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# Inattentive professional forecasters

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ABSTRACT

Using the ECB Survey of Professional Forecasters to characterize expectations at the micro-level, we emphasize two new facts: forecasters (i) fail to systematically update their forecasts and (ii) disagree even when updating. It is moreover found that forecasters have predictable forecast errors. These facts are *qualitatively* supportive of recent models of inattention and suggest a setup where agents imperfectly process information due to both sticky information *à la* Mankiw–Reis, and noisy information *à la* Sims. However, building and estimating such an expectation model, we find that it cannot *quantitatively* replicate the error and disagreement observed in the data.



## 1. Introduction

Imperfect information and the formation of expectations have long been considered—in the tradition of Friedman (1968), Phelps (1968) and Lucas (1972)—an important transmission mechanism of economic fluctuations. Imperfect information has been, in particular, related to the inattention of agents to new information, a behavior that can be rationalized by costly access to information and limited processing capacities. One appeal of these models is to provide an alternative channel to sticky prices to explain the persistent effects of transitory shocks—and in particular, monetary shocks—on the economy. Moreover, this approach can parsimoniously account for patterns of individual expectations observed in survey data that are at odds with the standard perfect information, rational expectations framework, such as predictable forecast errors and forecasts differing across forecasters.[1]

The present paper exploits the panel dimension of such a survey of forecasts—namely the ECB Survey of Professional Forecasters (SPFs)—to produce new micro-facts characterizing the formation of expectations. The ECB SPF is a quarterly panel starting in 1999 surveying around 90 forecasting units in either public or private institutions in the euro area, and allows us to track sequences of forecasts made by the same institution. This dataset is used to show that forecasters fail to systematically update their forecasts and that they disagree even when updating. We then elaborate on these new facts to assess whether models of inattention accurately describe the behavior of forecasters. Our focus is on two types of inattention models that have been discussed in the recent literature. On one hand, *sticky information* models developed by Mankiw and Reis (2002) and Reis (2006a,b), in which agents update their information set infrequently but get perfect information once they do. On the other hand, *noisy information* models proposed by Woodford (2002), Sims (2003) and Maćkowiak and Wiederholt (2009), in which agents continuously update their information but have an imperfect access to it at each period.

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[1] Mankiw and Reis (2011) and Veldkamp (2011) provide recent surveys.

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As in some related previous work, professional forecast data are here used to test imperfect information models. Expert forecasters may not be representative of less sophisticated agents, since professionals obviously allocate substantially more time, collecting and computing resources to the task of forecasting macroeconomic variables. However, Carroll (2003) shows that the opinion of professional forecasters spreads to firms and households, and hence also influences their expectations and decisions. Furthermore, professional forecasters are expected to be the agents in the best position to pay attention to relevant macroeconomic information. As a result, the extent of attention to news among professional forecasters can be seen as an upper bound for other agents' attention to aggregate conditions.

Our paper has two main contributions. The first one is to document the two aforementioned new facts, namely that (i) forecasters do not systematically update their forecasts even when new information is released, and that (ii) forecasters who update also disagree on their forecasts. The originality of our approach is to exploit the sequences of individual forecasts for a given event (say inflation at the end of a given year) provided by the ECB SPF to construct a direct micro-data estimate of the frequency of updating a forecast, which, to our knowledge, has not been documented in survey data before.[2] The results show that, on average, each quarter only 75% of professional forecasters update their 1-year or 2-year ahead forecasts. This first result is in line with the predictions of a *sticky-information* model *à la* Mankiw–Reis. Furthermore, in this setup the frequency of updating has a structural interpretation and corresponds to one key parameter, namely the attention degree. In addition to infrequent updating, the data also provide evidence that forecasters who update their information sets disagree about their forecasts. Consequently, disagreement among experts is not only related to differences in the information sets of forecasters who updated and of those who did not, but also to the fact that, when they update, they use different information sets. This second result is in line with the predictions of a *noisy-information* model *à la* Sims. Moreover, evidence found in previous work relying on survey data that forecasts of experts exhibit predictable errors and that forecasters disagree is observed in the ECB SPF data. These latter two characteristics are in line with both sticky and noisy information models.

The second main contribution of this paper is to perform a formal empirical assessment of inattention models exploiting the cross-section dimension of the survey expectations. Guided by the two aforementioned facts, we first develop a model that features both sticky and noisy information. The empirical performance of this model is assessed by comparing it to some key properties of the SPF through a Minimum Distance Estimation (MDE). More precisely, our approach is to compare moments characterizing the forecast errors and the disagreement generated by this theoretical model with their empirical counterparts observed in the ECB SPF data. Estimation results point to a rejection of the proposed inattention model. Fitting the smoothness observed in the average SPF forecasts would require a much lower attention degree than our micro-data estimates. Such a low attention would in turn lead to much more disagreement, and volatility of disagreement, than observed in the SPF data. Therefore, elements others than the type of inattention included in our expectation model are needed to reconcile the relatively low disagreement among professionals and the relatively high persistence of the aggregate forecasting error.

Our paper is related to studies which compare the properties of survey forecasts with the implications of theoretical expectation models (see Pesaran and Weale, 2006 for a survey). Numerous work found systematic aggregate forecast errors and disagreement in these data, at odds with the perfect information rational expectation framework. Our study provides additional evidence of such predictable forecast errors and disagreement for the European SPF data and a recent sample period. It also complements these results by providing new evidence on the infrequency of individual expectations revision.

Our paper is also closely linked to the literature relying on survey expectation data to assess inattention and, more generally, imperfect information theories. A prominent contribution to this literature is Coibion and Gorodnichenko (2012a). They use aggregated survey data to examine the conditional response of the average forecast error and of the disagreement across forecasters to various structural shocks in order to disentangle the sticky-information from the noisy-information models of inattention. They find mixed support in favor of the two, a result to which our evidence concurs. Their empirical evidence covers a broader range of forecasters than ours as they exploit information from the US SPF as well as forecasts from survey of US firms and consumers, while ours relies specifically on the ECB SPF. Our analysis however exploits the individual data, which allows to observe individual forecast updating, and to assess arguably more directly some implications of the two types of inattention. An advantage of our approach compared to Coibion and Gorodnichenko (2012a) is that it does not require the identification of structural shocks. Moreover, while Coibion and Gorodnichenko (2012a) consider different variants of each type of inattention separately, a distinctive feature of our approach is that a model featuring the two types of inattention simultaneously is here devised and estimated.

Other papers that rely on survey data to assess imperfect information models include Mankiw et al. (2003), Branch (2007), Patton and Timmermann (2010), Sarte (2010), and Coibion and Gorodnichenko (2012b). Mankiw et al. (2003) and Branch (2007) focus on the cross-section distribution of forecasts to calibrate the sticky-information attention parameter mentioned above. By comparison, we underline the importance of investigating the consistency of these parameter values with both the cross-section dispersion of forecasts and the aggregate forecast errors. Furthermore, our approach improves on theirs by considering a model that can explain the disagreement among forecasters who update their information set. Lastly, rather than being calibrated, the attention parameter is here estimated using alternatively direct micro-data estimates and a MDE procedure. Patton and Timmermann (2010) rely on the patterns of forecasts observed over different horizons to emphasize the importance of model disagreement rather than differences in information sets. The model considered here is an alternative approach that generates disagreement without relying on "deep" heterogeneity among

[2] Since the first version of the present paper was circulated, other papers have applied the same methodology to other survey datasets: the Michigan Survey of Consumers (Dräger and Lamla, 2012) and the Consensus Economics survey (Dovern et al., 2013).

forecasters and that can moreover account for infrequent updating. Sarte (2010) derives an indirect estimate of the attention degree of firms by matching the balance of opinions in the US ISM business condition survey to the US manufacturing production index. Coibion and Gorodnichenko (2012b) find evidence that average forecast errors are positively related to the past average forecast revisions, as implied by both sticky and noisy information models.

