionists and financial directors) more important in determining inflation dynamics? The active learners identified in the present study play a crucial role in wage and price-setting behavior. These are issues that modellers of inflation dynamics based on 'sticky information expectations' need to consider.

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Tab. 1 – Inflation forecasts series by group of agents over the 1986q4-2005q1 period

Group [a]:	*gp*	*ae*	*fd*	*tu*	*be*
Univariate analysis:					
Levels' unit root test, *p-values* [b]	0.5305	0.7533	0.6901	0.6835	0.7146
First differences' LM test, *p-values* [c]	0.4868	0.8950	0.7250	0.5268	0.9471
Bivariate cointegration: [d]					
gp		41.67	38.53	38.69	36.63
ae	-2.85		28.66	32.17	20.70
fd	-5.50	-2.94		35.82	29.45
tu	-3.07	-2.86	-6.08		35.65
be	-5.23	-2.89	-3.26	-3.23	

([a]) The surveyed five groups of agents are: general public (*gp*), academic economist (*ae*), finance director (*fd*), trade unionist (*tu*), and business economist (*be*).

([b]) Dickey and Fuller (1979) test equation truncation lags are set by applying the MAIC (Modified AIC) selection rule of Ng and Perron (2001).

([c]) Godfrey (1988) 4th order autocorrelation LM test for inflation forecasts in first differences.

([d]) Below the diagonal, Engle and Granger (1987, EG) unit-root test on the residual of the two-in-two regression: $E_t^j(\pi_{t+1}) = c + \beta\ E_t^i(\pi_{t+1}) + u$, where *i* is the row-group and *j* the column-group (truncation lags of the residuals unit-root test equation are MAIC-selected). EG 1%, 5% and 10% critical values: -3.77, -3.17 and -2.84 (see Engle and Granger, 1987, Table II).
Above the diagonal, Johansen (1995) trace test for $r = 0$; r is the cointegration rank in the VAR for $E_t^i(\pi_{t+1}), E_t^j(\pi_{t+1})$ with intercept restricted to lie in the cointegration space; 5% critical values: 20.26 (see MacKinnon *et al.*, 1999). VAR lag-order is selected on the basis of Schwarz Information Criterion, see Ivanov and Kilian (2005).

Tab. 2 – Estimates of the bivariate cointegration parameters

Group [a, b]	*gp*	*ae*	*fd*	*tu*	*be*
gp		0.997	1.063	0.937	1.179
ae	0.935		1.061	0.938	1.174
fd	0.980	1.048		0.885	1.100
tu	0.865	0.917	0.868		1.242
be	1.041	1.149	1.089	1.223	

([a]) Group labels: general public (*gp*), academic economist (*ae*), finance director (*fd*), trade unionist (*tu*), and business economist (*be*).

([b]) Below the diagonal, the OLS β estimates of the two-in-two EG regressions: $E_t^j(\pi_{t+1}) = c + \beta\ E_t^i(\pi_{t+1}) + u$, where *i* is the row- and *j* the column-group.
Above the diagonal, the β estimates of the two-in-two $E_t^i(\pi_{t+1}), E_t^j(\pi_{t+1})$ Johansen cointegrating vector (1 -β) normalized for the i^{th} group in the row.

Tab. 3 – Estimates of the loading parameters in bivariate VECMs

Group [a, b]	*gp*	*ae*	*fd*	*tu*	*be*
gp		0.5094**	0.4554**	0.3996**	0.3867**
ae	0.1105		0.2346	0.0022	0.4882**
fd	0.1040	-0.4142*		0.0047	0.7087**
tu	0.0132	-0.6839**	-0.7885**		0.7232**
be	0.0536	0.1109	0.1587	0.1286	

([a]) Group labels: general public (*gp*), academic economist (*ae*), finance director (*fd*), trade unionist (*tu*), and business economist (*be*).

([b]) Each estimate below the diagonal refers to the loading parameter α_j of the group of agents in the row from a bivariate VECM (11) whose long run relationship is normalized for the i^{th} group in the column; the symmetrical estimate above the diagonal refers to α_i in the same VECM. ** and * respectively reject at 1% and 10% the null that the loading parameter estimate is zero; in other terms, any not significant estimate classifies as weakly exogenous the group of agents in the row, whose forecasts lead those of the group of agents indicated in the column.

Tab. 4 – Multivariate analysis: VECM diagnostics and cointegration testing

	Group/equation [a]					
[A] Misspecification tests, p-val.	*gp*	*ae*	*fd*	*tu*	*be*	*sys*
Autocorrelation LM of						
1st order	0.2666	0.6778	0.6054	0.5624	0.8956	0.2303
5th order	0.7178	0.7158	0.8154	0.7621	0.9735	0.8086
White heteroskedasticity	0.1832	0.7431	0.1991	0.3258	0.169	0.0001
ARCH test of						
1st order	0.1100	0.0032	0.1621	0.0005	0.0810	0.0199
5th order	0.0000	0.0174	0.0029	0.0189	0.4082	0.0553
Normality	0.0539	0.0331	0.0723	0.2463	0.0431	0.2013
[B] Cointegration test H_0:	*Eigenvalue*	*Trace statistic*	*P-val.* [b]	*Max-eigenval.*	*P-val.* [b]	
rank = 0	0.4515	135.19	0.0000	43.84	0.0032	
rank ≤ 1	0.4002	91.35	0.0000	37.31	0.0030	
rank ≤ 2	0.3495	54.04	0.0002	31.39	0.0021	
rank ≤ 3	0.2365	22.65	0.0230	19.70	0.0120	
rank ≤ 4	0.0397	2.96	0.5886	2.96	0.5886	

([a]) Groups: general public (*gp*), academic economist (*ae*), finance director (*fd*), trade unionist (*tu*), and business economist (*be*). There is an equation for each group, the last column is for the system as a whole (*sys*).

