Oxford Economic Papers, 2021, 1–20
doi: 10.1093/oep/gpab012

Professionals Inflation Forecasts: The Two Dimensions Of Forecaster Inattentiveness

Joshy Easaw[a], and Roberto Golinelli[b]

[a]Economics Section, Cardiff University Business School, Cardiff University, Aberconway Building, Colum Drive, Cardiff CF19 3EU, United Kingdom; e-mail: EasawJ1@cardiff.ac.uk (Corresponding Author)
[b]Department of Economics, University of Bologna, Piazza Scaravilli 2, Bologna, 40126, Italy; e-mail: Roberto.golinelli@unibo.it

Abstract

This article explores professionals' inflation forecasts, specifically the structure of their forecast error. Recent papers considering professionals' inflation forecast have focused on the role of forecaster inattentiveness. We consider a new additional dimension of inattentiveness which is observed when forecasters form multi-period forecasts, and implicitly their perceived momentum of inflation. The present analysis introduces a novel model that is investigated empirically using survey-based data for the US. It establishes a new structure for the professionals' forecast error accounting for both dimensions of inattentiveness, which relates respectively to forecast updating and multi-period forecasting in each period.

JEL classifications: E3, E4, E5.

1. Introduction

Inflation expectations affect actual inflation and, consequently, central banks' price stability policy. Overall, as suggested by Bernanke (2007), a deeper understanding of the determinants of inflation expectations can have significant practical payoffs in improving monetary policy. By and large, monetary policymakers have consistently referred to professional inflation forecast surveys as measures of an agent's inflation expectations (see, for example, Bernanke, 2007, Miskin, 2007, and Coibion et al, 2018). The aim of the present analysis is to gain a greater understanding of inflation expectations (or forecasts) persistence and how it may differ from actual inflation persistence. In this paper, in addition to the inattentiveness forecasters exhibit when updating their forecasts, we consider a second dimension of forecaster inattentiveness when they simultaneously form multi-period forecasts.

In the recent literature, attempts to understand the dynamics of inflation expectations have shifted away from the framework of agents' rational expectations with full information toward assessing their learning and inattentiveness behaviour. Indeed, in an innovative paper Fuhrer (2017) includes actual survey expectations of professional forecasters, rather than the usual stylized rational expectations, in a DSGE model. He 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 professionals' forecasts.

If a central bank is committed to its inflation target, there should be less persistent inflation deviations from that target. For instance, if there is a substantial increase in energy prices and forecasters believe that central banks' price stability commitment is credible, they would view inflation increases as temporary. Nevertheless, inflation expectations that are well-anchored to the inflation target may continue to display persistence. Agents with well-anchored inflation expectations will still need to forecast both the inflation core and gap, where the former pertains to inflation targets and the latter is associated with deviations from the target. Disentangling these two components of inflation entails that there are two dimensions to inflation forecast inattentiveness. We introduce a novel model to consider their implications for inflation forecast error. Coibion and Gorodnichenko (2015) (henceforth CG) extend and adapt Nordhaus's (1987) concept of 'weak efficiency' forecast into the contemporary inattentiveness literature. They use a simple framework where forecast errors are investigated empirically as deviations from the full-information rational expectations. The present analysis extends this framework to include the additional, or second, dimension of inattentiveness.

The second dimension of inattentiveness relates directly to the multi-period forecast of inflation, specifically to the forecast of inflation gap persistence. Cogley et al (2010) and Chan et al (2018) argue that the persistence of the inflation gap is affected by monetary policy regimes, and this, in turn, affects overall inflation dynamics. Using survey-based data for the USA, we establish a new structure for the professional's forecast error. The new structure now accounts for both dimensions of inattentiveness, which relate respectively to forecast updating and multi-period forecasting in each period.

Several theoretical models explain deviations from full-information rational expectations through informational rigidities (see, for example, Mankiw and Reis, 2002, Woodford, 2003, Sims, 2003, Caplin and Dean, 2015, and Steiner et al, 2017). 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. They may choose periodically 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 it as well as the costs of reoptimisation. 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) with implications for monetary policy (Ball et al, 2005). Mankiw et al (2003) also argued that the main source of forecaster disagreements is due to these information rigidities and differing rates of updating. The second type of informational friction model (Woodford, 2003, and Sims, 2003) argues that agents update their information set continuously but can never fully observe the true state because of signal extraction problems. On the other hand, for instance, in Sims (2003) agents pay the cost of acquiring information, which is proportional to the reduction of their uncertainty by the entropy. Importantly, CG point out that both types of models predict quantitatively similar forecast errors.

In the sticky information (SI) scenario, the first dimension of inattentiveness arises when the forecaster attempts to update or revise their forecast based on full-information rational expectations in the current period. The forecasters either update their information set or, alternatively, rely on the forecast they formed in the previous period. The probability of the forecaster updating their inflation forecasts in each period depicts the first dimension of inattentiveness. The present study shows that the second dimension of inattentiveness pertains to how they form multi-period forecasts. On the other hand, in the case of the noisy or imperfect information (NI) scenario, the forecaster needs to form a nowcast of current inflation. So, the first dimension of inattentiveness is whether there are adequate observable signals in the current period to form a nowcast of current inflation rates or whether to rely on the previous period forecast. Once again, the second dimension of inattentiveness relates to the forecasting of multi-period inflation.

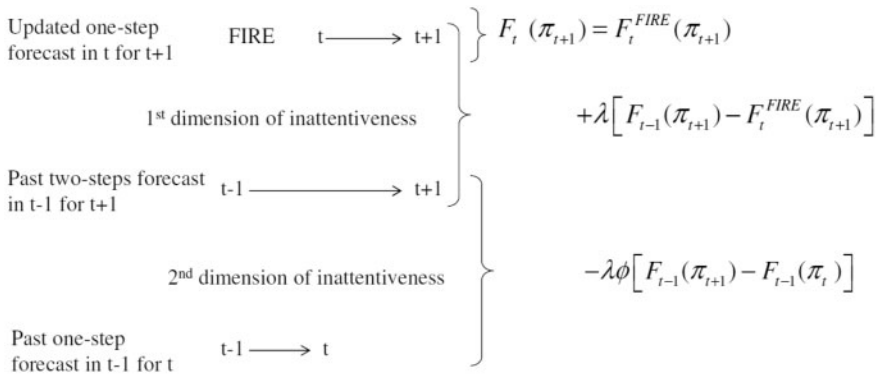
We use USA survey-based data of professional forecasters where they are asked for their forecasts over alternative horizons. We find clear evidence for both dimensions of inattentiveness. Thereby, revealing a new structure for the professional forecaster's inflation forecast error with clear implications for inflation dynamics and the effects of monetary policy.