Finally recent contributions, e.g. Döpke et al. (2008) and Coibion (2010), also use survey forecasts together with a set of auxiliary assumptions about the economy to estimate the attention degree in a sticky-information Phillips curve. By contrast, our approach provides a direct, arguably more reliable, micro-data estimate of this parameter. While it is found to be much higher than in these previous works, the frequency of forecast updating still, remarkably, is lower than one.

The remainder of the paper is organized as follows. Section 2 describes the European SPF data and provide some basic facts. Section 3 introduces our approach to estimate the Mankiw–Reis parameter directly on micro-data, and present our two main new facts. Section 4 develops a model of inattention that incorporates both sticky and noisy information and put it to a test, relying on a moment-matching method. Some concluding remarks are provided in Section 5.[3]

## 2. The ECB survey of professional forecasters: data and basic facts

This section first provides details about the ECB SPF survey. It then documents some basic facts about forecast errors and the disagreement between forecasters.

### 2.1. The ECB SPF

The ECB's survey of professional forecasters has been conducted every quarter since 1999. The survey covers around 90 institutions involved in forecasting the euro area economy. The sample used in this paper ends with the survey round of 2012Q4, so that the sample size is 56 time periods. Each institution is asked to report, inter alia, forecasts for the (year-on-year) euro area inflation rate, the (year-on-year) real GDP growth rate and the unemployment rate for forecasting horizons of one year and two years.[4] These data are matched with the corresponding (final release) realizations of the forecasted variable. More specifically, the Eurostat aggregate data for the euro area in changing composition are used for this purpose (see Appendix A.1 for details).

The ECB SPF has been rarely used for research purposes so far. In spite of a rather short sample in the time dimension, the ECB SPF has some specific advantages compared to some other survey expectation data. To start with, the data base is a panel so that one can track the response of a particular individual institution over time. Moreover, the responses are quantitative rather than qualitative. By contrast, many of the surveys that cover firms or households are typically repeated cross-sections, and report qualitative data. Furthermore, the number of actual respondents is relatively high (typically around 60 in a given quarter) compared with other surveys of professional forecasters. This number is for example twice as large as the typical number of actual respondents in the more widely used US-SPF. Finally, the ECB SPF tracks almost the same institutions over time. By contrast there are changes in the set of institutions sampled in the US-SPF.

Respondents provide two types of forecasts. The first one is a ‘rolling horizon’ forecast, with a fixed horizon of one or two years ahead of the last available observation. To be specific, in 2010Q2, each forecaster was asked about his forecast for the inflation rate one year ahead of the last observation, *i.e.* for March 2011.[5] Then in 2010Q3, forecasters were asked about their inflation rate forecast for June 2011. The second type of forecast is a ‘calendar horizon’ forecast: in each quarter, forecasters are also asked to report their forecast for two fixed events, namely the current and the next calendar years. For instance, in both 2010Q2 and 2010Q3, forecasters were surveyed about their annual inflation forecast for the end of 2010 and the end of 2011. This information together with the fact that a given respondent can be tracked over time allow to observe individual forecast revisions of the same event, a feature that is key in the present study.

Some notation is now introduced. $f^x_{it,t+h}$ denotes individual $i$'s rolling forecasts for the variable $x$ at date $t$ and $h$ quarters ahead. The variable $x$ is either $\pi$ (the year-on-year inflation rate measured by the HICP, the Harmonized Index of Consumer Prices), $u$ (the unemployment rate), or $\Delta y$ (the year-on-year GDP growth rate). The forecast horizon $h$ is set to 4 or 8 quarters ahead of the last observation of variable $x$ available at the date of the response to the survey. Importantly there is an observation lag between the date of the response to the survey $t$ and the date of the last available figure of $x$. This lag varies across variables: inflation is observed with a one month lag, unemployment with a two month lag and GDP growth with a two quarter lag.[6] $f^x_{it,T}$ denotes individual $i$'s calendar forecast associated with the last quarter $T$ of a specific calendar year in the sample, with the calendar year being either the current or the next year. The so-called consensus forecast, *i.e*. the average forecast, associated with rolling horizons is $f^x_{t,t+h}=(1/n_t)\sum_i^{n_t} f^x_{it,t+h}$, with $n_t$ the number of respondents to the survey at date $t$. Finally, letting $x_t$ be the realization of the forecasted variable at date $t$, $e^x_{it,t+h}$ will denote individual's $i$ forecast error at date $t+h$, namely $e^x_{it,t+h}=x_{t+h}-f^x_{it,t+h}$. Its average will be denoted $e^x_{t,t+h}=x_{t+h}-f^x_{t,t+h}$.

[3] Supplemental materials about the data, the robustness of our empirical findings, and the properties of the sticky-noisy information model are presented in a separate appendix.

[4] See Bowles et al. (2007) for a thorough presentation and discussion of the survey.

[5] This illustration takes into account a variable-specific observation lag that is discussed in further length below.

[6] To economize on notation, the observation lag is omitted in the formulas. The reader should keep in mind that for horizon $h=4$, the notation $f^x_{it,t+h}$ refers to year-on-year growth rate forecast of $x$, 2 quarters ahead of current date $t$ when $x$ is real GDP, 10 months ahead when $x$ is unemployment, and 11 months ahead when $x$ is inflation.

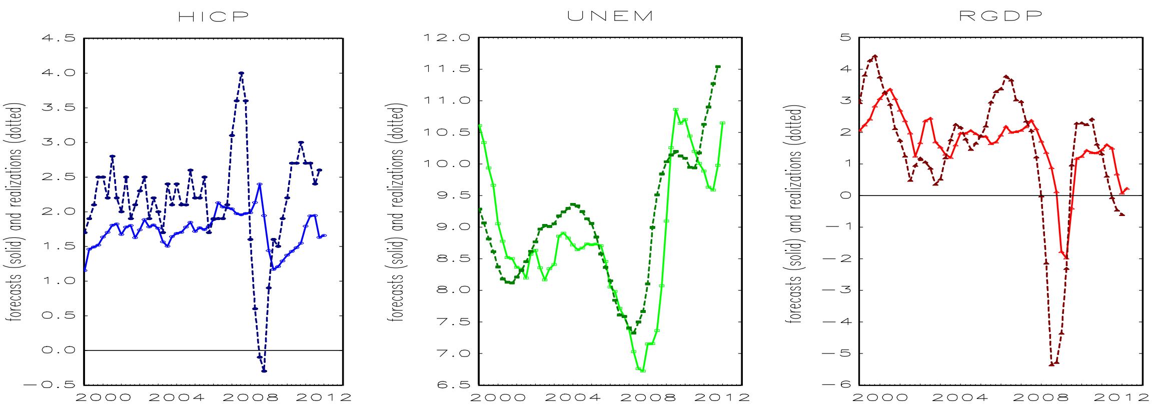


**Fig. 1.** Average of (1Y ahead) forecasts and realizations. The figure shows the average of individual 1-year ahead point forecasts for the three different target variables (solid line)—inflation (HICP), unemployment rate (UNEM) and real GDP growth rate (RGDP)—together with their realized values (dashed line) over the 2000Q1–2012Q4 sample.

