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# Inflation Expectations and the Two Forms of Inattentiveness

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## Inflation Expectations and the Two Forms of Inattentiveness


## Abstract

The purpose of the present paper is to investigate the structure and dynamics of professionals' forecast of inflation. Recent papers have focused on their forecast errors and how they may be affected by informational rigidities, or inattentiveness. In this paper we extend the existing literature by considering a second form of inattentiveness. While showing that both types of inattentiveness are closely related, we focus on the inattentiveness that forecasters face when undertaking multi-period forecast and, thereby, the expected momentum of inflation. Using number survey-based data for the US and UK, we establish a new structure for the professional's forecast error with direct implications for the persistence of real effects



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# I. Introduction

Most models explaining aggregate outcomes, such as business cycles and inflation dynamics, include professionals' forecasts. Nevertheless, until recently most macroeconomic models simply assumed that these forecasts were formed rationally with full information. In a recent innovative paper, Fuhrer (2013) includes actual survey expectations of professional forecasters, rather than the usual stylized rational expectations, in a DSGE model and finds that it performs considerably better by exhibiting strong correlations to key macroeconomic variables. Consequently, he proposes methods for endogenizing survey expectations in general equilibrium macro models for improving monetary policy. Clearly, this asks for a greater understanding of the nature and dynamics of survey expectations of professionals. Hence, the present analysis establishes the dynamics of their forecast error which enable clearer insights into how to generate better general equilibrium macro models and understanding actual inflation dynamics and persistence.

Recent models have focused on deviations from full-information rational expectations due to informational rigidities (see, for example, Mankiw and Reis (2002), Woodford (2003) and Sims (2003)). The different forms of information rigidities, or agent's inattentiveness, form the basis of the competing rational expectations models with informational frictions. Firstly, there is the sticky-information model of Mankiw and Reis (2002). Here the agents update their information set sporadically. Agents do not continuously update their expectations but choose an optimal time at which to be inattentive, that is they receive no news about the economy until it is time to plan again. The slow diffusion of information is due to the costs of acquiring information as well as the costs of reoptimization. Such sticky information expectations have been used to explain not only inflation dynamics (Mankiw and Reis, 2002) but also aggregate outcomes in general (Mankiw and Reis, 2006) and the implications for monetary policy (Ball et al., 2005). The second type of informational friction models (Woodford (2003) and Sims (2003)) argue that agents update their information set continuously but can never fully observe the true state because of signal extraction problems. Importantly, as pointed out by Coibion and Gorodnichenko (2012), henceforth CG, both types of model predict quantitatively similar forecast errors.

The purpose of the present paper is to consider these rational expectations models with information frictions in the light of a new, or additional, form of inattentiveness. Using the simple framework suggested in CG, where forecast errors are investigated empirically as deviations from the full-information rational expectations, we consider two forms of inattentiveness. In the existing literature the standard inattentiveness arises when the agents try to revise or update their expectations formed in the previous period. We also consider an additional form of inattentiveness. Typically, in each period, professional forecasters not only revise their forecast from the previous period but also form multi-period forecasts. The second form of inattentiveness arises when the agent is trying to distinguish the forecasts between the different horizons.

We show that the first form of inattentiveness is a necessary condition for the second form to exist. We also argue that establishing the second form and distinguishing between the two forms of inattentiveness sheds valuable insights into the type of information rigidities that causes agents' inattentiveness and, consequently, which rational expectations model with informational frictions is likely to prevail. CG suggests a number of interesting empirical tests to differentiate between the two sources of information rigidity. The present analysis also introduces another test to establish whether imperfect or sticky information prevails.

We use different survey data of professional forecasters for both the USA and the UK. These surveys ask a number of professionals their forecasts over alternative horizons, hence, allowing for interesting comparisons. We find strong evidence for both forms of inattentiveness.  A new structure for the professional forecaster's inflation forecast error with clear implications for inflation dynamics and also the aggregate economy is therefore indicated.

The structure of the paper is as follows. The next section outlines the simple theoretical framework which forms the basis for empirical analysis. Section III outlines the main data and econometric issues raised by our theoretical framework. Section IV reports the estimation results. Finally, Section V outlines the summary of the key results and draws the concluding remarks. Details about the forecasting process are given in Appendix A1, while alternative inflation forecast measures together with other variables of interest are described in Appendix A2.

## II. The Two Forms of Inattentiveness: The Theoretical Framework

When professional forecasters form inflation forecasts, they attempt to revise or update forecasts from the previous period. Using the most recently available information, they form full-information rational expectations (hereafter referred to as FIRE). However, due to informational rigidities, agents are inattentive and their forecasts invariably deviate from FIRE. Such deviations arise, for example, when forecasters revise their forecast for the period $t+h$ while updating their information set from the previous to the current period (i.e. from $t-1$ to $t$).  We refer to this as the first form of inattentiveness.

Typically, professional forecasters also form multi-period inflation forecasts. Such forecasts capture the expected momentum of actual inflation, so if a shock occurs in the current period ($t$), the forecaster has to determine the propagation of this shock to inflation. Will the shock just last into the next forecast period ($t+h$) or transmit beyond ($t+h+1$)? One way to think this issue is the short-run Phillips curve trade-off. Therefore, for instance, if there is a shock that leads to a reduction in unemployment, the forecaster needs to determine the expected momentum that this would have on actual inflation. The ability to observe and distinguish the propagation of such shocks leads to the second form of inattentiveness.

Figure 1 illustrates both forms of inattentiveness:

***Figure 1 [about here]***

FIRE is depicted in the upper part of Figure 1. At time *t* forecasters make the one-step ahead forecast, $F_t\ (\pi_{t+1})$, using all available and updated information:

$$E_t\ (\pi_{t+1}) = E_t^{FIRE}\ (\pi_{t+1}) = \pi_{t+1} + \varepsilon_{t+1} \tag{1}$$

and the forecasted inflation rate (where *h*=1) is FIRE. The middle part of Figure 1 highlights the effect of the first form of inattentiveness on the inflation forecast: $F_t\ (\pi_{t+1})$ (weighted by *λ*, where $0 \le \lambda \le 1$). Finally, the lower part of Figure 1 shows the effect on the forecast (weighted by $\phi$ parameter, $0 \le \phi \le 1$) of the second form of inattentiveness. The additional deviation from FIRE depends on the past (in *t-1*) forecast of inflation momentum. Intuitively, this second effect further exacerbates the effect of the first form of inattentiveness. The closer $\phi$ is to one, the less relevant is the expected propagation of the past shock (in *t-1*) to the one- and two-steps ahead forecast.

Importantly, the second form of inattentiveness also gives valuable insights into the nature of information rigidity. The question is: what generates this type of information rigidity and, therefore, which form of rational expectations model with information frictions? First and foremost, the existence of the first form of inattentiveness is a necessary condition for the second form to exist. The second type of inattentiveness takes place when forecasters are trying to form multi-period forecasts in a particular period (for example, period *t*). The only reason forecasters are unable to form forecasts that distinguishes the different forecast horizons is because they face a signal extraction problem due to noisy information in the period *t*. Hence, the existence of the second form of inattentiveness clearly suggests that information rigidities arise due to imperfect information.

Formally, following the CG framework, we can generalize to the horizon *h* the first form of inattentiveness depicted in Figure 1 as:

$$F_t\ (\pi_{t+h}) = (1-\lambda)E_t\ (\pi_{t+h}) + \lambda F_{t-1}(\pi_{t+h}) \qquad (2)$$

The professional forecaster tries in the current period (*t*) to form an inflation forecast for the *h* period ahead. In the sticky information model $\lambda$ denotes the probability that no new information is acquired, while in the imperfect information case it captures the level of noise. When forecasters are unable to forecast FIRE, they resort to their previous inflation forecast for period *t+ h*. As shown in CG, the forecast errors are derived by substituting (1) into (2) and rearranging as follows:

$$\pi_{t+h} - F_t\ (\pi_{t+h}) = \frac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t+h}) - \varepsilon_{t+h} \qquad (3)$$

where $\Delta F_t\ (\pi_{t+h}) = [F_t\ (\pi_{t+h}) - F_{t-1}(\pi_{t+h})]$.

As highlighted above, the second form of inattentiveness arises only when the first form is present.[1] Having to rely on the agents' forecast momentum in the previous period necessitates the second form of inattentiveness. Now forecasters have to rely on their multi-period forecasts (i.e. on their forecast for period *t+h* made in period *t-1*), and noisy information would restrict their ability to distinguish between the relevant information pertinent for the different horizons.

In a recent seminal paper, Stock and Watson (2007) put forward a general unobservable components (UC) representation of actual inflation rate, where observable inflation rates are composed of two components, a stochastic trend ($\tau_t$) and a stationary factor, or inflation gap ($\xi_t$)[2]:

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[1] In fact, if the first form of inattentiveness does not exist ($\lambda = 0$), equation (3) collapses to: $\pi_{t+h} - F_t\ (\pi_{t+h}) = -\varepsilon_{t+h}$, i.e. any explanatory role is left to unpredictable shocks.

[2] Recent papers have investigated the nature of this stationary component, or inflation gap (see Cogley et al (2010) and Nason and Smith (2013)).

$$\pi_t = \tau_t + \xi_t \tag{4}$$

and $$\tau_t = \tau_{t-1} + \eta_t \tag{4'}$$

where $\eta_t$ denotes a trend innovation. The inflation gap, assumed to be persistent, is modelled for simplicity as a stationary AR(1) process:

$$\xi_t = \rho\xi_{t-1} + \mu_t \tag{5}$$

where $\mu_t$, similar to $\eta_t$, is a martingale difference series. Both $\tau_t$ and $\xi_t$ may be correlated and we assume the persistence parameter $\rho$ to be time-invariant.