2. The two dimensions of inattentiveness: the theoretical framework

When professional forecasters form inflation forecasts, firstly, they attempt to revise or update forecasts from a previous period. Using the most recently available information, they might form full-information rational expectations (hereafter referred to as FIRE). However, due to either informational rigidities and/or noise, agents' forecasts invariably deviate from FIRE. This is the first dimension of inattentiveness. In order to fully understand the deviation, we must also consider how professionals forecast the momentum of inflation and, thereby, their multi-period inflation forecast. The second dimension of inattentiveness arises when the agent is trying to distinguish the forecasts between different horizons in a similar vein to Nordhaus (1987). An important background to this is the classic Muthian dictum, "the best forecast for the time period immediately ahead is the best forecast for any future time period" (Muth, 1960, pp. 299). In the literature, there is substantial evidence that the multi-period forecast of inflation can be based on a reduced form IMA (1,1) representation of inflation when inflation is unforecastable beyond one-step ahead. In addition, Andrade and Le Bihan (2013), also using survey data, report that the probability of the forecasters updating their two-year ahead forecasts when they update their one-year ahead forecast is not equal to one (pp. 976).

Typically, professional forecasters 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 must determine the propagation of this shock to inflation. Will the shock merely last into the next forecast period ($t+1$) and no longer or transmit beyond ($t+h$)? One way to think about this issue is to consider 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 form and update multi-period forecasts leads to the second dimension of inattentiveness.

Figure 1 illustrates both dimensions of inattentiveness when $h=1$:



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

Fig. 1. Full information Rational Expections and the two dimensions of inattentiveness, h = 1[a].

FIRE forecast is depicted in the upper part of Figure 1. Under FIRE assumptions, at time t forecasters make the one-step ahead forecast using all available and updated information:

$$F_t^{FIRE}(\pi_{t+1}) = \pi_{t+1} - \nu_{t+1|t} \tag{1}$$

and the forecasted inflation rate is FIRE, where both the one-step ahead inflation forecast and the corresponding forecast error $\nu_{t+1|t}$ are FIRE, and $\nu_{t+1|t}$ is unrelated to information dated t or earlier. The middle part of Figure 1 highlights the effect of the first dimension of inattentiveness (weighted by λ parameter, where $0 \leq \lambda \leq 1$) on the inflation forecast $F_t(\pi_{t+1})$. Finally, the lower part of Figure 1 shows the effect on the forecast of the second dimension of inattentiveness (weighted by the $-\lambda\phi$ parameter, where $0 \leq \varphi \leq 1$); the closer ϕ is to one, the less relevant is the expected propagation of the shock in *t*−*1* to the one- and two-step ahead forecast. In the context of models with information rigidities, this second dimension of inattentiveness can further exacerbate the effect of the first dimension.

Now we focus on the formal depiction of the main components of the one-step ahead forecast of the two distinct approaches: the sticky and the noisy information models. In the case of the SI model, we define the *one-period* ahead forecast as:

$$F_t(\pi_{t+1}) = (1-\gamma)F_t^{FIRE}(\pi_{t+1}) + \gamma\{(1-\gamma)F_{t-1}^{FIRE}(\pi_{t+1}) + \gamma[(1-\gamma)F_{t-2}^{FIRE}(\pi_{t+1}) + ..]\} \tag{2}$$

which collapses to:

$$F_t(\pi_{t+1}) = (1-\gamma)F_t^{FIRE}(\pi_{t+1}) + \gamma F_{t-1}(\pi_{t+1}) \tag{3}$$

where $F_t^{FIRE}(\pi_{t+1})$ is the one-step ahead FIRE forecast at *t*, $F_{t-1}(\pi_{t+1})$ is the two-step ahead forecast formed in *t*−*1*. The parameter $1-\gamma$ is the probability that agents acquire new information (that is, $1-\lambda$ in Figure 1). Alternatively, with probabilityγ, they rely on their pre-existing forecasts, which is based on old information. In the SI model outlined in

Mankiw and Reis (2002), γ measures the degree of information rigidity, as the forecaster considers the relevance of the past forecast $F_{t-1}(\pi_{t+1})$ when explaining the new one $F_t(\pi_{t+1})$[1].

Faust and Wright (2013) provide a comprehensive review of the prevailing ways to model inflation. They capture the varying local mean by measuring the trend level of inflation. They define the 'inflation gap' as the difference between actual inflation and the stochastic trend level. Faust and Wright (2013) also advocate that the forecasting of the inflation gap around some slow varying local mean has proved to have successful predictive qualities (see also Stock and Watson, 2007, 2009, 2010, and Nason and Smith, 2013). In the context of these unobservable components (UC) models, the corresponding reduced form IMA (1,1) representation of inflation gives the forecasts originally presented in Muth (1960). The professional forecasters can estimate past forecasts using $F_{t-1}(\pi_t)$, and not necessarily $F_{t-1}(\pi_{t+1})$, if they forecast inflation using an IMA (1,1) model. Therefore, estimating the probability that forecasters use past forecasts using $F_{t-1}(\pi_t)$, as opposed to the alternative $F_{t-1}(\pi_{t+1})$, is of interest. Indeed, as pointed out earlier, Andrade and Le Bihan (2013) highlight an important finding; notably that the probability of the forecasters updating their two-year ahead forecasts when they update their one-year ahead forecast is not equal to one.

We can define a general SI model of (3) where both possibilities are nested in $\tilde{F}_{t-1}(\pi_{t+1})$:

$$F_t(\pi_{t+1}) = (1-\gamma)F_t^{FIRE}(\pi_{t+1}) + \gamma\tilde{F}_{t-1}(\pi_{t+1}) \tag{4}$$

where the encompassing two-step ahead past forecasts are a weighted average:

$$\tilde{F}_{t-1}(\pi_{t+1}) = \varphi F_{t-1}(\pi_t) + (1-\varphi)F_{t-1}(\pi_{t+1}) \tag{4'}$$

where φ (ϕ in Figure 1) is the probability, following the findings of Andrade and LeBihan (2013), that the forecasters' multi-step inflation forecast, or inflation momentum, is based on a reduced form IMA (1,1) representation and not updated[2]. Substituting equations (4') into (4), we have the SI model with two dimensions of inattentiveness equation (5):

$$F_t(\pi_{t+1}) = F_t^{FIRE}(\pi_{t+1}) + \gamma[F_{t-1}(\pi_{t+1}) - F_t^{FIRE}(\pi_{t+1})] - \gamma\varphi[F_{t-1}(\pi_{t+1}) - F_{t-1}(\pi_t)] \tag{5}$$

Finally, following CG, we substitute equation (1) into (5), rearrange the terms and extend the forecast horizon to h-steps ahead. We obtain the testable stochastic equation (6)

1 Carrol (2003 and 2006), while providing microfoundations for the Mankiw and Reis SI model depicted by equation (3), introduced an epidemiological model of how non-experts (or non-professionals) such as households may form expectations arguing that changes in the inflation rate beyond one-step ahead are unforecastable. Hence, the SI equation (3) now becomes: $F_t(\pi_{t+1}) = (1-\gamma)F_t^{FIRE}(\pi_{t+1}) + \gamma F_{t-1}(\pi_t)$ and, therefore, the one-step ahead inflation forecasts for the next period are a weighted average of the updated FIRE forecast and of last period one-step ahead inflation forecast. It is important to note that in this epidemiological model households absorb professionals' forecast which propagates throughout the population with a portion, or fraction, of them updating each period (see Easaw et al, 2013). This should be contrasted with the professionals' updating proposed by CG which considers the probability that agents acquire new information in each period (see pp. 2648).