([b]) MacKinnon et al (1999) p-values

Tab. 5 – Multivariate analysis: imposing cointegration restrictions

[A] Long run relationships [a, b]	*#1*	*#2*	*#3*	*#4*
gp	1	0	0	0
ae	0	1	0	0
fd	0	0	1	0
tu	0	0	0	1
be	**-1.1855**	**-1.1911**	**-1.1124**	**-1.2559**
const	-0.6508	**0.5455**	**0.2636**	**0.4884**

[B] *be* exogeneity and feedback effects independence [a, b, c]

long run relationships:	*#1*	*#2*	*#3*	*#4*
gp	1	0	0	0
ae	0	1	0	0
fd	0	0	1	0
tu	0	0	0	1
be	**-1.1714**	**-1.1752**	**-1.1040**	**-1.2492**
	(0.0734)	(0.0353)	(0.0270)	(0.0396)
const	**-0.7025**	**0.4973**	**0.2341**	**0.4687**
	(0.2789)	(0.1341)	(0.1024)	(0.1504)
loading parameters α:				
gp	**0.4115**	0	0	0
	(0.0456)			
ae	0	**0.4661**	0	0
		(0.0721)		
fd	0	0	**0.6408**	0
			(0.0850)	
tu	0	0	0	**0.6617**
				(0.0817)
be	0	0	0	0
correlation coefficients [d]	0.5670	0.8773	0.8450	0.6853

([a]) In bold, 5% significant estimates.

([b]) Groups: general public (*gp*), academic economist (*ae*), finance director (*fd*), trade unionist (*tu*), and busi-ness economist (*be*).

([c]) Figures in brackets are parameter standard errors. Overall, the 16 zero overidentifying restrictions imposed to loading parameters are not rejected (p-value = 0.7363).

([d]) Each column reports the estimate of the coefficient of correlation with respect to *be* equation's residuals of, respectively, *gp*, *ae*, *fd* and *tu* equations' residuals.

Tab. 6 –TAR asymmetric cointegration test [a]

Group [b, c]	*gp*	*ae*	*fd*	*tu*	*be*
gp		0.0436	0.0043	0.0091	0.0254
ae	10.16		0.0300	0.0795	0.0282
fd	9.70	6.70		0.0003	0.3359
tu	7.19	16.57	17.15		0.0768
be	7.88	10.40	13.85	7.25	

([a]) Following Chan (1993), superconsistent thresholds estimates are obtained by searching over the 20% trimmed residuals of the EG approach, and taking the τ yielding the lowest sum of squared errors from the fitted model.

([b]) Group labels: general public (*gp*), academic economist (*ae*), finance director (*fd*), trade unionist (*tu*), and business economist (*be*).

([c]) Below the diagonal there are the no-cointegration ϕ test statistics on any pair of EG static regression residuals which lead to below-the-diagonal Table 1 results, see Enders and Siklos (2001, ES); ϕ 1%, 5% and 10% critical values are respectively: 9.58, 7.10 and 6.00, on the basis of ES, Tab. 5 p. 172. The truncation lag is set following the testing down approach of Ng and Perron (1995) from a max-lag = 4, and keeping the higher augmentation parameter estimate when 10% significant; the resulting truncation lag was zero with few exceptions.
Above the diagonal there are the standard (under cointegration) F statistic p-values of equal adjustment speed (symmetric adjustment and linear context) null hypothesis.

Tab. 7 – FIML estimates of alternative conditional VECMs

			TAR dynamics (1)		4-speed linear (2)		2-speed linear (3)		1-speed linear (4)	
		τ	*estimate*	*s.e.*	*estimate*	*s.e.*	*estimate*	*s.e.*	*estimate*	*s.e.*
α_{gp}	+	0.486	0.2470	0.1052	0.4115	0.0450	0.4201	0.0414	0.4725	0.0422
	–		0.4364	0.0477						
α_{ae}	+	0.114	0.2332	0.1254	0.4661	0.0708				
	–		0.5382	0.0832						
α_{fd}	+	-0.120	0.6883	0.0994	0.6408	0.0836	0.6452	0.0630		
	–		0.4897	0.1437						
α_{tu}	+	0.189	0.3830	0.1308	0.6617	0.0805				
	–		0.7769	0.0985						
η_i	*gp*		0.7448	0.1201	0.7135	0.1201	0.7103	0.1200	0.6964	0.1469
	ae		1.0216	0.0639	1.0307	0.0652	1.0333	0.0652	1.0299	0.0687
	fd		0.9305	0.0670	0.9355	0.0689	0.9349	0.0688	0.9476	0.1019
	tu		0.8196	0.1041	0.8452	0.1050	0.8473	0.1048	0.8726	0.1209
	LogL		58.78		52.91		52.63		46.07	
restriction:					*(2) vs (1)*		*(3) vs (2)*	*(3) vs (1)*	*(4) vs (3)*	
	LR				11.73		0.57	12.30	13.12	
	d.o.f.				4		2	6	1	
	P-val				0.0195		0.7512	0.0556	0.0003	

Fig. 1 – Inflation forecasts one-year ahead by group