If agents choose to form their inflation forecasts by estimating only the stochastic trend component of inflation based on information at time *t*, we have:

$$F_t\ (\pi_{t+h}) = F_t\ (\tau_t) \tag{6}$$

However, current information may also enable them to include the estimate of the stationary component. Hence, equation (6) becomes:

$$F_t\ (\pi_{t+h}) = F_t\ (\tau_t) + \rho^h F_t\ (\xi_t) \tag{6'}$$

Given that: $F_t\ (\pi_{t+\infty}) = F_t\ (\tau_t) + \rho^\infty F_t\ (\xi_t) = F_t\ (\tau_t)$, the long horizon forecasts depend solely on $F_t\ (\tau_t)$, while any short horizon forecasts will depend on the estimates of both stochastic trend and inflation gap. Therefore, the multi-period forecasts made in *t* will be entirely shaped by the estimates, or forecasts, of the inflation gap $F_t\ (\xi_t)$. The main purpose of the multi-period forecasts is to capture the persistent nature of the stationary component of inflation (the inflation gap), or the propagation of any stationary shock.

This distinction can be elaborated in the context of professional forecasters' inattentiveness. As argued earlier, any inattentiveness when forming multi-period forecasts based on current information amounts to an imperfect or noisy information problem. We also assume that professional forecasters are able to distinguish between information which pertains to trend innovation and the inflation gap. Nevertheless, they observe both components imperfectly or as noisy signals. Individual professional forecasters *i* cannot observe $\tau_t$ and $\xi_t$ directly but receive signals $\tau_t^i$ and $\xi_t^i$:

$$\tau_t^i = \tau_t + \omega_t^i \tag{7}$$

$$\xi_t^i = \xi_t + \kappa_t^i \tag{7'}$$

where $\omega_t^i$ and $\kappa_t^i$ denote the respective noise which may be correlated across agents.

When revising or updating their inflation forecasts, the *ith* forecaster forms optimal forecasts, given the information set, which includes both the stochastic trend and inflation gap, via the Kalman filter. The forecaster estimates, or forecasts, the inflation $F_t\ (\pi_t)$ as follows:

$$F_t^i(\pi_t) = G\pi_t^i + (1-G)F_{t-1}^i(\pi_t) \tag{8}$$

where $G$ denotes the Kalman gain, which represents the relative weight placed on new information pertaining to the stochastic trend and inflation gap relative to the previous inflation forecasts. The optimal forecast of inflation is: $F_t^i(\pi_{t+h}) = \rho^h F_t^i(\pi_t)$.

On the other hand, when the *ith* professional forecaster is forming multi-period inflation forecasts and, thereby, the estimated momentum of inflation rates, same forecaster focuses on information relating to the inflation gap. The *ith* agent's forecast of the inflation gap $F_t^i(\xi_t)$ is:

$$F_t^i(\xi_t) = K\xi_t^i + (1-K)F_t^i(\tau_t) \tag{8'}$$

where $K$ denotes the Kalman gain, which now represents the relative weight placed on new information pertaining to the inflation gap, or inflation momentum, relative to the current information enabling the forecasts of the stochastic trend. As shown in Appendix A1, when the inflation gap has high levels of signal to noise ratio, its persistence and auto-correlation coefficient levels are low and the correlation between the permanent and transitory innovations approaches its maximum. Hence, the agent has little, or no, incentive to use past forecasts of inflation gap instead of current forecasts of stochastic trend. In other words, the inflation gap mainly matters when forming multi-period forecasts and the alternative is to forecast no inflation momentum ($F_t^i(\tau_{t+h}) = F_t^i(\tau_t)$). The optimal forecast of the inflation gap is: $F_t^i(\xi_{t+h}) = \rho^h F_t^i(\xi_t)$.

Finally, the Kalman gains *G* and *K* are both formed independently as the professional forecaster is assumed to be able to distinguish information which pertains to trend innovation and the stationary component. Also, in each period, the professional forecaster independently revises and forms multi-period forecasts. When information is perfect we have $G = K = 1$ while, if it is noisy, $G < 1$ and $K < 1$. Therefore, $(1-G)$ and $(1-K)$ measure the amount of information rigidity. So when agents revise their forecasts (i.e. the first form of inattentiveness), both trend innovation and inflation gap matter. On the other hand, when agents form multi-period forecasts, the focus is just on the inflation gap and its persistence. The expected momentum of future inflation rates matters then.

Averaging across agents, the second form of inattentiveness can be incorporated by extending equation (1) as follows:

$$F_t\,(\pi_{t+h}) = (1-\lambda)E_t\,(\pi_{t+h}) + \lambda[\phi F_{t-1}(\pi_{t+h-1}) + (1-\phi)F_{t-1}(\pi_{t+h})] \tag{9}$$

where $\lambda = (1-G)$ denotes information rigidity when revising inflation forecasts, and $\phi = (1-K)$ denotes information rigidity when observing the stationary component and the ability to form multi-period forecasts and momentum of future inflation. Forecasters revert to $F_t\,(\pi_{t+h}) = F_{t-1}(\pi_{t+h-1})$ when unable to do so (i.e. when $\lambda = \phi = 1$), bearing in mind that the second form of inattentiveness is prevalent only when the first form exists.[3] By substituting

[3] Interestingly, within our extended inattentiveness model, the Carroll (2003) epidemiological model can be specified empirically without *ad hoc* assumptions (see p. 276) where expectations are affected by a complete second-form inattentiveness, i.e. $\phi$=1. In fact, under this assumption, our equation (9) becomes: $F_t\,(\pi_{t+h}) = (1-\lambda)E_t\,(\pi_{t+h}) + \lambda F_{t-1}(\pi_{t+h-1})$. Being unable to exploit multistep forecasts information, the inattentive general public only uses the past *h*-steps ahead forecast $F_{t-1}(\pi_{t+h-1})$ rather than $F_{t-1}(\pi_{t+h})$.

equation (1) into equation (9) we can derive the following (extended) forecasts error structure:

$$\pi_{t+h} - F_t\ (\pi_{t+h}) = \frac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t+h}) + \frac{\lambda}{1-\lambda} \phi [F_{t-1}(\pi_{t+h}) - F_{t-1}(\pi_{t+h-1})] - \varepsilon_{t+h} \qquad (10)$$

The forecast error now has an additional term that depicts the second form of inattentiveness. It directly captures the expected inflation momentum formed in *t-1*, such that may arise due to the short-run Phillips curve trade-off and the persistence of the stationary component.

## III: Data and Econometric Issues

In order to empirically assess fully the forecasters' inattentiveness, we have to use a sequence of multi-period forecasts. In the present paper we focus on professional forecasters in the US and UK, using two different US datasets (the Survey of Professional Forecasters, SPF, and the Livingston Survey, LS) and one UK dataset (the Barclays Basix survey, BB).

The datasets differ in five aspects: (i) the frequency at which the survey is conducted (SPF and BB are quarterly, LS is conducted twice a year); (ii) the predicted inflation measures (all three surveys forecast the consumer price index, CPI, while only SPF also forecasts the GDP deflator); (iii) the multi-period forecast horizon (the quarterly SPF predicts from one to six quarters ahead, the semi-annual LS predicts one and two semesters ahead, and the quarterly BB predicts one and two years ahead);[4] (iv) the available level of disaggregation (that is, anonymous agents' forecasts are available for SPF and LS datasets,

[4] Note that the quarterly releases of SPF predictions have forecasted step lengths of one quarter; since our forecast horizon is one year (to be comparable with CG), the use of SPF data to estimate our models implies that its regressors are computed by differences between pair of forecasts which are partially overlapping. The same is not true for the other two surveys (i.e. their regressors do not come from differences between pairs of overlapping forecasts): LS is released by semester, step length of one semester and our forecast horizon is one semester; BB is quarterly, with a step length of one year and our forecast horizon is of one year.

while only averages of agents' forecasts by group are available for BB);[5] (v) the time span covered by the different surveys (SPF forecasts are available from 1965 to date, LS from 1946 to date, and BB from 1986 to 1995).[6]

Such heterogeneity allows for alternative forecast measurements to be exploited, thereby assessing the robustness of the estimation results across different forecast horizons and frequencies, which are characterized by various degrees of overlapping forecast, groups of forecasters and countries. Detailed definitions of the specific time series used in this paper are given in Appendix A2, along with the description of their main statistical features.

The econometric approach raises two main issues: the possible correlation of explanatory variables with the rational expectation forecast error $\varepsilon_{t+h}$ which necessitates instrumental variables estimators such as IV and GMM (see Sargan, 1958, and Hansen, 1982, respectively) and, related with the use of IV/GMM estimators, the need for all the variables to be stationary. Appendix A2 clearly indicates that all the three variables concerned (the forecast error, the forecast revision and the forecast momentum) are generated by stationary data generation processes in all the three surveys. Hence, they are consistent with the statistical properties required by the IV/GMM estimators.

As also noted in CG, the average (across agents) forecast revisions at time *t* may be affected by a nonzero average noise which, though uncorrelated with information dated from *t-1* and earlier, is related to the rational expectation error ($\varepsilon_{t+h}$). In addition, forecasts may be affected by measurement errors (for example, Appendix A2 shows that this is surely the case with the LS forecasts). Therefore, consistent coefficient estimates require IV/GMM with

[5] Although anonymous, a LS multinomial variable classifies individual forecasters in groups. Therefore, it is possible to compute averages by group also with LS data. As far as SPF is concerned, we cannot use averages by group because the SPF multinomial variable is regularly available only since 1991q4.