2 One could argue that φ represents the probability of the *Muthian-Andrade-LeBihan* effect, where the agent forecasts multi-step inflation forecast based on the reduced form IMA(1,1) representation but it is not updated.

that measures the extent of the first and second dimension of inattentiveness in forecasters' behavior:

$$\pi_{t+h} - F_t(\pi_{t+h}) = \frac{\gamma}{1-\gamma}[F_t(\pi_{t+h}) - F_{t-1}(\pi_{t+h})] + \frac{\gamma}{1-\gamma}\varphi[F_{t-1}(\pi_{t+h}) - F_{t-1}(\pi_{t+h-1})] + \nu_{t+h|t} \tag{6}$$

The first term in squared brackets of equation (6) measures the forecast update (or forecast revision) when the information set is extended from *t-1* to *t*. When γ tends to zero, the degree of information rigidity is progressively lower, and the forecast revisions are not related to the forecast error. The information is almost perfect, and the forecast errors tend to be FIRE.

The second term in the square brackets of equation (6) is the forecast momentum in *t-1*, that is the difference between the predications in h steps and $h-1$ steps ahead. When φ tends to one, the forecasters almost always predict inflation using models such as the IMA (1,1). Here, the multi-step forecasts are the same beyond the one-step ahead forecast, as there is no useful information to forecast inflation beyond the first step and, therefore, the forecaster does not update their multi-period forecasts. Instead, when φ tends to zero, the forecaster almost always uses persistent AR models to forecast inflation.

We now turn to the NI model, where agents know the structure of the model and its parameters and keep updated information sets. But they never observe the state of inflation; rather, they only receive a noisy signal of it. CG assume inflation evolves as an AR model and more recent models have assumed different versions of this. For instance, Jain (2019) assumes a stationary version of the UC model. Ryngaert (2017) also assumes that inflation evolves as a stationary AR(1) model with a constant. This assumption is better suited to representing the inflation dynamics for short sample periods where inflation is deemed to revert to a constant long-run (core) inflation with no regime breaks or changes to core inflation. We propose a more general specification where we model inflation dynamics to evolve independently of the occurrence of permanent shocks. We allow significant breaks to core inflation, which are more likely for longer sample periods. Nevertheless, for shorter sample periods and the absence of significant breaks our approach collapses to the Ryngaert (2017) specification. The model we propose here relies on two related strands of the existing literature.

The first strand of literature pertains to the UC model (see, among others, Kim, 1993, Stock and Watson, 2007, 2009, 2010, Piger and Rasche, 2008, Grassi and Proietti, 2010, Nason and Smith, 2013, Mertens and Nason, 2015, Morley et al, 2015, Stella and Stock, 2015, Chan et al, 2018, Hwu and Kim, 2019, and Dixon et al, 2020). The UC approach models the stochastic trend component of inflation—which could be the core, target or fundamental rate of inflation—as a latent random walk (τ_t) and the inflation gap (ξ_t) represents the transitory deviations of the actual inflation from its trend: $\pi_t = \tau_t + \xi_t$. The actual inflation rate has a unit root, that is$\pi_t \sim I(1)$, as it embodies the unobservable random walk τ_t, while the gap is a stationary ARMA process, that is $\xi_t \sim I(0)$. Perron and Wada (2009) show that the neglect of structural breaks in the deterministic components of UC models as well as of other approaches (such as the Beveridge-Nelson decomposition and the Hodrick-Prescott filter) yields very different trend-gap decompositions. They ascribe most of the movements to the stochastic trend leaving little to the gap, and often this implies a negative correlation between the noise to the cycle and the trend. However, these negative relationships are overcome once the shifts in trends properly account for structural breaks. The weakness of the UC models in the presence of structural breaks leads to the second strand of the literature.

The second strand of the literature relates to the break-stationary models that have evolved since Perron's (1989) seminal paper. The non-stationary patterns of inflation—which in the UC models are due to τ_t- can be explained by m relevant events (the fundamental shocks) occurring over the sample period at times T_j^B ($j = 1, 2, \ldots, m$), rather than by the existence of unit roots. In this context, inflation dynamics can be decomposed into m permanent effects—modelled as deterministic shifts producing $m+1$ regimes of core inflation τ_{m+1} - plus a sequence of transitory shocks to the stationary inflation gap ξ_t. Corvoisier and Mojon (2005) show that ignoring breaks in the mean of inflation leads to exaggerating inflation persistence. Meanwhile, conditional on the estimated breaks, inflation usually exhibit little persistence.

In general equilibrium models, trend inflation is typically equated to a central bank's long-run target. For instances, Cogley et al (2010) argue that movements in trend inflation shifts with the Federal Reserve's target (a similar point was also made by Stock and Watson, 2010). Hence, the empirical literature mainly focuses on possible structural breaks in the mean of inflation associated with changes in monetary policy in the US and other developed economies in the postwar period (see, among the others, Benati and Kapetanois, 2003, Levin and Piger, 2004, Altissimo et al, 2006, Cecchetti and Debelle, 2006, and Benati, 2008).[3] Overall, these studies suggest that the persistence in (core) inflation can be captured by an optimal sequence of breaks in constant and, consequently, the inflation gap is stationary as predicted by the theoretical models.

Perron (1989) argues that the trend stationary processes with breaks are observationally equivalent to unit root processes with strong mean reversion and fat-tailed distribution for the error sequence. So, in practice, it may be advantageous to adopt the trend stationary view with breaks and detrend the actual series to analyze the remaining inflation gap. In fact, under the unit root view, one must ensure the validity of the procedures under fat-tailed disturbances and be aware of the risks of neglecting breaking parameters.

Therefore, we model the unobservable inflation state with a stationary model with structural breaks:

$$\pi_t = \tau_{m+1} + \xi_t \tag{7}$$

where τ_{m+1} is a series of $m+1$ constants along $m+1$ inflation regimes, and the inflation gap ξ_t is the single unobservable state assumed to evolve according to the stationary AR(1) model: $\xi_t = \rho\xi_{t-1} + \mu_t$. The measurement (or observation) equation is:

$$\pi^*_{i,t} = \pi_t + \omega_{i,t} \tag{8}$$

where $\omega_{i,t}$ are *iid* zero-mean individual measurement noises.

3 Benati and Kapetanios (2003) find that all inflation series display structural breaks, often they appear to broadly coincide with readily identifiable macroeconomic events. Levin and Piger (2004) find that the very high persistence in inflation reflects more the influence of occasional shifts in the central bank's inflation objective, rather than the intrinsic persistence of inflation in response to other macroeconomic shocks. Conditional on breaks in the intercept, the process generating inflation appears to be reasonably stable over the entire sample period with little evidence of structural breaks in the dynamic parameters of each time-series model. Altissimo et al. (2006) note that the timing of breaks in inflation mean generally coincides with observed shifts in the monetary policy regime. Cecchetti and Debelle (2006) show that the conventional wisdom that inflation has a high level of persistence is not robust; once one controls for a break in the mean of inflation, measured persistence is considerably lower. Benati (2008) results support this view.

The *a posteriori* forecast is, therefore, formed as the weighted sum of the new (noisy) information and the *a priori* forecast, as follows:

$$F_{i,t}\pi_t = G\pi^*_{i,t} + (1-G)F_{i,t-1}\pi_t \tag{9}$$

where G is the weight and $0 \le G \le 1$.