### 2.2. *Predictable forecast errors*

This section and the following one document some basic facts about individual expectations, subsequently focusing on predictable forecast errors and on the disagreement among forecasters. Similar facts have been evidenced by previous research on other data sets than the ECB SPF, and interpreted as signs in favor of imperfect information models.[7]

Predictable forecast errors are indeed an implication of both *sticky information* and *noisy information* inattention models. In a *sticky information* model, agents update their information set infrequently with a given, constant, probability. As a result, at each date, only a fraction of the population has access to the last vintage of macroeconomic news. The forecast error at date $t+1$ of agents who did not update their information set at date $t$ will be predictable, based on the information available at date $t$. As a consequence, the aggregate forecast error will also be predictable. In a *noisy information* model agents update their information but know that the news they get is imperfect and therefore only partly pass it onto their forecast. The average forecast thus incorporates only part of this new information, which makes the forecast error predictable with respect to the (perfect) information available ex post to the econometrician.

A first sense of the predictability of the average forecast errors in the ECB SPF sample is provided in Fig. 1 which plots the time series of the 1-year ahead consensus forecast together with the realizations of the predicted variable. Strikingly, periods of under/overestimation of the target variable realizations are very persistent, and last for more than 1 year, *i.e.* over time periods that are longer than the forecast horizon.[8]

Table 1 provides some descriptive statistics and tests on forecasts errors. Over the sample period, inflation has been underestimated by an average annual rate of .43%. Unemployment exhibits a small underestimation of about .15% over the period. Finally, real GDP growth rate has been overrated by an average of .25%, due mainly to the recent crisis. Systematic biases go along with persistent forecast errors. Their first order auto-correlations range from .743 for inflation to .914 for unemployment. The bottom panel of Table 1 displays the results of a regression of the average forecast error on first a constant and second a constant and the last error known at the date when the forecast was made (that is $h$ quarters before, with, due to the observation delay, $h=2$, 3 or 4 depending on the variable). For the three variables studied either the bias or the link with past errors is significant at the 10% level so that errors are predictable.

### 2.3. *Disagreement among forecasters*

As predictable forecast errors, disagreement among forecasters can be rationalized by both *sticky-information* or *noisy-information* models of expectations. In both cases, disagreement is a consequence of imperfect information which implies that agents do not have the same information set. A distinguishing feature of the two models is that while *sticky-information* models can account for time variations in disagreement, a basic version of *noisy-information* models with constant noise in the signal and homogenous forecasters cannot. Indeed, in a *sticky-information* setup, when a large shock hits the economy, individuals who update their information set produce very different forecasts than individuals who do not. These differences are less pronounced in the wake of a small shock. Consequently, the extent of disagreement evolves over time due to the magnitude of the shocks. By contrast, in a *noisy-information* basic model, forecasters have different opinions

[7] See in particular Mankiw et al. (2003) and Coibion and Gorodnichenk (2012a,b).

[8] This is noticeably the case for inflation which, up to 2006, was systematically underestimated. Note that part of the visible overestimation of unemployment early in the sample is due to substantial revision as discussed by Bowles et al. (2007).

**Table 1**
Average forecast errors—descriptive statistics and tests.

The table provides descriptive statistics and tests for the 1-year ahead average (across forecasters) forecast error ($e=x-f$) for different macroeconomic variables observed in the European SPF data. The variables that are forecasted are the euro area Harmonized Index of Consumer Prices year-on-year inflation rate (HICP), the euro area unemployment rate (UNEM) and the euro area real GDP year-on-year growth rate (RGDP). All variables are in %. Mean ($e$) denotes the mean of the average forecast errors across dates, and $\sqrt{\text{Mean}(e^2)}$ the Root Mean Square Error of the average forecast. $\rho_e(h)$ stands for the $h$-order autocorrelation of the error. Numbers in brackets are standard errors of estimates using a robust Newey–West procedure.

| Average forecast errors, $e$ <br> Sample period: 2000Q1–2012Q4 | HICP | UNEM | RGDP |
|---|---|---|---|
| A. Descriptive statistics | | | |
| Mean ($e$) | .42 | .15 | −.26 |
| $\sqrt{\text{Mean}(e^2)}$ | .90 | .84 | 1.57 |
| $\rho_e(1)$ | .741 | .914 | .849 |
| B. Tests | | | |
| Bias: $e=\alpha+u$ | | | |
| $\hat{\alpha}$ | .426 (.117)*** | .154 (.199) | −.258 (.383) |
| Efficiency: $e=\alpha+\beta e_{-h}+u$ | | | |
| $\hat{\beta}$ | −.370 (.453) | .447 (.312)* | .522 (.227)** |

*** Indicates significance respectively at the 1% levels.
** Indicates significance respectively at the 5% levels.
* Indicates significance respectively at the 10% levels.

**Table 2**
Disagreement among forecasters—descriptive statistics and bivariate regressions.

The table presents statistics and regression results for the disagreement across forecasters ($\sigma$) on their 1-year ahead forecast ($f$) for various macroeconomic variables ($x$) observed in the European SPF data. Disagreement is measured as the cross-section standard deviation of individual point forecasts at each date of the sample. The variables forecasted are the euro area Harmonized Index of Consumer Prices year-on-year inflation rate (HICP), the euro area unemployment rate (UNEM) and the euro area real GDP year-on-year growth rate (RGDP). All variables are expressed in %.Mean($\sigma$) and Std−Dev($\sigma$) denote, respectively, the average and the standard deviation of the disagreement over time. $\Delta x_{-1}$ is the last period change in the forecasted variable, $\Delta f$ the current change in the average forecast, and $e_{-1}$ the last period average forecast error. All regressions include a constant term and numbers in brackets are standard errors of estimates using a robust Newey–West procedure.

| Disagreement, $\sigma$ <br> Sample period: 1999Q1–2012Q4 | HICP | UNEM | RGDP |
|---|---|---|---|
| A. Descriptive statistics | | | |
| Mean($\sigma$) | .29 | .30 | .38 |
| Std−Dev($\sigma$) | .08 | .11 | .16 |
| B. Bivariate regressions, $\sigma$ on | | | |
| $(\Delta x_{-1})^2$ | .078 (.047)** | .669 (1.224) | .049 (.036)* |
| $(e_{-1})^2$ | .031 (.018)** | .055 (.034)** | .007 (.006) |
| $(\Delta f)^2$ | .145 (.558) | .876 (1.158) | .141 (.053)*** |

*** Indicates significance respectively at the 1% levels.
** Indicates significance respectively at the 5% levels.
* Indicates significance respectively at the 10% levels.