[6] Within each survey, specific time series are subject to sample restrictions: in SPF, GDP deflator forecasts start from 1970, and CPI inflation from 1980; in LS a statistical reliable CPI measure is given since 1970 (because of the small number of agents surveyed before that date); in BB the availability is full for CPI inflation but, since 2005 Q1, they abandoned collecting the relevant information for professional forecasters and just focused on the 'general public' (i.e. not professional forecasts).

instruments dated from *t-1* and earlier. However, in view of the Hausman (1978) approach, efficient OLS estimates can also be compared with IV/GMM estimates which are consistent under both true and false assumptions of orthogonality between the error term and regressors.

## IV. Estimation Analysis and Results:

Following the derived equation (10) in Section II, the empirical analysis here considers the general equation (11) which is able to account for the different datasets described in the preceding section[7]:

$$\pi_{t+h} - F_t\ (\pi_{t+1,t+h}) = \frac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t+1,t+h}) + \frac{\lambda}{1-\lambda}\phi[F_{t-1}(\pi_{t+1,t+h}) - F_{t-1}(\pi_{t,t+h-1})] - \varepsilon_{t+h} \quad (11)$$

The first regressor in equation (11), $\Delta F_t\ (\pi_{t+1,t+h}) = F_t\ (\pi_{t+1,t+h}) - F_{t-1}(\pi_{t+1,t+h})$ denotes the *revision* (*update*) of the forecast over the horizon from *t+1* to *t+h*, measuring the impact on the forecast formed in *t*, namely the information shocks observed in period *t.* The second regressor, $F_{t-1}(\pi_{t+1,t+h}) - F_{t-1}(\pi_{t,t+h-1})$, depicts the *momentum* of the forecast, measured by the inflation forecast made in period *t-1* and this time made for *t+h-1* and *t+h*.

In general, when the frequency of the forecast releases is the same as the length of each step and shorter than the forecast horizon (*h*), both regressors in equation (11) are computed by differences between pairs of forecasts which may overlap.

Table 1 reports the estimates for the SPF data when we impose the restriction $\phi$ = 0. This restricted model corresponds to the CG model found in equation (3) of Section II. The results in column (1) refer to the GDP inflation, and replicate quite closely those in the first column of Table 1 panel B of CG. As expected, the intercept is not significant, and the

[7]Appendix A2 outlines how equation (11) must be emended to fit the alternative survey data features.

slightly different estimate of information rigidity ($\hat{\lambda}$ = 0.548, while theirs: 0.552) is simply due to our longer sample period, ending in 2013q1 rather than in 2010q2.

***Table 1 here***

When we test for parameters' constancy using the Andrews (1993) test statistic for structural change with unknown break date, a clear break emerges in 1979q3. This date coincides with two relevant events: firstly, the beginning of the Great Moderation phase where actual inflation rates became harder to forecast (see Stock and Watson (2007)); and, secondly, the beginning - with Volker - of the decline of a phase in which the Federal Reserve placed increasing weight on inflation stability and inflation persistence (see Clarida et al. (2000), and Beechey and Osterholm (2012) for detailed discussions).

Subsequently, column (2) in Table 1 reports the OLS estimates after removing the 1970s from the sample period, focusing only on the period since the Great Moderation. In the shorter sample period, the $\lambda$ estimate drops by more than 50%, from 0.55 to 0.25, representing a considerable reduction in forecaster inattentiveness. Forecasters' ability to acquire new information improved markedly because since 1980 they perceive inflation to be less persistent than the 1970s, when there was larger inflation shocks and loose monetary policy.

The discussion in the preceding section regarding the more appropriate estimator in the present context suggests comparing the OLS estimates (with potential bias) with those using IV and GMM (both always consistent regardless of the correlation between explanatory variables and equation errors). The instruments used here, and elsewhere in the paper, are both internal (the first two lags of the actual inflation rate, and one lag of one- and two-steps ahead inflation forecasts) and external (lags of the anxiety index, the real time GDP growth, the unemployment rate, the Federal funds rate, and its spread with respect to the 10-year Treasury constant maturity rate).

Columns (3)-(4) respectively report estimates obtained with IV and GMM over the whole sample (i.e. including the 1970s decade). Despite the statistically significant Hausman test and downwardly biased OLS estimates, both OLS and IV-GMM estimators indicate statistically significant information rigidities. The IV-GMM estimates are quite close to those reported in column (1) and , over the full sample period, informational rigidity due to forecast revisions is significant and above 0.5. The results reported in columns (5)-(7), obtained using alternative inflation measures and estimators over the sample period beginning with the 1980s, is used to assess its robustness. The OLS estimates of CPI inflation (in column 6) support the sharp reduction in forecasters' inattentiveness after 1980, while the instrumental variables estimates - with (column 4) and without (column 5) from the 1970s – indicate a narrower fluctuations than OLS.

The overall results in Table 1 suggest that inattentiveness has lowered in the US since the start of the Volker mandate (end 70s - beginning 80s), when inflation persistence decreased and its predictability was more difficult because of the Great Moderation phase. This outcome is quite robust as to the different inflation measures used. The GMM estimates are more stable than the OLS ones, even though both estimates are lower. In addition, the use of GMM is supported by the Hausman test: the exploitation of instrumental information enables GMM to cope better with omitted variable biases and structural breaks. The larger GMM inattentiveness estimate when using the GDP deflator (column 5) rather than CPI (column 7) can be explained by the greater emphasis on the latter during monetary policy debates.

Finally, it is important to note that the GMM estimator can account for nonzero average individual noises which might affect the average forecast revisions and, therefore, correlated to $\varepsilon_{t+h}$. GMM are therefore more reliable than OLS estimates, which assume zero average individual noises. On the other hand, since both GMM and OLS give significant parameter estimates, the usefulness of the forecast revisions in explaining the forecast errors is established clearly. In other words, the predictability of forecast errors and their revision cannot be ascribed to invalid exogeneity assumptions made by OLS estimators.

In their paper CG used lagged control variables (such as oil price or unemployment rate) to capture the effect of other macroeconomic determinants on inflation forecast errors. In these extended regressions, the null that the control variables' parameters are zero tests whether forecast revision due to information rigidity adequately characterize (through the $\lambda$ parameter) the predictability of ex post forecast errors. The results reported in CG partially invalidate models with information rigidities, as the parameter of the lag of the unemployment rate rejects the null of zero.

The first two columns of Table 2 replicate the CG finding of a significant lagged unemployment effect respectively using OLS and GMM, and column (3) report the estimates excluding the 1970s. If the significant unemployment effect was a mere anomaly, it would not have been so robustly evident over the alternative sample periods and estimation methods.

***Table 2 here***

Despite the significant unemployment effect, all three $\lambda$ estimates are also significant and very close to those reported in columns (1), (4) and (5) of Table 1 respectively. This suggests that even though an important effect is not captured (and proxied by unemployment), the omission cannot be related to forecast revisions. Indeed, the Andrews (1993) test for the OLS estimates constancy in column (1) still supports a break in 1979$q$3, indicating that the change in the monetary policy stance and great moderation both induced a break which cannot be offset by inclusion of the unemployment rate.

A possible explanation of the significant unemployment parameter is that it represents a sort of reduced-form short-run Phillips curve effect which proxies the forecast momentum that is omitted from equation (10) by the invalid restriction: $\phi = 0$. In order to investigate this further, in column (4) of Table 2 we estimate a specification of equation (11) which includes the unemployment effect (through parameter $\gamma$). The insignificant estimate of $\gamma$ suggests that model (11), which embodies both forms of inattentiveness, better explains the forecast error than the CG model augmented by the unemployment effect.

Columns (5)-(6) report GMM estimates of equation (11) where the inflation rate is respectively measured by the GDP deflator and CPI. The results are clear: the model with both forms of inattentiveness can explain the forecast error regardless of the inflation measure. Finally, column (7) reports the estimates of equation (11) over the full sample period, including the 1970s. The forecast momentum is no longer significant because it is possibly obscured by the noisy shocks of the period from 1970 to 1979 due to the higher signal to noise ratio. More specifically, the lower amount of information can be exploited to predict non trivial (zero) forecast momentum; on this point see also Section II and Appendix A1.

The SPF predictions are not the only source of information to assess the empirical validity of equation (11) for the US. As noted in Appendix A2, the regressors measured by the forecasts series of SPF unavoidably overlap. We assess the robustness of the empirical findings by reporting estimates of equation (11) using another source of forecasts in Table 3: the semi-annual series of the Livingston survey (LS). One interesting feature of the LS dataset is that its regressors do not overlap and that CPI forecasts are also available for the 1970s (enabling an extended coverage of our empirical investigation using CPI inflation).

***Table 3 here***

With LS data, both forms of inattentiveness (parameters $\lambda$ and $\phi$) are always significant regardless of the sample period and not much different from each other. If we compare the SPF and LS results, the estimates of $\lambda$ and $\phi$ using CPI inflation are remarkably similar over the period excluding the 1970s. The same is true for the $\lambda$ estimate over the period including the 1970s even though the inflation rate is measured by CPI in LS and by GDP deflator in SPF. However, the momentum effect $\phi$ parameter estimate is very different and fairly close to that of $\lambda$ when inflation is measured by the CPI forecasts of LS but not significant when inflation is measured by the GDP deflator forecasts of SPF.