Subsequently, following the state equation (7),[4] the NI agent uses the *a posteriori* state estimate $F_{i,t}\pi_t$ in equation (9) to iterate forward their forecasts h-steps ahead as:

$$F_{i,t}\pi_{t+h} = \tau_{m+1} + \rho^h(F_{i,t}\pi_t - \tau_{m+1}) \tag{9'}$$

Substituting equation (9) into (9'), we have:

$$F_{i,t}\pi_{t+h} = \tau_{m+1} + \rho^h[G\pi^*_{i,t} + (1-G)F_{i,t-1}\pi_t - \tau_{m+1}] \tag{10}$$

and if we substitute above the measurement equation (8), we will obtain:

$$\begin{aligned} F_{i,t}\pi_{t+h} &= \tau_{m+1} + \rho^h[G(\tau_{m+1} + \xi_t + \omega_{i,t}) + (1-G)F_{i,t-1}\pi_t - \tau_{m+1}] \\ &= \tau_{m+1} + \rho^h[G(\xi_t + \omega_{i,t}) + (1-G)(F_{i,t-1}\pi_t - \tau_{m+1})] \end{aligned}$$

Now we can forecast the inflation gap h-steps ahead using the AR dynamics:

$$F_{i,t}\pi_{t+h} = \tau_{m+1} + G(\rho^h\xi_t + \rho^h\omega_{i,t}) + (1-G)\rho^h(F_{i,t-1}\pi_t - \tau_{m+1}) \tag{11}$$

By rearranging the definition of the FIRE forecast h steps ahead[5] as: $\rho^h\xi_t = \pi_{t+h} - \tau_{m+1} - \nu_{t+h|t}$ and by substituting it into equation (11), we derive:

$$F_{i,t}\pi_{t+h} = \tau_{m+1} + G(\pi_{t+h} - \tau_{m+1} - \nu_{t+h|t} + \rho^h\omega_{i,t}) + (1-G)\rho^h(F_{i,t-1}\pi_t - \tau_{m+1})$$

Further rearranging to obtain:

$$F_{i,t}\pi_{t+h} = G(\pi_{t+h} - \nu_{t+h|t} + \rho^h\omega_{i,t}) + (1-G)[\rho^h(F_{i,t-1}\pi_t - \tau_{m+1}) + \tau_{m+1}]$$

So, we obtain the inflation forecast for $t+h$, given the information set available in *t-1*: $\rho^h(F_{i,t-1}\pi_t - \tau_{m+1}) + \tau_{m+1} = F_{i,t-1}\pi_{t+h}$. Hence:

$$\begin{aligned} F_{i,t}\pi_{t+h} &= G(\pi_{t+h} - \nu_{t+h|t} + \rho^h\omega_{i,t}) + (1-G)F_{i,t-1}\pi_{t+h} \\ &= G\pi_{t+h} + (1-G)F_{i,t-1}\pi_{t+h} - G(\nu_{t+1|t} - \rho^h\omega_{i,t}) \end{aligned} \tag{12}$$

Finally, averaging across agents, we obtain the aggregate stochastic equation for the NI representation of forecasts:

$$F_t(\pi_{t+h}) = G\pi_{t+h} + (1-G)F_{t-1}(\pi_{t+h}) - G(\nu_{t+1|t} - \rho^h\overline{\omega}_t) \tag{12'}$$

where $\overline{\omega}_t$ is the common noise (the average across individuals of the noise $\omega_{i,t}$, which is different from zero if individual noises are cross-correlated, that is if $Cov(\omega_{i,t}\omega_{j,t}) = \sigma^2_{ij} > 0$.[6]

As discussed earlier, the second dimension of inattentiveness pertains to the way information is used to obtain the multi-step ahead inflation forecast, for example $F_{t-1}(\pi_{t+h})$ in equation (12'). Crucially, this depends on the forecasted inflation momentum is:

4 See also the equation (A1.1) in Appendix A1.

5 See equations (A1.2)-(A1.4) in Appendix A1.

6 Regarding the way the average noise is extrapolated into the future, in equation (9') we assume that the NI agents iterate forward their forecasts by treating the measurement error as a part of the inflation gap.

$$F_t(\Delta\pi_{t+h+1}) = F_t(\pi_{t+h+1}) - F_t(\pi_{t+h}) = (\rho^{h+1} - \rho^h)\xi_t \tag{13}$$

Hence, $F_t(\Delta\pi_{t+h+1}) = 0$ if the forecasted inflation gap is: $\xi_t = 0$[7]. Therefore, if the forecasters form their multi-step ahead forecasts at time *t-1* using only the trend component of inflation, for example the core inflation τ_{m+1} known in *t-1*, the forecasts will be the same at all horizons:

$$F_{t-1}(\pi_{t+h}) = \cdots = F_{t-1}(\pi_{t+1}) = F_{t-1}(\pi_t) = \tau_{m+1} \qquad (13')$$

The equations above summarize the issue faced by the forecaster when making the multi-step ahead forecast. Therefore, the issue arises of estimating the probability that forecasters use past forecasts $F_{t-1}(\pi_t)$ rather than the alternative $F_{t-1}(\pi_{t+1})$. We can define a two-step ahead inflation forecast $\tilde{F}_{t-1}(\pi_{t+1})$ encompassing the two cases above—with or without inflation gap forecasts—by restating equation (12') (when $h = 1$) as:

$$F_t(\pi_{t+1}) = G\pi_{t+1} + (1-G)\tilde{F}_{t-1}(\pi_{t+1}) - G(\nu_{t+1|t} - \rho\overline{\varpi}_t) \tag{14}$$

where the encompassing two-step ahead past forecasts are a weighted average:

$$\tilde{F}_{t-1}(\pi_{t+1}) = (1-K)F_{t-1}(\pi_t) + (K)F_{t-1}(\pi_{t+1}) \qquad (14')$$

where K is the probability that the forecaster predicts and updates the inflation gap beyond one-step ahead.

The second dimension of inattentiveness can be incorporated in the NI scenario by substituting $\tilde{F}_{t-1}\pi_{t+h}$ in equation (14) with the definition given in equation (14'), while extending the case to h steps ahead forecast. Rearranging, we obtain the forecast error structure for the NI model as follows:

$$\pi_{t+h} - F_t(\pi_{t+h}) = \frac{1-G}{G}[F_t(\pi_{t+h}) - F_{t-1}(\pi_{t+h})] + \frac{1-G}{G}(1-K)[F_{t-1}(\pi_{t+h}) - F_{t-1}(\pi_{t+h-1})] + \varepsilon_{t+h} \tag{15}$$

where $\varepsilon_{t+h} = \nu_{t+h|t} - \rho^h\overline{\varpi}_t$ includes both the FIRE forecast error $\nu_{t+h|t}$ as in the SI model (6), and the additional (weighted) average random noises $\overline{\varpi}_t$.

The G and K parameters in (15) are formed independently. We assume the professional forecaster can distinguish information that pertains to the core inflation (trend innovation) and to the inflation gap (stationary component). When agents form multi-period forecasts, the focus is just on the inflation gap and its persistence and, therefore, the expected momentum of future inflation rates matters.