because they randomly get different perceptions of reality. Whenever the variance of the noise is constant over time and across individuals, disagreement will not be affected by the size of the shocks hitting the economy.[9]

A natural measure of disagreement among forecasters is the cross-section standard deviation of forecasts at each date, namely, using notations introduced above: $\sigma^x_{t,h}=\sqrt{(1/n_t)\sum_{i=1}^{n_t}(f^x_{it,t+h}-f^x_{t,t+h})^2}$. Like in several other studies, in particular Mankiw et al. (2003) for the US, one clearly observes in the ECB-SPF that the cross section-distribution of forecasts never degenerates to a single peak, *i.e.* disagreement is non-zero (see Appendix A.2 for a figure illustrating this feature), and that this distribution often presents several modes. Table 2 reports that the time average disagreement for the 1-year horizon rolling forecasts is equal to .29 for inflation, .30 for unemployment and .38 for real GDP. Fig. 2 presents the time series of disagreement for the 1-year horizon rolling forecasts of the three macroeconomic variables of interest.[10] Disagreement also

[9] Coibion and Gorodnichenko (2012a) emphasize this difference between the basic versions of the sticky and the noisy information models. It is however possible to generate time-varying disagreement with more refined versions of noisy-information models, for instance, by introducing conditional time variance of the noisy signal correlated with the size of the true shock, or heterogeneity in the noise among the population of forecasters.

[10] Relying on rolling-horizon forecasts to evaluate forecasters' disagreement is important to avoid the seasonal patterns emerging from the resolution of uncertainty as time gets closer to the forecasted event one gets when relying on calendar-horizon forecasts instead.

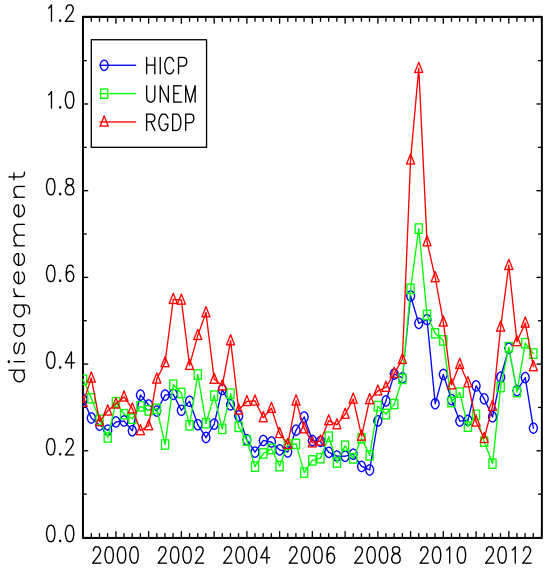


**Fig. 2.** Time series of disagreement among forecasters. The figure presents the cross-sectional standard deviation of individual 1-year ahead mean point forecasts for the three different target variables (solid line)—inflation (HICP), unemployment rate (UNEM) and real GDP growth rate (RGDP). The sample is 1999Q1–2012Q4.

varies over time, and is strongly positively correlated across variables. Noticeably, disagreement increased markedly for all three variables at the onset of the Great Recession.

It is worth investigating whether this disagreement is state dependent and reflects a slow diffusion of new information, as would be the case in a sticky-information model. A simple approach is to regress the disagreement $\sigma^x_{t,h}$, on several rough measures of the amplitude of shocks hitting the economy: the squared last variation in the forecasted variable $(\Delta x_{t-1})^2$, the squared last forecast error $(e^x_{t-h-1,t-1})^2$, and the squared current change in the forecast $(\Delta f^x_{t,t+h})^2$. Results are presented in Panel B of Table 2. Coefficients are all positive and significant in 5 cases out of 9. These results broadly support that disagreement is an increasing function of the amplitude of the shocks hitting the economy.[11] This last evidence contrasts with Coibion and Gorodnichenko (2012a) who find that the response of dispersion of inflation forecasts to structural shocks is in general not significant. However their results are mixed across types of forecasters and of structural shocks, and while they fail to reject the null, the response they obtain is often positive.

Overall, predictable and biased forecast errors and disagreement among forecasters suggest that both *sticky information* and *noisy information* models may be good candidates to describe expectation formation. The next section goes further by documenting new facts, related to the infrequent updating of forecasts that can be directly related to each of the two types of inattention.

## 3. The frequency of forecast revision: micro-estimates

In this section, we propose a direct measure of the degree of attention using the individual answers to the ECB SPF survey. Using this measure it is shown that the frequency of forecast revision differs from one, *i.e.* there is evidence of inattention in this sample of data. The effects of rounding and measurement errors on this result are then assessed. Finally, it is also enlightened that the disagreement among forecasters that do revise their forecasts is non-zero, so disagreement does not appear to be entirely driven by infrequent information updating.

### 3.1. Measuring the degree of attention

The frequency of updating a forecast provides a measure of the extent with which agents pay attention to new information by incorporating it in their forecasts. This implicitly assumes that there is a systematic link between information and forecast updating. Such an assumption is arguably acceptable since, absent any reason for inaction—an issue that is

[11] Alternatively, these results could reflect the impact of uncertainty shocks affecting the size of the innovations to macroeconomic variables. If these shocks also contribute to the future level of macroeconomic variables, and if uncertainty co-moves with disagreement, the above relationship may also emerge.

discussed at the end of this section—a forecast revision is observed whenever the statistical innovation of the forecaster's model is non-zero.

Formally, the probability to be estimated is $P(f^x_{it,t+h} \neq f^x_{it-1,t+h})$. Thanks to the structure of the ECB SPF data, $f^x_{it,t+h}$ can be directly compared to $f^x_{it-1,t+h}$ for each individual in the sample. Thus, assuming that the probability is homogeneous across agents, the panel dimension of the SPF data allows us to deliver several empirical counterparts to this attention degree, which will be denoted $\lambda^x_t(h)$.

A first indicator relies on the "calendar horizon" forecasts and gives the probability of updating after a quarter of new information. At each date, each forecaster is surveyed about his expectations for the current and next calendar years, as well as, in each third and fourth quarter vintages of the survey, about their expectations two years ahead. Therefore, for each calendar year $Y$, ending in quarter $T$, a sequence of 10 forecasts is observed: two sets of forecasts made at the third and the fourth quarters of year $Y-2$, and 8 sets from the first quarter of year $Y-1$ onwards. A sequence of 9 forecast revisions, for the same date $T$ event, and the different forecast horizons $h=T-t=1,\ldots,9$, can then be built. The degree of attention for the calendar year ending in $T$ and the horizon $h$ can the be estimated using the empirical frequency:

$$\widehat{\lambda}^x_{t,cal}(h) = \frac{1}{n_t}\sum_{i=1}^{n_t} I(f^x_{it,T} \neq f^x_{it-1,T}), \tag{1}$$

with $h=T-t=1,\ldots,9$, $n_t$ the number of respondents to the survey at date $t$ and $I(f^x_{it,T} \neq f^x_{it-1,T})$ an indicator function equal to 1 if $f^x_{it,T} \neq f^x_{it-1,T}$ and 0 otherwise.