The disaggregated estimates by group of forecasters indicate that academics and policy-makers have the lowest information rigidity due to forecast revisions ($\hat{\lambda}$=0.53), while the financial sector forecasters have the highest ($\hat{\lambda}$=0.65). Interestingly, academic and policy-makers experience similar informational rigidities when $\hat{\phi}$=0.55. Conversely, the financial and non-financial sectors experience considerably higher rigidities due to forecast momentum when $\hat{\phi}$= 0.71 and 0.67 respectively. It is not surprising that academic and policy-makers have lower informational rigidities as they should have superior knowledge and access to relevant information.

A couple of noteworthy remarks are required. The coefficient $\phi$ and unemployment control variable captures forecast momentum related to the short-run Phillips curve relationship. CG suggests that a significant control variable such as unemployment invalidates the notion of informational rigidities, as such a variable captures the short-run Phillips curve trade-off. However, the current analysis shows that the statistically significant inclusion of the forecast momentum affirms informational rigidities. Hence, the best way to capture informational rigidity is to include the forecast momentum variable.

Secondly, an explanation is required for the finding that the SPF forecast momentum is only significant for the period that excludes the 1970s. First and foremost, it must be noted that this result is not replicated for LS. This may just reflect the nature of the dataset. The overlapping forecast horizon for the SPF (but in the case of LS) may be important. Putting this issue aside, the period from the appointment of Volker and the Great Moderation has clearly had a significant impact on the dynamics of actual inflation and its formation expectations. Following the Great Moderation, inflation persistence has reduced and the propagation of shocks curtailed. Prior to the Great Moderation any shocks that where observed in the current period would last beyond the next period. So a forecaster making a multi-period forecast in $t$ is able to confidently forecast a shock that is observed in $t$ lasting beyond $t+h$ into $t+h+1$. This is less so after the Great Moderation, and so before the Great Moderation $\hat{\phi}=0$.

These findings for the US can be compared with estimates by group of forecasters using the Barclays Basics (BB) data for the UK. BB data are available for groups of forecasters as quarterly averages of the inflation forecasts one and two years ahead. Similar to those compiled by LS, the BB data do not overlap and the survey reports forecasts over longer horizons (details are in Appendix A2). Two of the BB groups are of particular interest: business economists and financial directors. They correspond closely to the two LS groups: non-financial sector and financial sector forecasters. Using the same BB dataset, Easaw and Golinelli (2010) found that the group of business economists displayed features consistent with professional forecasters, who acquire information before the others.

Table 4 outlines estimates of equation (11) by using alternative estimators (OLS, IV and GMM) for both business economists' and financial directors' forecasts:

***Table 4 here***

As with LS data, even though instrumental variable approaches have better statistical properties than OLS, results in Table 4 suggest a similar pattern to that for the US: UK forecasts~~-~~ revisions and momentum are always significant explanatory variables of the forecast errors. Business economists are less inattentive than financial directors. This is coherent with the findings in Easaw and Golinelli (2010) and also with the estimates in the last two columns of Table 3 for the US.

## V. Summary and Concluding Remarks:

The purpose of this paper is to investigate the structure and dynamics of professional forecasters of inflation. Recent papers have focused on their forecast errors and how it may relate to informational rigidities. In this paper we extend the existing literature by considering a second form of inattentiveness.

Both forms of inattentiveness relate to the necessary activity a professional forecaster needs to undertake and, therefore, are related to each other. Professional who forecast inflation rates need to, in the first instance, update their information set and revise their forecast from the previous period. Professional forecasters may also wish to perform a multi-period forecast of inflation, and in this instance they are assessing the momentum of future inflation. As in the case with the short-run Phillips curve trade-off, they need to assess the propagation, or persistence, or transitory shocks, or the inflation gap. Both instances involve~~s~~ the ability to observe relevant but different information and, therefore, the forms of inattentiveness. They are also related because the existence of inattentiveness when revising their forecasts necessitates resorting to their multi-period forecasts in the previous period. Importantly, the existence of the second form relating to forecasting momentum indicates that inattentiveness arises as a result of imperfect information (rather than sticky information).

The empirical investigation using various surveys of professional forecasts for both the US and the UK establishes the existence of both forms of inattentiveness. It also clearly indicates that short-run Phillips curve reflecting inflation momentum captured by the unemployment effect is best depicted by this form of inattentiveness. The structure of the professional's forecast error is now considerably extended and different, with direct implications for the persistence of real effects

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## Appendix A1: Inflation Persistence and the Signal to Noise Ratio in the UC Model

The general unobservable components (UC) representation of the observable inflation rate is defined as:

$$\pi_t \equiv \tau_t + \xi_t \tag{A1.1}$$

where the unobserved stochastic trend, or permanent, component is assumed to be a random walk:

$$\tau_t = \tau_{t-1} + \eta_t \tag{A1.2}$$

and the disturbance $\eta_t$ ~ *iid* $N(0,\ \sigma_\eta^2)$ is the permanent innovation. We also assume that the unobservable inflation gap has the following stationary and invertible ARMA(1,0) representation:

$$\xi_t = \rho\xi_{t-1} + \mu_t \tag{A1.3}$$

where $\mu_t$ ~ *iid* $N(0,\ \sigma_\mu^2)$ is the transitory innovation, which may be correlated with the permanent innovations through the covariance $\sigma_{\eta\mu}$ [8] Following, for example, Morley et al. (2003), if we substitute the permanent component (A1.2) and the inflation gap (A1.3) in the UC model (A1.1), we obtain the canonical form of the UC model that has the reduced-form ARIMA representation: $(1-\rho L)(1-L)\pi_t = (1-\rho L)\eta_t + (1-L)\mu_t$ . In terms of stationary inflation changes, the canonical form above can be also seen as:

$$\Delta\pi_t = \eta_t + \frac{\Delta\mu_t}{(1-\rho L)} = \eta_t + \sum_{i=0}^{\infty}\rho^i \Delta\mu_{t-i} \tag{A1.4}$$

The $\Delta\pi_t$ autocovariances of order zero and one (that is, $\gamma_i$ for *i* = 0, and 1) measure what the forecaster is able to learn in the short run about the persistence of such inflation

[8] Similarly to Morley *et al*. (2003), we assume that the covariance between permanent and transitory innovations is different from zero only at lag zero.

changes. These autocovariances can be expressed in terms of the hyperparameters of the UC model as follows:

$$\gamma_0 = \sigma_\eta^2 + 2\frac{\sigma_\mu^2}{1-\rho^2} + 2\sigma_{\eta\mu}$$

$$\gamma_1 = -(1-\rho)\sigma_{\eta\mu} - \frac{1-\rho}{1+\rho}\sigma_\mu^2$$

Therefore, the first-order autocorrelation coefficient of (A1.4) is:

$$AC_1 = \frac{\gamma_1}{\gamma_0} = \frac{-\sigma_{\eta\mu} - \dfrac{\sigma_\mu^2}{1+\rho}}{(1+\rho)\sigma_\eta^2 + 2\dfrac{\sigma_\mu^2}{1-\rho} + 2(1+\rho)\sigma_{\eta\mu}} \qquad \text{(A1.5)}$$

If we define the signal to noise ratio as $s = \dfrac{\sigma_\eta^2}{\sigma_\mu^2}$ and the correlation coefficient between permanent and transitory innovations as $r = \dfrac{\sigma_{\eta\mu}}{\sigma_\eta \sigma_\mu}$, the representation of $AC_1$, or the persistence of the changes in the inflation rate, can be expressed as follows:

$$AC_1 = \frac{-r\sqrt{s} - \dfrac{1}{1+\rho}}{(1+\rho)s + \dfrac{2}{1-\rho} + 2(1+\rho)r\sqrt{s}} \qquad \text{(A1.6)}$$

The information available to the forecaster is noisier as *s* goes to zero (i.e. when the signal to noise approaches very low values) and *r* goes either to one or minus one (i.e. the correlation between the permanent and transitory innovations approaches its maximum levels).

Figure A1.1 reports alternative $AC_1$ dynamics of (A1.6) as a function of the persistence of the inflation gap $\rho$ (from zero to 0.9, i.e., from the case of only noise to that of a very high persistence)[9] in noisy situations, when $r$= 1 or = -1 and $s$ = 0.1 or 0.5.

***Figure A1.1 here***

The low level of information which the forecaster can extract in the short run from past values of the changes to the inflation rate tends to be even lower when the inflation gap is more persistent. This pattern continues independently from the positive or negative covariance between permanent and transitory innovations. Also, the signal to noise level ($s$ = 0.1 or 0.5) does not appear to be relevant in shaping the short run information content of past values of inflation.

Stock and Watson (2007) find that from the 1960s up to the beginning of the 1980s the autocorrelation of $\Delta\pi_t$ at lag 1 was -0.187, then over the great moderation phase (since 1984) it went to -0.416 corroborating their random walk plus noise model where the correlation between permanent and transitory innovations is assumed to be zero.

[9] Stock and Watson (2007) find that the univariate inflation process is well described by a random walk plus noise model with stochastic volatility or, equivalently, the inflation rate is a reduced-form ARIMA(0,1,1) model. More explicitly, that in (A1.3) $\rho$ = 0.