Comparing the SI and NI models in (6) and (15) suggests two relevant points. In the first instance, the dynamics of the two models are the same: the probability $1-\gamma$ of updating the information set in SI model (6) corresponds to the weight G placed on the new information in NI model (15). Secondly, the stochastic errors of the two models are different. The SI error term in (6) is the scaled FIRE forecast error $\nu_{t+1|t}$ and pertains to macroeconomic shocks, while the NI error term in (15) also embodies the average of the individual noises. Therefore, $\nu_{t+1|t}$ in (6) is the full-information rational expectations error uncorrelated with

7 The other possibility is if $\rho = 1$, but this is inconsistent with a stationary inflation gap. It is also noteworthy that Morley et al (2015) assume that the unconditional mean of the inflation gap is zero: $E(\varepsilon_1) = 0$.

information dated t or earlier, while the NI error term in (15) is uncorrelated with information dated only t-1 or earlier, but is correlated with information dated t.[8]

3. Data and econometric issues

In order to empirically assess the forecasters' inattentiveness, we must use a sequence of multi-period forecasts. In the present paper, we focus on professional forecasters using two different US datasets: the Survey of Professional Forecasters (SPF) and the Livingston Survey (LS).

The datasets differ in four aspects: (i) the frequency at which the survey is conducted (the SPF is quarterly, while the LS is conducted twice a year); (ii) the predicted inflation measures (both surveys forecast the consumer price index, CPI, while the SPF also forecasts the GDP deflator); (iii) the multi-period forecast horizon (the quarterly SPF predicts from one to six quarters ahead, and the semi-annual LS predicts one and two semesters ahead); and (iv) the time span covered by the different surveys (the SPF forecasts are available from 1965 to date, while the LS from 1946 to date).[9]

Such heterogeneity allows for alternative forecast measurements to be exploited, thereby, assessing the robustness of the estimation results across different forecast horizons and frequencies. These are characterized by various degrees of overlapping forecasts and groups of forecasters.[10] 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 choice of the most appropriate econometric approach raises two main issues: the possible correlation of explanatory variables with the error term ε_{t+h} in model (15) 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 both stationary variables and valid (i.e. relevant and exogenous) instruments.

As shown in equation (15), and noted by CG, the individual noises at time t may be affected by nonzero averages across agents which, though uncorrelated with information dated from t-1 and earlier, are related to the error ε_{t+h}. CG decided to use the downward-biased OLS estimates as a lower bound on the degree of information rigidity.[11] However, this approach is not appropriate for our case for two reasons. Firstly, as discussed at the end of the previous section, our model (15) extends CG's information rigidity measurement to the presence of an additional regressor (the forecast momentum). The assumption that OLS will be downward biased is no longer true as they can also be affected by the covariance between forecast revisions and forecast momentum. Secondly, in addition to the effect of the average noise, endogeneity can also be due to measurement errors affecting forecasts.[12] For example, Appendix A2 shows that this is clearly the case with the LS forecasts.

8 This latter point raises one of the endogeneity issues we will tackle in the next section.

9 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 the LS a statistically reliable CPI measure is given from 1970 (because of the small number of agents surveyed prior to that date).

10 Although only anonymous agents' forecasts are available for SPF and LS datasets, a LS multinomial variable classifies individual forecasters in groups. Therefore, it is possible to compute averages by groups for the LS data, while we are unable to use averages by group for the SPF data as the multinomial variable is only consistently available from 1991q4.

11 See footnote 4 in CG, and their online Appendix A.

Therefore, consistent coefficient estimates require IV/GMM with valid 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.

Regarding stationarity, 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. Hence, they are consistent with the statistical properties required by the IV/GMM estimators.

As far as the choice of the instruments is concerned, we use both internal (the first two lags of the actual inflation rate, and one lag of one- and two-step ahead inflation forecasts) and external instruments (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). To assess the validity of these instruments, we follow Stock et al (2002) by computing the first-stage F-statistics. We assume the inferences are reliable (because the instruments are not weak) when the F-statistics are large, typically exceeding 10. Finally, with regards to the exogeneity of instruments, as our estimates are over-identified, we can assess whether the instruments are jointly exogenous through the Hansen (1982) test. It is also worth noting that—despite the long list of instruments above—the p-values of the Hansen (1982) test that we found in our estimates are low (i.e. far from one) indicating that they are not biased due to the proliferation of instruments.[13]

4. Estimation analysis and results

Following the derived equations (6) and (15) in Section 2 for SI and NI models respectively, the empirical analysis here considers the general equation (16) which can account for the different datasets described in the preceding section[14]:

$$\begin{aligned}\pi_{t+h} - F_t(\pi_{t+1,t+h}) = \frac{\lambda}{1-\lambda}\Delta F_t(\pi_{t+1,t+h}) + \\ \frac{\lambda}{1-\lambda}\phi[F_{t-1}(\pi_{t+1,t+h}) - F_{t-1}(\pi_{t,t+h-1})] + \varepsilon_{t+h}\end{aligned} \tag{16}$$

The first regressor in equation (16), $\Delta F_t(\pi_{t+1,t+h}) = F_t(\pi_{t+1,t+h}) - F_{t-1}(\pi_{t+1,t+h})$ 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* for $t+h$*-1* and $t+h$ periods ahead. So, λ denotes eitherγor $(1-G)$, while ϕ denotes either φ or $(1-K)$distinguishing between the SI and NI models depicted in equations (6) and (15) respectively.

12 On this point, Roberts (1998, p. 11) notes that "another reason is measurement error, which can be an especially important problem for survey expectations, since they are based on small samples, and so may be very noisy indicators". Of course, this issue affects both the NI and the SI models.

13 An extensive discussion of this problem and remedies are found in Bontempi and Mammi (2015) and references therein.

14 Appendix A2 outlines how equation (16) must be emended to fit the alternative survey data features. Appendix A3 tackles the issue of testing restrictions that allows the specific model which is nested in the general model (16).

Table 1. Estimates of the Coibion and Gorodnichenko (2015) model with SPF data [a]

	(1)		(2)		(3)		(4)	
Start in:	1970q1		1970q1		1980q1		1981q4	
Estimation method:	IV		GMM		GMM		GMM	
Inflation measure:	GDP		GDP		GDP		CPI	
λ [b]	**0.6630**	***	**0.6366**	***	**0.4979**	***	**0.4108**	***
	(0.0579)		(0.0447)		(0.0620)		(0.0588)	
Intercept	**-0.0306**		**-0.1057**		**-0.2581**	***	**-0.0747**	
	(0.1131)		(0.0809)		(0.0832)		(0.0963)	
T	171		171		133		127	
Mean [c]	−0.0423		−0.0423		−0.3536		−0.1603	
SER [d]	1.1116		1.0885		0.6885		1.0838	
Specification tests: [e]								
– Andrews (1993)	1979q3	***						
– Hausman (1978)	0.0000		0.0246		0.1111		0.1274	
– Stock et al (2002)	15.2		15.2		11.5		11.4	
– Hansen (1982)	0.0538		0.4641		0.3479		0.6058	

[a] $\pi_{t+3} - F_t(\pi_{t,t+3}) = \frac{\lambda}{1-\lambda}[F_t(\pi_{t,t+3}) - F_{t-1}(\pi_{t,t+3})] + Intercept + \varepsilon_{t+3}$. Estimation period: from *start* to 2013q1 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: IV (Sargan, 1958) and GMM (Hansen, 1982). Inflation measure: GDP deflator or CPI (consumer price index). In bold: estimates; in parentheses: HAC standard errors, see Newey and West (1987); given the estimates of linear $\beta = \frac{\lambda}{1-\lambda}$, λ standard errors are obtained using the delta method; *** ** 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 λ is 0.552.