A second measure of the probability to update a forecast exploits the "rolling horizon" forecasts and gives the probability of updating a forecast after a year of new information. Consider the 8-quarter horizon forecast released at date $t-4$ by forecaster $i$, $f^x_{it-4,t+4}$. This can be compared to the 4-quarter horizon forecast released 4 quarters later ($f^x_{it,t+4}$) so as to define an empirical estimate of the probability of updating on a yearly basis $\widehat{\lambda}^x_{t,rol} = (1/n_t)\sum_{i=1}^{n_t} I(f^x_{it,t+4} \neq f^x_{it-4,t+4})$, with $I(f^x_{it,t+4} \neq f^x_{it-4,t+4})$ an indicator function equal to 1 if $f^x_{it,t+4} \neq f^x_{it-4,t+4}$ and 0 otherwise. By contrast with the previous measure, the horizon is bound to 4 quarters due to the design of the survey. The horizon index is therefore skipped in the notation, referring to $\widehat{\lambda}^x_{t,rol} = \widehat{\lambda}^x_{t,rol}(4)$. This probability of updating on a yearly basis can be converted to a quarterly adjustment rate, $\widehat{\lambda}^x_{t,rol,q}$, if one assumes (consistently with Mankiw and Reis's, 2002 model) that it is constant over the 4 quarters of a given year. In that case, the probability of *not* updating over the whole year is $(1-\lambda^x_t(4)) = (1-\lambda^x_t(1))^4$ so that a quarterly attention rate estimate is $\widehat{\lambda}^x_{t,rol,q} = [1-(1-\widehat{\lambda}^x_{t,rol})^{1/4}]$

Finally, assuming the various $\lambda^x_t(h)$ measures are constant over time and across horizons, direct micro-data based estimates of the average attention degrees $\widehat{\lambda}^x_{cal}$ or $\widehat{\lambda}^x_{rol,q}$ can also be recovered simply by taking the time average of the empirical frequencies defined above.

One concern with interpreting $\lambda^x_t(h)$ as a measure of attention is that a forecaster may choose not to revise his forecast in spite of having updated his information set. However, given the vast information set available to professional forecasters we deem unlikely that updating the information set leads to an exactly unchanged optimal forecast after one quarter. Rather, such a situation could more plausibly correspond to cases where either the forecaster chooses to avoid the cost of processing the new information by running a full statistical exercise, or to avoid the cost of communicating the new forecast outside the institution. Both situations relate to the existence of information cost, and arguably this lack of reaction to news can be characterized as (potentially optimal) inattention.[12] It may also be argued that forecasters can refrain from revising their forecast for strategic motives (say because they value commitment to a scenario). To our knowledge however, no model relating infrequent forecast updating to strategic considerations has been developed so far. In the present paper, the infrequent forecast updating observed in the data is linked to the mere sticky information setup.

### *3.2. Results*

Five results about the frequency of updating a forecast are highlighted below. The first two exploit calendar horizon forecasts while the remaining three make use of rolling horizon forecasts.

#### *3.2.1. The frequency of forecast revision: evidence from calendar horizon forecasts*

Our first result is that forecasters actually fail to update systematically their forecasts on a quarterly basis. Fig. 3 presents the estimate of attention $\widehat{\lambda}^x_{t,cal}(h)$ for the HICP inflation variable.[13] Each line in the figure reports a sequence of probability of forecast revision pertaining to the same calendar year $Y$, with $Y$=2001–2012. At each point in time, $t$, $\widehat{\lambda}^\pi_{t,cal}(h)$ is the proportion of forecasters revising their forecast for a given target calendar year $Y$ ending with quarter $T$. The associated forecasting horizon is thus $h=T-t$. Sequences of forecast revisions partially overlap since, in each vintage of the survey, respondents are asked their forecast for both current and next calendar year.

[12] The first situation would arguably be consistent with the Reis (2006a) micro-foundation for infrequent updating. The second one could be related to Alvarez et al. (2011) who develop a model where firms pay an information cost to calculate the optimal reset price (*i.e.* implement a price review) and then decide to pay or not the usual menu cost of changing the price. By analogy, the forecaster could be seen as incurring the cost of calculating the optimal forecast but not the one of changing the optimal forecast because of the cost of communicating the reasons of this change.

[13] Figures for the unemployment rate and real GDP growth are not reported to save space but exhibit a similar pattern.

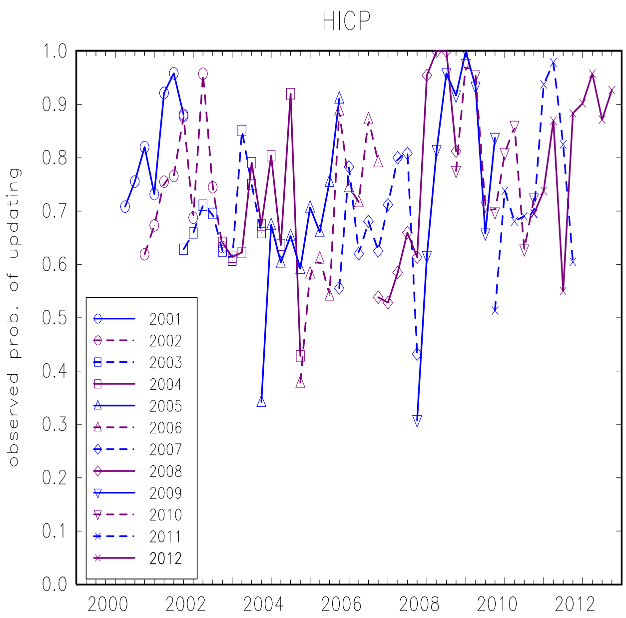


**Fig. 3.** Probability of updating after one quarter of information—calendar horizon forecasts. The figure reports the probability of updating a calendar (end-of-year) inflation forecast between two subsequent quarters as estimated from the SPF data. Each line corresponds to a given year in the sample. Each point on a given line corresponds to a date at which forecasters are asked to report their forecast for the end of the associated year. Hence, each line is made of a sequence of probabilities to update a given end-of-year forecast and is thus associated with a sequence of (decreasing) forecast horizons.

**Table 3**
Probability of updating a forecast.

The table reports different measures of the probability ($\lambda$) of updating a forecast ($f$) for various macroeconomic variables ($x$) as observed in the European SPF data. The variables forecasted are the euro area Harmonized Index of Consumer Prices year-on-year inflation rate (HICP), the euro area unemployment rate (UNEM) and the euro area real GDP year-on-year growth rate (RGDP). $\lambda_{cal}$ is the frequency of revising a calendar horizon forecast between two subsequent quarters. $\lambda_{rol}$ is the frequency of revising a rolling horizon forecast between two subsequent years. $\lambda_{rol,q}$ derives a frequency of updating a forecast on a quarterly basis from the previous $\lambda_{rol}$.

| Probability of updating a forecast, $\lambda$<br>Sample period: 1999Q1–2012Q4 | $x$ | | |
|---|---|---|---|
| | **HICP** | **UNEM** | **RGDP** |
| Revising $f^x$ | | | |
| Mean ($\lambda_{cal}$) | .72 | .75 | .80 |
| Mean ($\lambda_{rol}$) | .88 | .96 | .94 |
| Mean ($\lambda_{rol,q}$) | .41 | .55 | .51 |
| Revising $f^y$ if revising $f^x$ | | | |
| $y$ HICP | 1 | .884 | .882 |
| UNEM | .956 | 1 | .951 |
| RGDP | .940 | .941 | 1 |
| Others | | | |
| Rev. next year if rev. current year | .876 | .851 | .924 |
| Rev. at least one macro variable | | | 1 |