**Appendix A2 - Variables Definition and Their Preliminary Analysis**

***The Survey of Professional Forecasters (SPF) regression data*** [10]

The specification of equation (11) that is consistent with the timing of the quarterly SPF forecasts is the following:

$$\pi_{t+3} - F_t\ (\pi_{t,t+3}) = \frac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t,t+3}) + \frac{\lambda}{1-\lambda} \phi [F_{t-1}(\pi_{t,t+3}) - F_{t-1}(\pi_{t-1,t+2})] - \varepsilon_{t+3} \quad \text{(A2.1)}$$

where the forecast update is $\Delta F_t\ (\pi_{t,t+3}) = F_t\ (\pi_{t,t+3}) - F_{t-1}(\pi_{t,t+3})$, and the latter term is the first lag of the forecast time series $F_t\ (\pi_{t+1,t+4})$.

Data for the GDP deflator inflation rate, which measures actual inflation ($\pi_t$), are obtained from the levels of GDP deflator (*PGDP*) of the NIPA vintages available at the month the SPF is conducted (i.e. in February, May, August and November) using the formula:

*100*( PGDP/PGDP(-4) -1 )*

The use of data vintages is motivated by the relevant revisions which affect NIPA releases. The source of data vintages is the Real-Time Data Set for Macroeconomists at the Federal Reserve Bank of Philadelphia.

The CPI inflation rate, the alternative measure of actual inflation ($\pi_t$), is computed from the averages of the monthly seasonally adjusted levels of the Consumer Price Index for All Urban Consumers: All Items *(CPIAUCSL)* using the formula:

*100*( CPIUCSL/ CPIUCSL (-4) -1 )*

[10] For further information, see the following link to the SPF site at the Federal Reserve Bank of Philadelphia: http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/

Data revisions are almost ineffective for quarterly frequencies, as they are only due to the seasonal adjustments of some items. The source of data vintages is ALFRED (ArchivaL Federal Reserve Economic Data), at the Economic Research Division of the Federal Reserve Bank of St. Louis.

The two forecasts $F_t\ (\pi_{t,t+3})$ and $F_t\ (\pi_{t+1,t+4})$ for both PGDP and CPI inflation rates are computed by defining *P = PGDP* or *P = CPI* in the following formulas, written in terms of the SPF labels (for details, see also the SPF survey documentation):

*onestepP =100*( ((1+P2/100)*(1+P3/100)*(1+P4/100)*(1+P5/100))^.25 -1)*

*multistepP =100*( ((1+P3/100)*(1+P4/100)*(1+P5/100)*(1+P6/100))^.25 -1)*

More explicitly, as highlighted in CG, the one-year-ahead forecast of *P* is defined as the mean of the SPF forecasts released in quarter *t* for the current and the next three quarters (i.e. *t,t+1, t+2, t+3*), in symbols $F_t\ (\pi_{t,t+3})$; the corresponding multi-step forecast is the mean of the SPF forecasts - again released in quarter *t* - for the next four quarters (i.e. *t+1, t+2, t+3, t+4*), in symbols: $F_t\ (\pi_{t+1,t+4})$. Therefore, the one-step- and the multistep-ahead horizons of the SPF forecasts overlap for three quarters.

The forecast error $\pi_{t+3} - F_t\ (\pi_{t,t+3})$, the explanatory forecast update $\Delta F_t\ (\pi_{t,t+3})$ = $F_t\ (\pi_{t,t+3}) - F_{t-1}(\pi_{t,t+3})$, and the forecast momentum $F_{t-1}(\pi_{t,t+3}) - F_{t-1}(\pi_{t-1,t+2})$ combine the three variables described above.

Given that stationarity is one of the assumptions to be met in order to support the IV-GMM statistical properties, Figure A1 depicts the temporal patterns of the three variables in equation (A2.1) over the period 1969q4-2013q1 which suggest mean reversion. Apart from episodes of quite persistent under-prediction of the inflation rate during the 70s (mainly due to the oil shocks), in the rest of the sample forecast errors tend to fluctuate around zero. In general, the forecast revisions are prevalently downwards, especially immediately after the period of the oil shocks in the 70s. Finally, apart from the first half of the 80s and excluding the year 1991, the forecast momentum is positively persistent continuing up to the end of last century.

***Figure A2.1 [about here]***

The stationary of these patterns is confirmed by formal testing. Elliott et al. (1996) DFGLS test statistics (with intercept and MAIC automatic selection from a maximum lag equal to 5) for the dependent forecast error is -2.203 and -2.409 (GDP and CPI inflation); for the explanatory forecast update is -3.524 and -3.862 (GDP and CPI inflation); and for the forecast momentum is -1.658 and -1.623 (GDP and CPI inflation), against -2.58, -1.94 and -1.61 DFGLS critical values at 1, 5, and 10%. Therefore, the null of the unit root is always rejected.

***The Livingston Survey (LS) regressions' data*** [11]

The model that can be estimated for the Livingston data where *h*=1 and the frequency of both forecast releases and multistep ahead is semi-annual. Therefore, the notation of equation (11) becomes:

$$\pi_{t+1} - F_t\ (\pi_{t+1}) = \frac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t+1}) + \frac{\lambda}{1-\lambda} \phi [F_{t-1}(\pi_{t+1}) - F_{t-1}(\pi_t\ )] - \varepsilon_{t+1} \qquad \text{(A2.2)}$$

where: $\Delta F_t\ (\pi_{t+1}) = F_t\ (\pi_{t+1}) - F_{t-1}(\pi_{t+1})$. As data frequency is semi-annual, *t+1* refers one semester ahead of *t*.

[11] For further information, see the following link at the Federal Reserve Bank of Philadelphia: http://www.phil.frb.org/research-and-data/real-time-center/livingston-survey/

The actual semi-annual CPI inflation rate, $\pi_t$, is computed from the levels of the *Consumer Price Index for All Urban Consumers: All Items*, (monthly, seasonally adjusted, label CPIAUCSL) using the following formula with monthly data:

_100*( (CPIAUCSL/CPIAUCSL(-6))^2 -1 )_

The monthly data are then converted into semi-annual by taking the monthly inflation at the beginning of the month in which the Livingston Survey is conducted (i.e. in June and December). Similar to the quarterly SPF case, semi-annual frequency data revisions are almost ineffective. They only arise due to the seasonal adjustments of some items. The source of data on consumer price index is, again, ALFRED.

The one- and two-semesters ahead predictions of CPI, $F_t\,(\pi_{t+1})$ and $F_t\,(\pi_{t+2})$, are respectively computed using the following formula in terms of the Livingston Survey~~'s~~ data (for details, see also the survey documentation):

_f6m  = 100*( (Forecast6Month/BasePeriod    )^(12/8) -1 )_

_f12m = 100*( (Forecast12Month/Forecast6Month)^(12/6) -1 )_

There are two noteworthy points: (*a*) the two measures, *f6m* and *f12m*, cover two consecutive non-overlapping semesters; (*b*) *f6m* is only a proxy of the genuine one-semester ahead forecast, as the *Base Period* is the last monthly historical value known at the time the questionnaire is mailed (i.e. in April and October). In fact, *Forecast0Month* would have been the most appropriate starting point for the genuine *f6m*, but it has only been available since 1992. However, it is interesting that over the period in which they have both been available, the two measures have a 3% stationary (1, -1) cointegration vector in a data-congruent

VAR(2) representation without intercept,[12] and the genuine measure is weakly exogenous: the two months of news that it embodies significantly reduce the measurement error affecting *f6m*. In other words, the two measures share the same stochastic trend (the genuine *f6m*), and their discrepancy is a temporary measurement error. This error in *f6m*, due to a lack of relevant news occurring in the subsequent two months, gives additional support for estimating our models with GMM estimators in which past realizations of the same variables are valid instruments. Genuine information is bound to be persistent, but unrelated with the future measurement error.

Here too we have to establish whether the three variables of interest are stationary. Figure A2.2 reports the temporal pattern of the three variables of interest over the period 1970s1-2013*s*2. Understandably the patterns closely mimic SPF.

***Figure A2.2 here***

The DFGLS test statistics proposed by Elliott et al. (1996) (with intercept and MAIC automatic selection from a maximum lag equal to 3) for the forecast error is -2.710; for the forecast revision is -4.318; and for the forecast momentum is -4.524, against DFGLS critical values of -2.58, -1.94 and -1.61 at 1, 5, and 10%. Hence, the null of the unit root is always rejected at 1%.

***The Barclays Basix (BB) regressions' data***

Equation (11) can be estimated with BB quarterly data using the following notation:

[12] In this paper, when needed, we always tested for the cointegration rank and weak exogeneity by following the cointegrated VAR approach of Johansen (1995).

$$\pi_{t+4} - F_t\ (\pi_{t+1,t+4}) = \frac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t+1,t+4}) + \frac{\lambda}{1-\lambda} \phi [F_{t-4}(\pi_{t+1,t+4}) - F_{t-4}(\pi_{t-3,t})] - \varepsilon_{t+4} \tag{A2.3}$$

where the forecast revision is defined as: $\Delta F_t\ (\pi_{t+1,t+4}) = F_t\ (\pi_{t+1,t+4}) - F_{t-4}(\pi_{t+1,t+4})$. Notably, BB regressors are not overlapping.