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

[d] Standard error of the regression.

[e] Andrews (1993) = MaxF test statistic for structural change with unknown break date (trimming 20%) for IV estimates (the significant break date is reported); Hausman (1978) test for weak exogeneity (p-values); Stock et al (2002) first-stage F-statistic of the null of weak instruments; Hansen (1982) J test statistic for over-identification restrictions (p-values).

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 (16) are computed by differences between pairs of forecasts which may overlap. The discussion in the preceding section regarding the more appropriate estimator in the present context suggests using IV and GMM. In fact, the IV-GMM estimators can account for nonzero average individual noises which might affect the average forecast revisions and the error ε_{t+h}, and, therefore, they are more reliable than OLS estimates, which assume zero average individual noises.

Table 1 reports the estimates for the SPF data when we impose the restriction $\phi = 0$ which corresponds to the CG model. Columns (1)–(2) refer to the GDP inflation and report estimates obtained with IV and GMM, respectively, over the whole sample (that is, including the 1970s decade). Overall, IV-GMM estimators indicate statistically significant information rigidities (above 0.5) and confirm the main findings reported in the first column of Table 1 panel B of CG: 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. As expected, the intercept is not significant, and the overestimate of information rigidity ($\hat{\lambda} = 0.663$ with IV and 0.637 with GMM, while CG report $\hat{\lambda} = 0.552$) is due to the use of consistent instrumental variables estimators (see the significant Hausman, 1978, test). In addition, note that we used a longer sample period, ending in 2013q1 rather than in 2010q2.[15]

When we test for IV parameters' constancy in column (1) using the Andrews (1993) test statistic for structural change with unknown break date, a clear break emerges in 1979q3. This date coincides with a shift in the parameters of the Taylor rule at the time of Volker's appointment, that is at the beginning 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 (3) in Table 1 reports the GMM estimates after removing the 1970s from the sample period, mainly focusing on the Great Moderation period. In the shorter sample period, the λ estimate drops by more than 20%, from 0.637 to 0.498, representing a reduction in forecaster inattentiveness in the US since the start of the Volker mandate. Although this outcome is fairly robust with respect to the different measures of inflation (see also the results with CPI in column (4)), it is at odds with the prediction of Reis's (2006) SI model where the Great Moderation should increase the degree of inattentiveness. Also, CG reports similar results when all the SPF variables (and not just inflation) are pooled together. A better interpretation is that the outcome is more likely affected by a random structural shift due to the omission of relevant (momentum) effects, as shown and discussed in Table 2 below.

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 characterizes (through the λ parameter) the predictability of *ex postx post* forecast errors. The results reported in CG partially invalidate models with information rigidities, as the parameter of the lag of the unemployment rate is statistically significant.

Given the preceding evidence of parameters' breaks, column (1) of Table 2 replicates CG finding of a significant lagged unemployment effect using GMM in the sample excluding the 1970s. If the significant unemployment effect were a mere anomaly, it would not have been so robustly evident over the alternative sample periods and estimation methods.[16]

Despite the significant unemployment effect, λ estimate is significant and close to those reported in column (3) 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. 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 CG because of the invalid $\phi = 0$ restriction. In order to investigate this further, in column (2) of Table 2 we estimate a specification of equation (16) which also includes the unemployment effect (through parameter δ). The insignificant estimate of δ suggests that both dimensions of inattentiveness better explain the forecast error than the CG model augmented by the unemployment effect, as the latter is no longer significant.

15 The comparison with CG model using IV-GMM and OLS estimators is at the end of Appendix A3, see Table A3.2.

16 See the details using OLS and IV-GMM over alternative samples are in Table A3.3 of Appendix A3.

Table 2. GMM estimates of the model with the two dimensions of inattentiveness (SPF)[a]

	(1)	(2)	(3)	(4)
Start in:	1980q1	1980q1	1980q1	1981q4
Estimation method:	GMM	GMM	GMM	GMM
Inflation measure:	GDP	GDP	GDP	CPI
λ	**0.4460***	**0.6566***	**0.6675***	**0.5903***
	(0.0304)	(0.0579)	(0.0523)	(0.0575)
φ [b]		**0.4633** **	**0.4353** **	**0.6062** **
		(0.2275)	(0.2149)	(0.2848)
δ	**-0.0702***	**-0.0456**		
	(0.0250)	(0.0496)		
Intercept	**0.1372**	**0.0621**	**-0.1983** **	**-0.0600**
	(0.1946)	(0.2955)	(0.0813)	(0.1359)
T	133	133	133	127
Mean [c]	−0.3536	−0.3536	−0.3536	−0.1603
SER [d]	0.6657	0.8440	0.8623	1.1703
Specification tests: [e]				
– Stock et al (2002)	11.0	9.3	10.2	11.1
– J-test	0.5070	0.2724	0.4298	0.3380

[a] $\pi_{t+3} - F_t(\pi_{t,t+3}) = \frac{\lambda}{1-\lambda}[F_t(\pi_{t,t+3}) - F_{t-1}(\pi_{t,t+3})] + \frac{\lambda}{1-\lambda}\phi[F_{t-1}(\pi_{t,t+3}) - F_{t-1}(\pi_{t-1,t+2})] + \delta\, Unempl_{t-1} + Intercept + \varepsilon_{t+3}$. 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: GMM (Hansen, 1982). Inflation measure: GDP deflator or CPI (consumer price index). In bold: estimates; in parentheses: HAC standard errors, see Newey and West (1987); given the estimates of linear $\beta = \frac{\lambda}{1-\lambda}$ and $\alpha = \frac{\lambda}{1-\lambda}\phi$, λ and ϕ standard errors are obtained using the delta method; *** ** 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] Stock et al (2002) first stage F-statistic of the null of weak instruments; Hansen (1982) *J* test statistic for over-identification restrictions.

Columns (3) and (4) report GMM estimates of equation (16) where the inflation rate is measured by the GDP deflator and CPI respectively. The results are clear: the model with both dimensions of inattentiveness can explain the forecast error regardless of the inflation measure.[17] Note also that, as anticipated earlier when discussing the results reported in Table 1, the λ estimates in Table 2 with two dimensions of inattentiveness are not subject to puzzling parameter shifts.

The SPF predictions are not the only source of information to assess the empirical validity of equation (16) for the USA. 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 (16) 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).

17 Results in Appendix A3 provide further evidence which is consistent with the notion that the professional forecasters are depicted by the two dimensions of inattentiveness starting from a general model that nests equation (16).

Table 3. GMM estimates using the Livingston Survey data [a].