As Fig. 3 illustrates, except for a few instances, attention is not complete: depending on the dates and the forecast horizon, the probability of forecast revision varies between 30% and 100%. Table 3 shows that the average $\widehat{\lambda}_{cal}^{x}$ across horizons, dates is 72% for HICP, 75% for the unemployment rate and 80% for GDP growth. Averaging across variables the typical degree of attention is thus around $\widehat{\lambda}_{cal} \simeq 75\%$. This is much higher than the values provided by previous empirical studies. By comparison, Mankiw et al. (2003) calibrated a value of $\widehat{\lambda} = 10\%$ for monthly data, *i.e.* a corresponding $\widehat{\lambda} = 27\%$ when converted to quarterly data, to reproduce the disagreement in US-SPF inflation rate forecasts. Other studies based on aggregate data (e.g. Kiley, 2007, or Döpke et al., 2008) also have found degrees of attention lower than 50%. One possible explanation of the discrepancy between our micro-estimates and these previous ones is that the latter have to rely on auxiliary assumptions. The Mankiw et al. (2003) calibration exercise relies on the auxiliary assumption that disagreement is

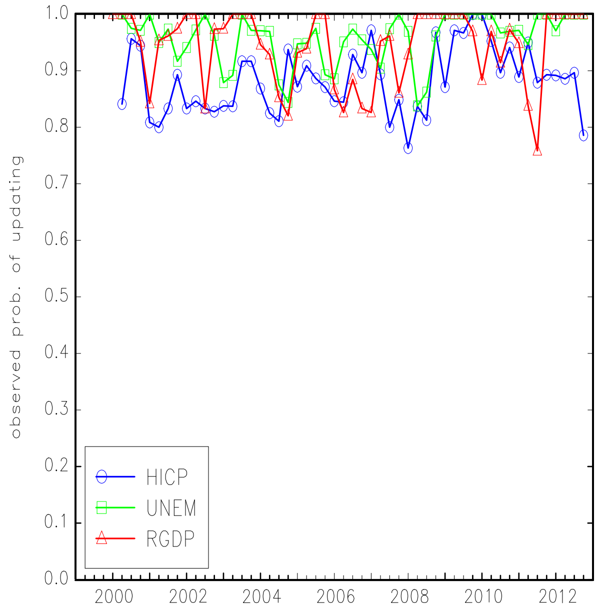


**Fig. 4.** Probability of updating after one year of information—rolling horizon forecasts. The figure shows the probability of updating a rolling (1-year ahead) forecast between two subsequent years as estimated from the SPF data. For each individual and each date in the sample, a revision of a forecast is derived by comparing its current 1-year ahead rolling forecast with the 1-year in 1-year ahead rolling forecast observed 1 year before the current date.

only generated by the infrequent updating of the information set by forecasters. Macro estimates of the "sticky information" Phillips curve typically assume flexible prices, which will presumably bias their estimation in favor of information stickiness if prices are actually sticky. An advantage of our direct measure is that it bypasses the need for these auxiliary assumptions.[14]

A second result that stands out from our estimation is that the average probability to revise a forecast increases when the forecast horizon is reduced: all lines in Fig. 3 are upward sloping. Two factors can explain this pattern: first, mean reversion implies that long run forecasts are close to the unconditional average of the process so that news that lead to revising short run forecast may leave the forecast at a long horizon unchanged. Second, it may be the case that forecasters put more attention on revising their forecast for closest forecast horizons. Experiments in the next section suggest that both factors are present.

### 3.2.2. *The frequency of forecast revision: evidence from rolling horizon forecasts*

A third pattern is that the degree of attention varies over time. This can be seen from the average level of each curves in Fig. 3. This is even clearer when one looks at the alternative attention indicator, $\widehat{\lambda}^x_{t,rol}$, which is built on rolling horizon forecasts. Indeed, looking at Fig. 4, which plots its time series for the three possible forecasted variables $x$, illustrates that there is a significant degree of time variation in these probabilities. By contrast, the sticky information model of Mankiw and Reis (2002) postulates that $\lambda$ is constant. Observing fluctuations in aggregate attention would not be direct evidence against the sticky information model of Mankiw–Reis if they were purely random. However, fitting an AR(1) or an MA(1) process to the attention degrees, $\widehat{\lambda}^x_{t,rol}$, for inflation, unemployment and real GDP shows that this is not the case: autocorrelations are found to be significantly positive. There is thus some persistence in the fluctuations of the attention degree. Fig. 4 also suggests that the degree of attention was larger for all three variables in late 2008 and 2009, that is after the large shocks associated with the 'Great Recession'. Coibion and Gorodnichenko (2012b) also find an increase in attention in the wake of large shocks such as the 9/11 attack and more generally over the US business cycle. These results could be reconciled with the more general state-dependent setup developed by Reis (2006a) in which the length between two updates of information is optimally chosen as a function of the shocks that can occur over the interval.

A fourth result stemming from the $\widehat{\lambda}^x_{t,rol}$ estimate is that forecasters do not update systematically their forecasts even on a yearly basis. This confirms our first result that attention is not equal to 100% when looking at $\widehat{\lambda}^x_{t,cal}(h)$ estimates. It is somewhat even more striking since here some forecasters choose not updating their one-year ahead forecast even after one more year of macroeconomic news became available. Table 3 reports the attention degree time average, $\widehat{\lambda}^x_{rol}$, for the three macroeconomic variables surveyed. It is equal, respectively, to 88% for inflation, 96% for unemployment and 94% for real

[14] The result that the estimated degree of attention is lower than one is not driven by some outliers among forecasters. Indeed, the cross-section distribution of the individual average frequency of updating, reported in Appendix A.3, reveals that individual attention degrees are larger than .5 for all forecasters.

GDP. Converting these average probabilities of forecast revision to quarterly figures gives average frequencies, $\widehat{\lambda}^{x}_{rol,q}$, of 41%, 55% and 51%. Averaging across variables $x$ one gets $\widehat{\lambda}_{rol,q} \simeq 50\%$. The difference between this result and the average $\widehat{\lambda}_{cal} \simeq 75\%$ is further evidence that the frequency of updating is not constant over forecast horizons. Our assessment is that $\widehat{\lambda}_{cal}$ is the most reliable indicator. Indeed, in practice, 8-quarter rolling horizon forecasts are usually not a conventional exercise implemented by professionals. Moreover, since calendar forecasts are available for adjacent quarters, it is more likely that they compare forecasts delivered by the same forecaster in the same institution.

A fifth and final result is that forecasts are not jointly updated across variables and across horizons. The middle panel of Table 3 reports the probability that a forecaster revises his forecast of either inflation, or GDP growth, or unemployment, conditional on having revised his forecast of another variable. Such conditional probabilities of revision range from 88.2% (probability of revising inflation forecast given that real GDP forecast was changed) to 95.6% (probability of revising unemployment forecast given that inflation forecast was changed). These figures are based on revisions of rolling horizon forecasts (not converted to quarterly figures). Finally, as reported in the last row of Table 3, a forecaster virtually always revises (on a yearly basis) at least one of his forecasts out of the three variables considered. The bottom panel of Table 3 also shows when the 1-year forecast of a variable is revised (on a yearly basis), the probability that the 2-year ahead forecast for the same variable is revised is always less than one. By contrast, in the basic version of a sticky-information model, whenever a forecasters update his information set he updates the forecasts of all variables and all future horizons.