The actual inflation rate $\pi_t$ is defined on the basis of the levels of the Retail Prices Index (RPI): monthly index numbers of retail prices 1947-2014 (base 1987m1=100, *CHAW*) using the formula:

*100*( (CHAW/CHAW(-12)) -1 )*

Monthly data are then converted to quarterly by taking the most recently available monthly inflation known in the first month of each quarter with respect to the corresponding month of the previous year. The source of data on RPI is the Office for National Statistics.[13]

The one- and two-years ahead forecasts are denoted by $F_t\ (\pi_{t+1,t+4})$ and $F_t\ (\pi_{t+5,t+8})$ respectively, and are compiled by Barclays Basix, based on surveys of various sections of the UK population about their expected inflation rate over the period 1986Q4-2005Q1. The available dataset reports the mean forecasts for the professional forecasters, or business economists, and for other groups of forecasters, but does not report the individual forecasts. The agents surveyed are asked their expectations of RPI in the following way: *"Can you tell me what you expect the rate of inflation to be over the next twelve months?".* The answers represent the one-year-ahead forecasts (label F1Y*j*, where *j* = business economists, academic,

[13] Although, in accordance with the Statistics and Registration Service Act 2007, the Retail Prices Index and its derivatives have been assessed against the Code of Practice for Official Statistics and found not to meet the required standards for designation as National Statistics, we use RPI because BB survey questions explicitly refer to it.

trade unionist, finance directors). The agents were then asked: *"And how about the following twelve months?"*. This represents the two-year-ahead forecasts (label F2Y*j*). Further details and discussion can be found in Easaw and Golinelli (2010).

As with SPF and LS, we investigate empirically whether the three variables of equation (A2.3) are stationary. Figure A2.3 reports their temporal pattern over the period 1987*q*4-2005*q*1. It indicates slightly greater persistence over time than the US case. Signals from 1992 to the end of the sample tend to converge towards zero for all the variables, coupled with lower inflation volatility. In fact since 1992q4 there has been a period of stable inflation when informal inflation targeting began (interest rate decisions were still made by the Chancellor of the Exchequer while there was an inflation target). Since 1997q4 UK further evolved towards a regime of inflation targeting under an operationally independent Bank of England.

***Figure A2.3 here***

In the DFGLS test by Elliott et al. (1996) (with intercept and MAIC automatic selection from a maximum lag equal to 5) the null of the unit root is always rejected at 5%. The test statistic for the forecast error is -2.391, the forecast revision is -2.265, and the forecast momentum is -2.078, against DFGLS critical values of -2.58, -1.94 and -1.61 at 1, 5, and 10%.

## Tables and Figures

**Table 1 - Estimates of the Coibion and Gorodnichenko (2012) model with SPF [a]**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Start in*: | 1969q1 | 1980q1 | 1970q1 | 1970q1 | 1980q1 | 1981q4 | 1981q4 |
| Estimation method: | OLS | OLS | IV | GMM | GMM | OLS | GMM |
| Inflation measure: | GDP | GDP | GDP | GDP | GDP | CPI | CPI |
| $\lambda$ [b] | **0.5481** *** | **0.2481** *** | **0.6630** *** | **0.6366** *** | **0.4979** *** | **0.2531** ** | **0.4108** *** |
| | (0.1017) | (0.0922) | (0.0579) | (0.0447) | (0.0620) | (0.1167) | (0.0588) |
| *Intercept* | **-0.0243** | **-0.3217** *** | **-0.0306** | **-0.1057** | **-0.2581** *** | **-0.1217** | **-0.0747** |
| | (0.1331) | (0.1008) | (0.1131) | (0.0809) | (0.0832) | (0.1459) | (0.0963) |
| T [c] | 172 | 133 | 171 | 171 | 133 | 127 | 127 |
| Mean [d] | -0.0304 | -0.3536 | -0.0423 | -0.0423 | -0.3536 | -0.1603 | -0.1603 |
| SER [e] | 1.0646 | 0.6499 | 1.1116 | 1.0885 | 0.6885 | 1.0711 | 1.0838 |
| Specification tests: [f] | | | | | | | |
| - Andrews (1993) | 1979q3 *** | | | | | | |
| - Hausman (1978) | | | 0.0000 | 0.0246 | 0.1111 | | 0.1274 |
| - Hansen (1982) | | | 0.0538 | 0.4641 | 0.3479 | | 0.6058 |

([a]) $\pi_{t+3} - F_t\ (\pi_{t,t+3}) = \frac{\lambda}{1-\lambda}\left[F_t\ (\pi_{t,t+3}) - F_{t-1}(\pi_{t,t+3})\right] + Intercept - \varepsilon_{t+3}$. Estimation period: from *start* to 2013*q*1 with quarterly data (*q*=quarter); the initial period (*start*) of the samples in different columns is reported in the row labelled "*Start in*". Estimation method: OLS, IV (Sargan, 1958) and GMM (Hamsen, 1982). Inflation measure: GDP deflator or CPI (consumer price index). In bold: estimates; in parentheses: HAC standard errors, see Newey and West (1987); *** ** and * denote significance from zero at 1, 5 and 10% levels.

([b]) In CG (Table 1, panel B, first column) the implicit OLS estimate of $\lambda$ is 0.552.

([c]) The number of observations of the full sample with OLS (172) is apparently not coherent with that of IV (171) because of the effect of some missing quarterly observations in years 1969 and 1970, and in 1974q4. To ease comparisons, IV and GMM samples are restricted to be the same (i.e. T=171 observations).

([d]) Mean of the one-semester ahead forecast errors.

([e]) Standard error of the regression.

([f]) P-values. Andrews (1993) = MaxF test statistic for structural change with unknown break date (trimming 20%) for OLS estimates (if significant, the break date is reported); Hausman (1978) test for weak exogeneity (IV and GMM estimates); Hansen (1982) *J* test statistic for over-identification restrictions.

## Table 2 - Estimates of the model with the two forms of inattentiveness with SPF [a]

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *Start in*: | 1969q1 | 1969q1 | 1980q1 | 1980q1 | 1980q1 | 1981q4 | 1969q1 |
| Estimation method: | OLS | GMM | GMM | GMM | GMM | GMM | GMM |
| Inflation measure: | GDP | GDP | GDP | GDP | GDP | CPI | GDP |
| $\lambda$ | **0.5185** *** | **0.6262** *** | **0.4460** *** | **0.6566** *** | **0.6675** *** | **0.5903** *** | **0.6911** *** |
| | (0.1101) | (0.0540) | (0.0304) | (0.0579) | (0.0523) | (0.0575) | (0.0460) |
| $\phi$ [b] | | | | **0.4633** ** | **0.4353** ** | **0.6062** ** | **-0.1619** |
| | | | | (0.2275) | (0.2149) | (0.2848) | (0.2218) |
| $\gamma$ | **-0.1770** *** | **-0.1151** ** | **-0.0702** *** | **-0.0456** | | | |
| | (0.0676) | (0.0565) | (0.0250) | (0.0496) | | | |
| *Intercept* | **1.1037** ** | **0.5506** | **0.1372** | **0.0621** | **-0.1983** ** | **-0.0600** | **-0.0679** |
| | (0.4921) | (0.3727) | (0.1946) | (0.2955) | (0.0813) | (0.1359) | (0.0920) |
| T | 172 | 172 | 133 | 133 | 133 | 127 | 172 |
| Mean [c] | -0.0304 | -0.0304 | -0.3536 | -0.3536 | -0.3536 | -0.1603 | -0.0304 |
| SER [d] | 1.0308 | 1.0766 | 0.6657 | 0.8440 | 0.8623 | 1.1703 | 1.1612 |
| Specification tests: [e] | | | | | | | |
| - Andrews (1993) | 1979q3 *** | | | | | | |
| - Hansen (1982) | | 0.1917 | 0.5070 | 0.2724 | 0.4298 | 0.3380 | 0.3597 |

([a]) $\pi_{t+3} - F_t\,(\pi_{t,t+3}) = \frac{\lambda}{1-\lambda}\left[F_t\,(\pi_{t,t+3}) - F_{t-1}(\pi_{t,t+3})\right] + \frac{\lambda}{1-\lambda}\phi[F_{t-1}(\pi_{t,t+3}) - F_{t-1}(\pi_{t-1,t+2})] + \gamma\; Unempl_{t-1} + Intercept - \varepsilon_{t+3}$.

Estimation period: from *start* to 2013*q*1 with quarterly data (*q*=quarter); the initial period (*start*) of the samples in different columns is reported in the row labelled "*Start in*". Estimation method: OLS and GMM (Hamsen, 1982). Inflation measure: GDP deflator or CPI (consumer price index). In bold: estimates; in parentheses: HAC standard errors, see Newey and West (1987); *** ** and * denote significance from zero at 1, 5 and 10% levels.

([b]) CG impose the restriction $\phi = 0$.

([c]) Mean of the one-semester ahead forecast errors.

([d]) Standard error of the regression.

([e]) P-values. Andrews (1993) = MaxF test statistic for structural change with unknown break date (trimming 20%) for OLS estimates (if significant, the break date is reported); Hansen (1982) *J* test statistic for over-identification restrictions.