Group: [b]	(1)	(2)	(3)	(4)	(5)
	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
λ [c]	**0.5831** ***	**0.6839** ***	**0.5388** ***	**0.6515** ***	**0.6261** ***
	(0.0963)	(0.0440)	(0.0907)	(0.0634)	(0.0411)
ϕ	**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] $\pi_{t+1} - F_t(\pi_{t+1}) = \frac{\lambda}{1-\lambda}\Delta F_t(\pi_{t+1}) + \frac{\lambda}{1-\lambda}\phi[F_{t-1}(\pi_{t+1}) - F_{t-1}(\pi_t)] + \varepsilon_{t+1}$. 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); given the estimates of linear $\beta = \frac{\lambda}{1-\lambda}$ and $\alpha = \frac{\lambda}{1-\lambda}\phi$, λ and ϕ standard errors are obtained using the delta method; *** ** 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 λ (with ϕ 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).

With LS data, both dimensions of inattentiveness (parameters λ and ϕ) 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 λ and ϕ using CPI inflation are remarkably similar over the period excluding the 1970s. The same is true for the λ estimate over the period including the 1970s even though the inflation rate is measured by CPI in the LS and by GDP deflator in the SPF. However, the momentum effect ϕ parameter estimate is very different and fairly close to that of λ when inflation is measured by the CPI forecasts of the LS but not significant when inflation is measured by the GDP deflator forecasts of the SPF. Again, the puzzling shift in the λ estimate found in Table 1 does not occur here. This is due to the specification of a model which now includes the two dimensions of inattentiveness.[18]

The disaggregated estimates by the group of forecasters indicate that academics and policymakers 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

18 Further supporting results are found in Appendix A3.

policymakers experience similar informational rigidities when $\hat{\varphi}$=0.55.[19] Conversely, the financial and non-financial sectors experience considerably higher rigidities due to forecast momentum when $\hat{\varphi}$= 0.71 and 0.67 respectively. It is not surprising that academics and policymakers have lower informational rigidities as they should have superior knowledge.

At this conjuncture it is worth introducing the assessment of the forecast unbiasedness and efficiency in the context of information rigidities (see details in Appendix A4) as well as offering some discussion pertaining to characteristic outcomes such as the relevance of inflation gaps to explain the forecast errors when using the 1970s.

A couple of noteworthy remarks are required. The coefficient φ and unemployment control variable capture 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 the LS. This may just reflect the nature of the dataset. The overlapping forecast horizon for the SPF (but not in the case of the LS) may be important. Putting this issue aside, the period from the appointment of Volker (at the end of the 1970s) and the Great Moderation (from the mid-1980s) has clearly had a significant impact on the dynamics of both actual inflation and the forecast of inflation. Following the Great Moderation, inflation persistence has reduced, and the propagation of shocks curtailed. Prior to the Great Moderation any shocks that were observed in the current period would last beyond the next period. So, a forecaster making a multi-period forecast in t can 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:ϕ=0.

As highlighted recently in Chan et al (2018), during the Great Moderation central banks had a very low tolerance for inflation gaps. Therefore, the primary focus of professional forecasters has been on permanent shocks to core inflation. During this period, forecasters have assumed a zero inflation gap (see Dixon et al, 2020) and appear to be inattentive when making multi-period inflation forecasts. The second dimension of inattentiveness pertaining to the forecast of the inflation gap or the momentum of inflation has an interesting perspective on the credibility of monetary policy. It appears consistent with the inflation gap forecast that approximates zero with little or no persistence and, hence, a lower sacrifice ratio.

5. 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 they may relate to informational rigidities. In this paper, we extend the existing literature by considering a second dimension of inattentiveness when forecasting inflation rates.

19 The finding of low information rigidities is consistent with Romer and Romer (2000). They maintain that the Federal Reserve commits far more resources to forecasting activity than even the largest commercial forecasters and, consequently, they can forecast closer to FIRE than the other groups of forecasters.

Both dimensions of inattentiveness relate to the necessary activity a professional forecaster needs to undertake and, therefore, they are related to each other. Professionals 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. This relates directly to the forecast of inflation gap persistence. As in the case with the short-run Phillips curve trade-off, they need to assess the propagation, or persistence, of transitory shocks, or the inflation gap. Both instances involve the ability to observe relevant but different information and, therefore, the dimensions 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. The existence of the second form relating to forecasting momentum could arise in both types of information rigidity models: sticky and noisy information.

The empirical investigation using two surveys of professional forecasts for the USA establishes the existence of both dimensions of inattentiveness. It also clearly indicates that the short-run Phillips curve reflecting inflation momentum captured by the unemployment effect is best depicted by this dimension 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.

Supplementary material

Supplementary material is available on the OUP website. These are the replication file and the Online Appendix.

Funding

The authors declare that they have not received any funding for the research/study which led to this paper.

Acknowledgements

We gratefully acknowledge the comments and suggestions of the two anonymous referees and Editor, Raoul Minetti. Also, the comments and suggestions of Carlo Favero and Adrian Pagan to an earlier draft. Nevertheless, any omissions and errors are entirely ours

References

Altissimo, F., Bilke, L., Levin, A., Mathä, T., and Mojon, B. (2006) "Sectoral and aggregate inflation dynamics in the euro area", *Journal of the European Economic Association*, **4**, 585–93.

Andrade, P., and Le Bihan, H.L. (2013) "Inattentiveness professional forecasters", *Journal of Monetary Economics*, **60**, 967–82.

Andrews, D.W.K. (1993) "Test for parameter instability and structural change with unknown change point", *Econometrica*, **61**, 821–56.

Ball, L., Mankiw, N.G., and Reis, R. (2005) "Monetary policy for inattentive economies", *Journal of Monetary Economics*, **52**, 703–25.

Beechey, M., and Osterholm, P. (2012) "The rise and fall of US inflation persistence", *International Journal of Central Banking*, 55–86.

Benati, A. (2008) "Investigating inflation persistence across monetary regimes", *Quarterly Journal of Economics*, **123**, 1005–160.

Benati, A., and Kapetanios, G. (2003) "Structural Breaks in Inflation Dynamics", *Computing in Economics and Finance*, Society for Computational Economics, **169**, 3, 563–87.

Bernanke, B. (2007) "Inflation Expectations and Inflation Forecasting." Speech at the Monetary Economics Workshop of the National Bureau of Economic Research Summer Institute, Cambridge, Massachusetts, July 10.

Bontempi, M.E., and Mammi, I. (2015) "Implementing a strategy to reduce the instrument count in panel GMM,", *The Stata Journal: Promoting Communications on Statistics and Stata*, **15**, 1075–97.

Caplin, A., and Dean, M. (2015) "Revealed preference, rational inattention, and costly information acquisition", *American Economic Review*, **105**, 2183–203.

Carroll, C.D. (2003) "Macroeconomic expectations of households and professional forecasters", *The Quarterly Journal of Economics*, **118**, 269–98.

Carroll, C.D. (2006) "The Epidemiology of Macroeconomic Expectations" in L. Blume and S. Durlauf (eds.), *The Economy as an Evolving Complex System*, Oxford University Press.

Cecchetti, S.G., and Debelle, G. (2006) "Has the inflation process changed?", *Economic Policy*, **21**, 312–53.

Chan, J.C.C., Clark, T.E., and Koop, G. (2018) "A new model of inflation, trend inflation and Long-Run expectations", *Journal of Money, Credit and Banking*, **50**, 5–53.