To sum up, we find that forecasters fail to update their forecasts at each period, a fact that is consistent with a *sticky-information* model. At the same time, several departures from a "pure" version of such sticky information model are also documented. In particular, and as Coibion and Gorodnichenko (2012b) also emphasize, the degree of updating varies over time, across horizons, across variables or with the nature of the forecast. Furthermore, another dimension in which a simple version of the sticky information model is at odds with the data is that forecasts are not jointly updated (across variables and across horizons).

### 3.3. Robustness: the influence of rounding and of measurement errors

Almost all forecasts (97% of forecast figures) in our data set are reported with only one digit. One caveat in the failure to revise a forecast documented above is that it may merely reflect the fact that these institutions report only rounded figures.

Rounding can be considered as a form of inattention. Indeed, this practice is not formally requested by the ECB SPF questionnaire. Providing rounded figures may reflect the costs of processing and communicating precise information as discussed previously. Still, as there exists a widespread consensus that higher order digits are not economically meaningful so that the forecasters find natural to report rounded forecasts even when they update them, it is important to gauge to what extent rounding leads to underestimates of the degree of attention. To do so, the following Monte Carlo experiment is carried out (see Appendix A.4 for details). An estimated VAR model is used to simulate sequences of forecasts for different horizons of the (year-on-year) inflation and GDP growth rates. Each generated forecast is rounded to the first digit. The frequency of revision is then computed, counting the number of instances in which two adjacent rounded forecasts corresponding to the same target date differ. Crucially, in this simulation exercise, there is no inattention in the underlying forecasting model. Absent any rounding, one would observe that forecasts are updated every period. So this exercise gives us an estimate of the bias to our measurement of attention that is due to rounding. Looking for example at inflation, the simulated probability of updating a forecast is 83% for the horizon $h=9$ quarters, and rises to 91% or the horizon $h=1$. These figures are lower than one, which suggest there is actually a rounding bias. The probability also increases when the target date gets closer to the forecast date, consistent with the pattern of Fig. 3. However, these figures are at all horizons markedly above the estimates of attention obtained on the actual SPF micro-data. Computation of standard errors shows that the difference is statistically significant. Our conclusion is thus that, independently of rounding effects, there is a degree of genuine inattention in professional forecasts.

Another possible concern is measurement error: if a forecast that has not been updated is reported with an error, this may lead us to spuriously conclude that the forecast has been updated. In contrast with the case of rounding, our estimator would then overestimate the probability of forecast revision. To assess the extent of such a bias, a simulation experiment featuring forecasts derived from a sticky information model with forecasters answering the survey with errors was designed and carried out (see Appendix A.5 for details on our experiment). More precisely, the exercise postulates that the probability of updating the information set is equal to $\lambda_0$ and that forecasters report forecasts $f_{t,t+h} = f^{*}_{t,t+h} + e_t$ where $f^{*}_{t,t+h}$ is there true unobserved forecast and $e_t$ is an i.i.d. normally distributed measurement error. Remark that in this set-up, the measured probability of forecast updating should always be one, given that the added error is a continuous variable. Another ingredient is thus needed to generate infrequent updating under measurement error. Our choice here is to rely on a source of discreteness present in the actual data, namely rounding: in the exercise carried out, forecasts are generated, then contaminated by measurement errors, then rounded to 1 digit.[15] The main result of the experiment (detailed in Appendix A.5) is that the bias is sizeable as long as the measurement error standard deviation is larger than around

[15] Another one option would be to consider discrete measurement errors: for instance there is a probability $p$ that the forecast is contaminated by measurement error. However, such an approach is not informative since one may rationalize any observed frequency of forecast revision $\widehat{\lambda}$, with any sticky information parameter, say $\lambda_0$ (lower than $\widehat{\lambda}$) by simply positing that $p = \widehat{\lambda} - \lambda_0$.

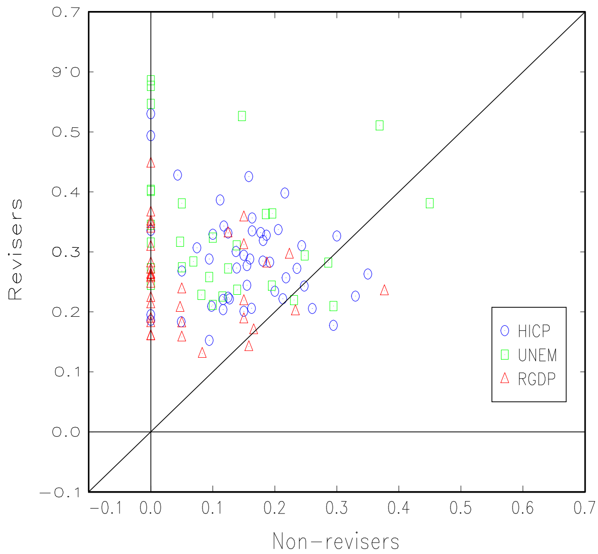


**Fig. 5.** Disagreement among non-revisers vs. among revisers. The figure plots, for each date in the sample, the cross-sectional standard deviation of individual 1-year ahead mean point forecasts among the subpopulation of forecasters who do not update their forecast against the same cross-sectional standard deviation obtained for the subpopulation of forecasters who update their forecast. Forecast revisions are revisions of a 1-year ahead forecast on a yearly basis. The sample is 1999Q1–2012Q4.

.05 percentage point. For instance, with a standard deviation of measurement error of .15 in GDP forecast, the observed frequency of forecast revision of .80 can be generated in a model in which the true attention parameter is only $\lambda = .25$. Thus, to the extent that measurement error is present, our estimate of the probability of forecast revision could be severely overestimated. However one should note that this outcome if anything reinforces our finding of evidence of infrequent updating. At the same time, that measurement error is a quantitatively important concern in the case of the SPF is debatable: professional forecasters are used to reporting their forecast, for many of them their forecast is public, and forecasters answer the survey by filling a written questionnaire they are familiar with. This contrasts with repeated cross-sections and with telephone interviews, typical of consumer surveys, often viewed as prone to measurement errors.

### *3.4. Disagreement among forecasters who revise*

The specificity of the data set is now further exploited to document the behavior of forecasters when they update their forecasts. This leads to a second main new fact: forecasters who update, disagree.

The disagreement among forecasters that do revise their forecast is computed at each date in the sample. Fig. 5 compares it with the disagreement of the forecasters who did not update, for the same forecast and date. The disagreement among revisers is shown on the vertical axis and the disagreement among non-revisers is on the horizontal axis. It is apparent that the disagreement among revisers differs from zero. Moreover, it is larger than the disagreement among non-revisers as the scatter is mostly above the 45° line. Lastly, sometimes all forecasters, or all forecasters but one, do revise, so there is zero disagreement stemming from the non-revisers.