**Table 3 - GMM estimates using time-series means of the Livingston Survey data [a]**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *Group:* [b] | All forecasters | | Policy Govt. & Academic | Financial sector | Non-Financial sector |
| *Start in:* | 1980*s*1 | 1970*s*1 | 1970*s*1 | 1970*s*1 | 1970*s*1 |
| $\lambda$ [c] | **0.5831** *** | **0.6839** *** | **0.5388** *** | **0.6515** *** | **0.6261** *** |
| | (0.0963) | (0.0440) | (0.0907) | (0.0634) | (0.0411) |
| $\phi$ | **0.6336** ** | **0.6814** *** | **0.5523** *** | **0.7087** *** | **0.6675** *** |
| | (0.2669) | (0.1870) | (0.1193) | (0.1965) | (0.2793) |
| *Intercept* | **0.3115** | **0.5964** ** | **0.7675** ** | **0.5591** ** | **0.4509** * |
| | (0.3599) | (0.2889) | (0.2220) | (0.2500) | (0.2565) |
| T | 68 | 88 | 88 | 88 | 88 |
| Mean [d] | -0.0402 | 0.5136 | 0.6475 | 0.5273 | 0.4155 |
| SER [e] | 2.0495 | 2.4880 | 2.4957 | 2.5982 | 2.4772 |
| J-test [f] | 0.5791 | 0.5170 | 0.4232 | 0.3568 | 0.6262 |

([a]) $\pi_{t+1} - F_t\ (\pi_{t+1}) = \dfrac{\lambda}{1-\lambda} \Delta F_t\ (\pi_{t+1}) + \dfrac{\lambda}{1-\lambda} \phi[F_{t-1}(\pi_{t+1}) - F_{t-1}(\pi_t\ )] - \varepsilon_{t+1}$. Estimation period: from *start* to 2013*s*2 with semi-annual data (*s*=semester); the initial period (*start*) of the samples in different columns is reported in the row labelled "*Start in*". In bold: GMM estimates; in parentheses: HAC standard errors, see Newey and West (1987); *** ** and * denote significance from zero at 1, 5 and 10% levels.

([b]) Definition of the group (more information in the Livingston Survey Documentation on the website of the FRB of Philadelphia): Policy, Govt. and Academic = Academic Institutions + Consulting + Federal Reserve + Government; Financial sector = Commercial Banking (B) + Insurance Company (R) + Investment Banking (I); Non-Financial sector = Industry Trade Group + Labor + Non-Financial Businesses. In this way, the sum of our three groups almost coincides with "All forecasters".

([c]) Over a similar period, CG (Table 4) implicit OLS estimates of $\lambda$ (with $\phi$ restricted to zero) are: 0.51 (all forecasters); 0.31 (academic institutions); 0.45 (commercial banks); 0.38 (non-financial business); for comparing their categories with ours, see footnote *b* above.

([d]) Mean of the one-semester ahead forecast errors.

([e]) Standard error of the regression.

([f]) Hansen (1982) test of over-identification restrictions (p-values).

**Table 4 - Estimates of the model with the two forms of inattentiveness with UK forecasters groups [a]**

| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Group:* | Business economists | | | | | | Financial directors | | | | | |
| Estimation method: | OLS | | IV | | GMM | | OLS | | IV | | GMM | |
| $\lambda$ | **0.4910** | *** | **0.3822** | *** | **0.3817** | *** | **0.4202** | *** | **0.4236** | *** | **0.3972** | *** |
| | (0.0813) | | (0.0950) | | (0.0789) | | (0.0744) | | (0.0474) | | (0.0512) | |
| $\phi$ | **0.6492** | ** | **0.6732** | *** | **0.8704** | *** | **0.9875** | ** | **0.9585** | *** | **0.9084** | *** |
| | (0.3113) | | (0.1743) | | (0.2310) | | (0.4290) | | (0.1258) | | (0.1034) | |
| *Intercept* | **0.2124** | | **0.2284** | | **0.2080** | | **-0.0051** | | **0.0254** | | **0.1256** | *** |
| | (0.3245) | | (0.1515) | | (0.2034) | | (0.3240) | | (0.0969) | | (0.0248) | |
| T | 70 | | 70 | | 70 | | 70 | | 70 | | 70 | |
| Mean [b] | 0.0543 | | 0.0543 | | 0.0543 | | -0.0871 | | -0.0871 | | -0.0871 | |
| SER [c] | 1.3445 | | 1.3659 | | 1.3664 | | 1.3427 | | 1.3430 | | 1.3508 | |
| Specification tests [d] | | | | | | | | | | | | |
| - Hausman (1978) | | | 0.0416 | | 0.1325 | | | | 0.1817 | | 0.0041 | |
| - Hansen (1982) | | | 0.1355 | | 0.1854 | | | | 0.0614 | | 0.2552 | |

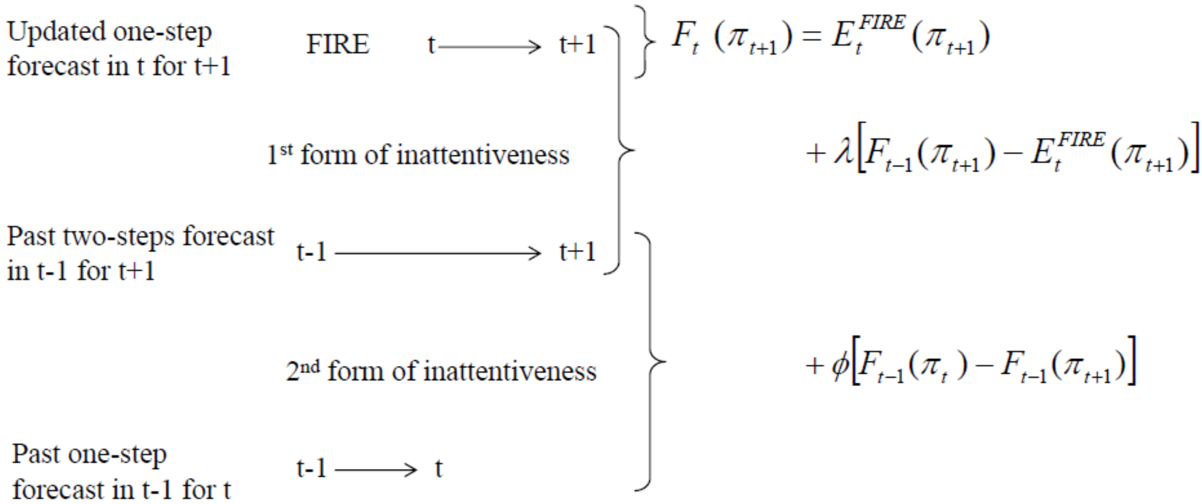
([a]) $\pi_{t+4} - F_t\,(\pi_{t+1,t+4}) = \frac{\lambda}{1-\lambda}\Delta F_t\,(\pi_{t+1,t+4}) + \frac{\lambda}{1-\lambda}\phi[F_{t-4}(\pi_{t+1,t+4}) - F_{t-4}(\pi_{t-3,t})] - \varepsilon_{t+4}$. Estimation period: from 1987*q*4 to 2005*q1* with quarterly data (*q*=quarter). In bold: model's estimates; in parentheses: HAC standard errors, see Newey and West (1987); *** ** and * denote significance from zero at 1, 5 and 10% levels.

([b]) Mean of the one-semester ahead forecast errors.

([c]) Standard error of the regression.

([d]) P-values. Hausman (1978) test for weak exogeneity (IV and GMM estimates); Hansen (1982) *J* test statistic for over-identification restrictions.

**Figure 1 – Full Information Rational Expectations and the two forms of inattentiveness, *h*=1 [a]**




([a]) Parameters $\lambda$ and $\phi$ , respectively measure to what extent the two forms of inattentiveness matter when forecasting one-step ahead: the closer they are to zero, the less relevant the two forms are for forecasting (*viceversa* when they are close to one).