Clarida, R., Galì, J., and Gertler, M. (2000) "Monetary policy rules and macroeconomic stability: Evidence and some theory", *Quarterly Journal of Economics*, **115**, 147–80.

Cogley, T., Primiceri, G.E., and Sargent, T.J. (2010) "Inflation-gap persistence in the U.S", *American Economic Journal: Macroeconomics*, **2**, 43–69.

Coibion, O., and Gorodnichenko, Y. (2015) "Information rigidity and the expectations formation process: a simple framework and new facts", *American Economic Review*, **105**, 2644–78.

Coibion, O., Gorodnichenko, Y., and Kamdar, R. (2018) "The formation of expectations, inflation and the phillips curve", *Journal of Economic Literature*, **56**, 1447–91.

Corvoisier, S., and Mojon, B., (2005) "Breaks in the Mean of Inflation. How They Happen and What to do With Them", *ECB Working Paper Series*, 451.

Dixon, H., Easaw, J., and Heravi, S. (2020) "Forecasting inflation gap persistence: Do financial sector professionals differ from nonfinancial sector ones?", *International Journal of Finance & Economics*, **25**, 461–74.

Easaw, J., Golinelli, R., and Malgarini, M. (2013) "What determines households inflation expectations? Theory and evidence from a household survey", *European Economic Review*, **61**, 1–13.

Faust, J., and Wright, J., (2013) "Forecasting Inflation", in G. Elliott and A. Timmermann (eds.), *Handbook of Economic Forecasting*, Volume **2A**, Elsevier.

Fuhrer, J. (2017) "Expectations as a source of macroeconomic persistence: Evidence from survey expectations in a dynamic macro model", *Journal of Monetary Economics*, **86**, 22–35.

Grassi, S., and Proietti, T. (2010) "Has the US volatility changed and how?", *Journal of Time Series Econometrics*, **2**, 1–22.

Hansen, L.P. (1982) "Large sample properties of generalized method of moments estimators", *Econometrica*, **50**, 1029–54.

Hausman, J.A. (1978) "Specification tests in econometrics", *Econometrica*, **46**, 1251–71.

Hwu, S.-T., and Kim, C.-J. (2019) "Estimating trend inflation based on unobserved components model: is it correlated with the inflation gap?", *Journal of Money, Credit and Banking*, **51**, 2305–19.

Jain, M. (2019) "Perceived inflation persistence", *Journal of Business & Economic Statistics*, **37**, 110–20.

Kim, C.-J. (1993) "Unobserved-Component Time-Series models with Markov-Switching heteroskedasticity", *Journal of Business and Economic Statistics*, **11**, 341–9.

Levin, A.T., and Piger, J.M., (2004) "Is Inflation Persistence Intrinsic in Industrial Economies?", *ECB Working Paper Series*, 334.

Mankiw, N.G., and Reis, R. (2002) "Sticky information versus sticky prices: a proposal to replace the new keynesian phillips curve", *The Quarterly Journal of Economics*, **117**, 1295–328.

Mankiw, N.G., and Reis, R. (2006) "Pervasive stickiness", *American Economic Review*, **96**, 164–9.

Mankiw, N.G., Reis, R., and Wolfers, J., (2003) "Disagreement About Inflation Expectations", in M. Gertler and K. Rogoff (eds.), *NBER Macroeconomics Annual 2003*, **18**, 209–248.

Mertens, E., and Nason, J.M., (2015) "Inflation and Professional Forecast Dynamics: An Evaluation of Stickiness, Persistence and Volatility", *mimeo*.

Morley, J., Piger, J., and Rasche, R. (2015) "Inflation in the G7: Mind the gap(s)?", *Macroeconomic Dynamics*, **19**, 883–912.

Mishkin, F. (2007) "Inflation Dynamics." Speech at the Annual Macro Conference, Federal **Reserve Bank of San Francisco**, March 23.

Muth, J.F. (1960) "Optimal properties of exponentially weighted forecasts", *Journal of the American Statistical Association*, **55**, 299–306.

Nason, J.M., and Smith, G.W., (2013) "Measuring the Slowly Evolving Trend in US Inflation with Professional Forecasts", *Queen's Economics Department Working Paper*, 1316.

Newey, W.K., and West, K.D. (1987) "A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance matrix", *Econometrica*, **55**, 703–8.

Nordhaus, W.D. (1987) "Forecasting efficiency: Concepts and applications", *The Review of Economics and Statistics*, **69**, 667–74.

Perron, P. (1989) "The great crash, the oil price shock and the unit root hypothesis", *Econometrica*, **57**, 1361–401.

Perron, P., and Wada, T. (2009) "Let's take a break: Trends and cycles in US real GDP", *Journal of Monetary Economics*, **56**, 749–65.

Piger, J., and Rasche, R.H. (2008) "Inflation: Do expectations trump the gap?", *International Journal of Central Banking*, **4**, 583–601.

Reis, R. (2006) "Inattentive producers", *The Review of Economic Studies*, **73**, 793–821.

Roberts, J.M. (1998) "Inflation Expectations and the Transmission of Monetary Policy", *Federal Reserve Board Working Paper*, 43.

Romer, C.D., and Romer, D.H. (2000) "Federal reserve information and the behavior of interest rates", *American Economic Review*, **90**, 429–57.

Ryngaert, J. (2017) "What Do (and Don't) Forecasters Know About U.S. Inflation?", *mimeo*.

Sargan, J.D. (1958) "The estimation of economic relationships using instrumental variables", *Econometrica*, **26**, 393–415.

Sims, C.A. (2003) "Implications of rational inattention", *Journal of Monetary Economics*, **50**, 665–90.

Steiner, J., Stewart, C., and Matějka, F. (2017) "Rational inattention dynamics: Inertia and delay in decision-making", *Econometrica*, **85**, 521

Stella, A., and Stock, J.H., (2015) "A State-Dependent Model for Inflation Forecasting", in S. J. Koopman and N. Shephard (eds.), *Unobserved Components and Time Series Econometrics*, Oxford University Press, Ch. 3, pp. 14–29.

Stock, J.H., and Watson, M.W. (2007) "Why has US inflation become harder to forecast?", *Journal of Money, Credit and Banking*, **39**, 3–33.

Stock, J.H., and Watson, M.W., (2009) "Phillips Curve Inflation Forecasts", in J. Fuhrer, Y. K. Kodrzycki, J. Sneddon Little and G. P. Olivei (eds.), *Understanding Inflation and the Implication for the Monetary Policy*, MIT Press, pp. 99–184.

Stock, J.H., and Watson, M.W., (2010) "Modeling Inflation After the Crisis", in *Macroeconomic Challenges: The Decade Ahead*, Federal Reserve Bank of Kansas City Economic Policy Symposium.

Stock, J.H., Wright, J.H., and Yogo, M. (2002) "A survey of weak instruments and weak identification in generalized method of moments", *Journal of Business & Economic Statistics*, **20**, 518–29.

Woodford, M. (2003) "Imperfect Common Knowledge and the Effects of Monetary Policy" in P. Aghion, R. Frydman, J. Stiglitz, and M. Woodford (eds.), *Knowledge, Information, and Expectations in Modern Macroeconomics*, Princeton University Press.