**Figure A1.1 - The pattern of the 1st order autocorrelation of $\Delta\pi_t$**

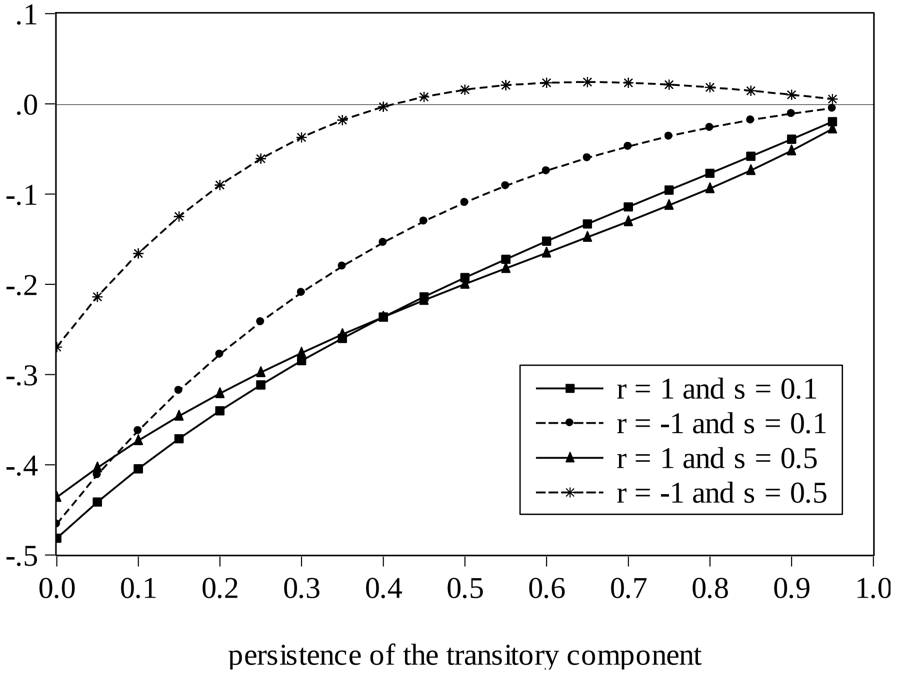
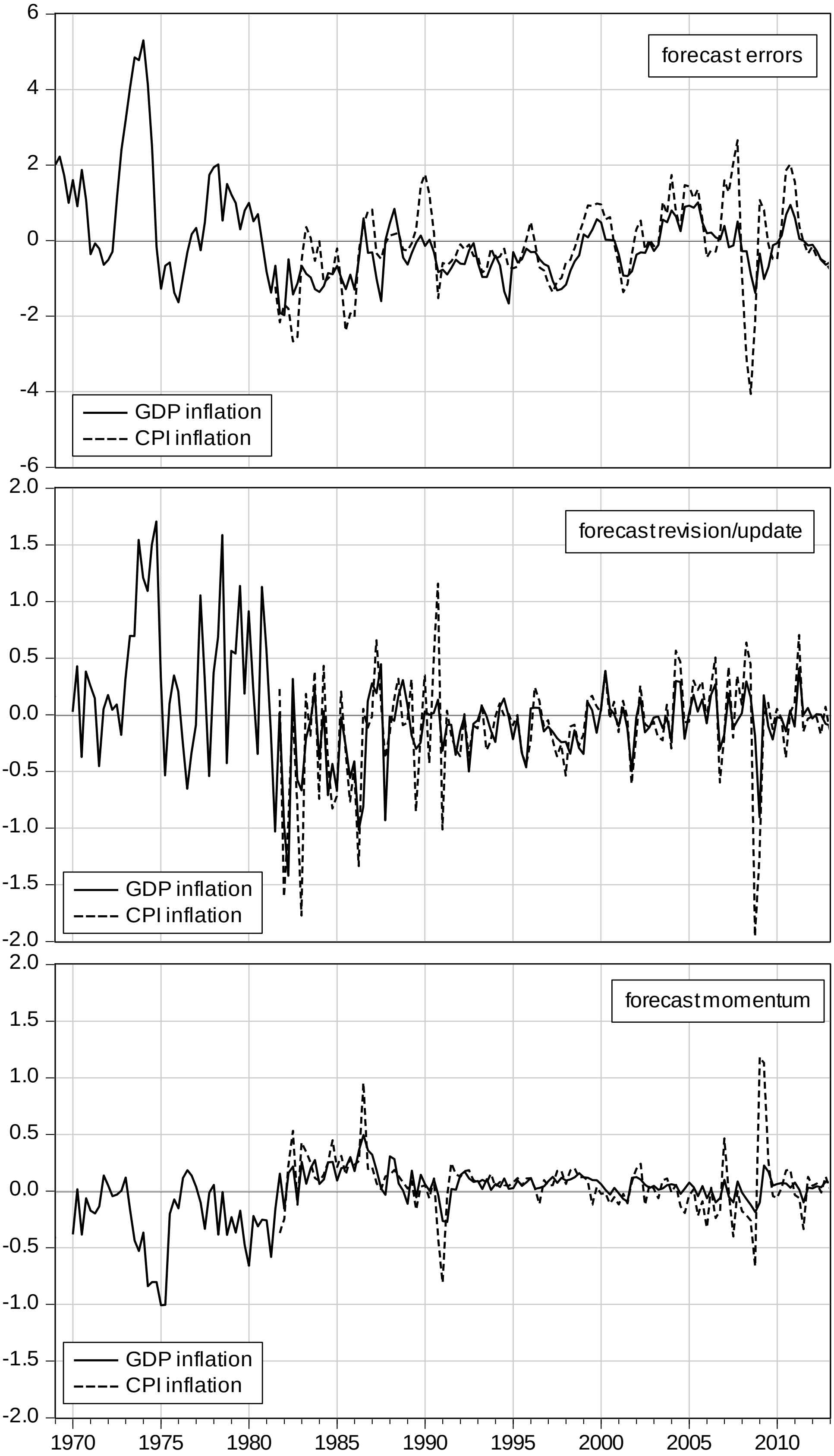
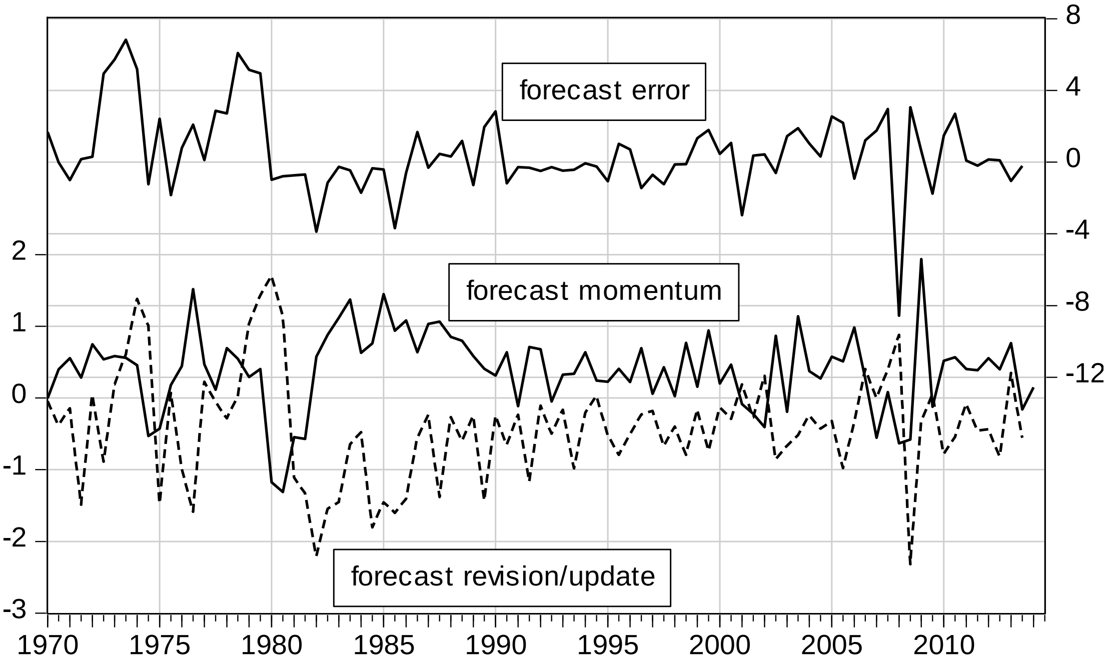


**Figure A2.1 - The variables of interest, means of SPF individual data [a]**




([a]) In equation (A1), forecast errors are the dependent variable; forecast revision is the first explanatory, and forecasts momentum is the second explanatory variable.

**Figure A2.2 - The variables of interest, means of Livingston individual data** [a]

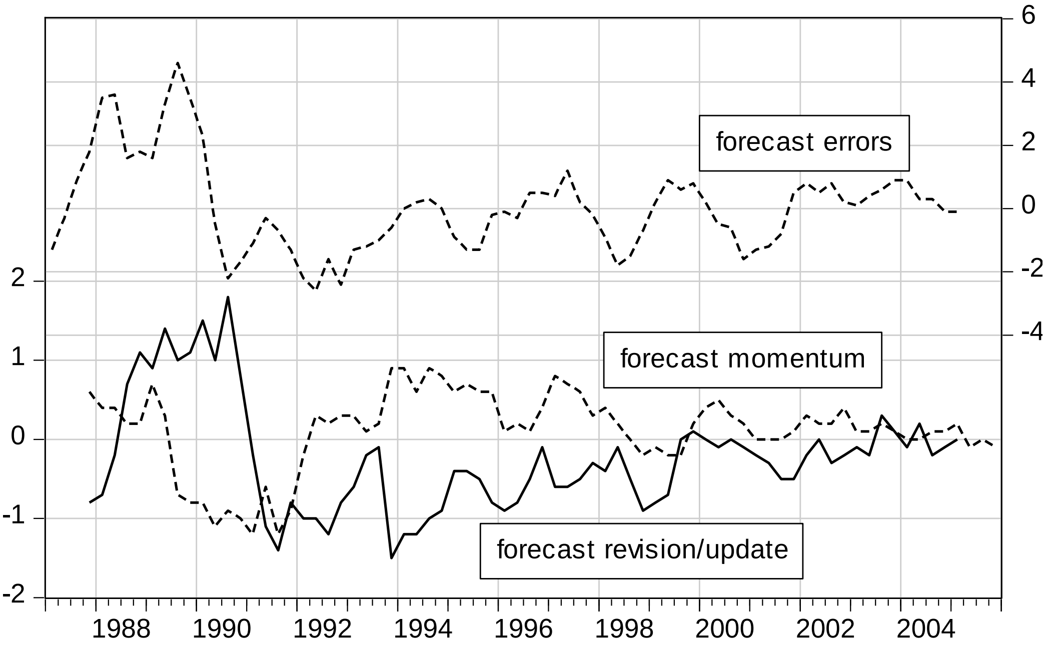



([a]) Forecast error in the right hand scale; forecast revision and momentum in the left hand scale.

$\pi_{t+1} - E_t^P(\pi_{t+1})$ = forecast error in *t+1* (i.e. the dependent variable);

$\Delta E_t^P(\pi_{t+1}) = E_t^P(\pi_{t+1}) - E_{t-1}^P(\pi_{t+1})$ = forecast revision/update (change in inflation forecast for *t+1* made in *t-1* and in *t*); $E_{t-1}^P(\pi_{t+1}) - E_{t-1}^P(\pi_t)$ = forecast momentum (i.e. change in forecast from one- to two-semesters ahead).

**Figure A2.3 - The variables of interest, means of Barclays-Basix groups [a]**




([a]) Forecast error in the right hand scale; forecast revision and momentum in the left hand scale.
In equation (A1), forecast errors are the dependent variable; forecast revision is the first expla-natory, and forecasts momentum is the second explanatory variable.