Observing disagreement among forecasters who revise their forecasts has clear-cut implications for models of information rigidity. Indeed, *sticky-information* models predict that forecasters who revise their information set will derive the same optimal forecast and thus should not disagree. This approach cannot explain the large degree of disagreement among forecasters updating their forecast found in the SPF data. By contrast, *noisy-information* models generate disagreement between forecasters who update since each of them has specific information due to the heterogenous signals on the true state they receive.

## 4. A model of inattention: quantitative assessment

The facts reported in the previous section suggest that modeling agents' expectations requires both types of inattention: agents infrequently update their information sets and when they do, they get a noisy perception of the true information. In this section, a hybrid model featuring both sticky and noisy information is developed. Its empirical performances are then assessed through a formal testing procedure.

### 4.1. A sticky and noisy information model

The structure of the model is first sketched. Salient properties about the average forecast errors and the disagreement the model generates are then put forward.

#### 4.1.1. DGP and information structure

It is assumed that the economy can be summarized by a state vector $Z_t$ made of $p$ lags of $n$ (centered) variables $X_t$ with associated innovation $\epsilon_t$. Its dynamics are described by a reduced form invertible VAR($p$) model which can be written in the compact companion form: $Z_t = FZ_{t-1} + \eta_t$, with $Z_t = (X'_t\ X'_{t-1}\ \cdots\ X'_{t-p+1})'$, and where $\eta_t = (\epsilon'_t\ 0\ \cdots\ 0)'$ has a covariance matrix $\Sigma_\eta$.

Let $i$ be an individual in the population of forecasters, $i=1,\dots,m$. Along the lines of Mankiw and Reis (2002), at each date, every forecaster may update his information set, with a constant probability, or *degree of attention*, $\lambda$. Index $j$ will denote the generation of forecasters who last updated their information set $j$ periods before the current one, *i.e.* in $t-j$. Our set-up extends Mankiw and Reis' model to include imperfect perception of the information when updating. It is assumed that, when an agent $i$ updates his information, he observes a noisy perception of the true state, $Z_t$, namely a signal $Y_{it}$ that follows

$$Y_{it} = H'Z_t + v_{it}, \quad v_{it} \sim \text{i.i.d.}(0, \Sigma_v), \tag{2}$$

where $H$ is a matrix that selects the state variables that are observed with such idiosyncratic noise, and which is assumed to be equal to $H=I$, and with $\Sigma_v$ a diagonal matrix. This idiosyncratic noise conveys the notion that forecasters pay attention to private information to assess current macroeconomic conditions. In particular, respondents to the ECB SPF are located in various European countries and thus likely to have a more precise and timely access to news about their national economy. In addition, a large share of respondents are forecast units in private banks that may have access to specific contacts with businesses.

#### 4.1.2. Model properties: average forecast errors

Some properties of the above hybrid sticky/noisy information model are now summarized. Our focus will be on how the model can reproduce the empirical regularities documented in the previous section, namely predictable forecast errors and disagreement among forecasters updating their information, with an emphasis on the link with the two inattention parameters, $\lambda$ and $\Sigma_v$. More details on the derivation of these properties as well as illustrating simulations are provided in Appendix A.6.

*Characterizing the average forecast errors*: Let $f_{it-j,t+h}$ denote the optimal forecast of the vector $X$ at date $t+h$ made by an agent $i$ within a given generation $j$ using the information vintage $t-j$. In this generation, every forecaster $i$ observes his own noisy signal and his optimal forecast is derived from the Kalman recursion: $f_{it-j,t+h} = F^{h+j}Z_{it-j|t-j-1} + F^{h+j}G_{t-j}(Y_{it-j} - Z_{it-j|t-j-1})$. Matrix $G_{t-j}$ is the Kalman gain which depends on the variance of the noise in the signal $\Sigma_v$ as follows: $G_{t-j} = P_{t-j|t-j-1}(P_{t-j|t-j-1} + \Sigma_v)^{-1}$, where $P_{t-j|t-j-1}$ denotes the variance of the perceived forecast error.

The average forecast error involves the average of individual forecasts across the different individuals $i$ in different generations $j$. Using, inter alia, that, with $\lambda$ the frequency of updating, each generation $j$ has a weight of $\lambda(1-\lambda)^j$ in the whole population of forecasters, one shows that, in the simple case where $H=I$, the average forecast error follows:

$$\mathcal{E}_{t,t+h} = F^{h-1}(I-G_t)\sum_{j=0}^{\infty}(1-\lambda)^j\lambda[Z_t - \mathrm{E}_i(Z_{it|t-j}|j)] + \sum_{k=0}^{h-1}F^{h-k}\eta_{t+k+1} \tag{3}$$

with $\mathrm{E}_i(\cdot|j)$ the average across individuals $i$ in generation $j$. Under imperfect information, *i.e.* whenever $I \neq G_t$ or $\lambda < 1$, the average forecast error is predictable with respect to the true state $Z_t$, since $\mathrm{E}(\mathcal{E}_{t,t+h}|Z_t) \neq 0$.

*Properties of the average forecast errors*: An increase in the degree of information imperfection generates more persistence and variance of the forecast errors (see Appendix A.6 for details). More specifically, everything else being constant, (i) a decrease in the attention degree $\lambda$ increases both the persistence and the variance of the forecast error. Moreover, (ii) an increase in a term on the first diagonal of the noise variance matrix $\Sigma_v$ leads both to an increase in persistence and variance of the forecast error of the corresponding forecasted variable.

#### 4.1.3. Model properties: disagreement

Some properties of the disagreement among forecasters generated by the model are now discussed. Again, the influence of the two inattention parameters, $\lambda$ and $\Sigma_v$, is emphasized.

*Characterizing the disagreement between forecasters*: Let $V_{ij}(f_{it-j,t+h})$ be the total cross-section variance of point forecasts across individuals $i$ using the different information vintages $j$. This cross-section variance has two sources. The first one stems from differences of opinions *within* a given generation $j$ of forecasters generated by the noise in individuals' signal. For a given generation $j$, one can show that it follows

$$\mathrm{V}_i(f_{it-j,t+h}|j) = F^{h+j}\{\mathrm{V}_i(Z_{it-j|t-j-1}|j) + G_t[\Sigma_v + \mathrm{V}_i(Z_{it-j|t-j-1}|j)]G'_t\}(F^{h+j})' \tag{4}$$

with $\mathrm{V}_i(\cdot|j)$ the variance across individuals $i$ in a generation $j$. This cross section variance evolves with the forecast horizon, shrinking progressively to zero with $h$. The contribution of this disagreement within a generation to the total is given by the share of this generation in the whole population of forecasters, $\lambda(1-\lambda)^j$, in the total population, so that $\mathrm{E}_j\{\mathrm{V}_i(f_{it-j,t+h}|j)\} = \sum_{j=0}^{\infty}(1-\lambda)^j\lambda\mathrm{V}_i(f_{it-j,t+h}|j)$. The second source in total disagreement comes from the differences in (average) opinion *between* the different generations $j$ of forecasters using different information vintages. More precisely, the contribution of the latter source to disagreement is

$$V_j\{E_i(f_{it-j,t+h}|j)\} = \sum_{j=0}^{\infty}(1-\lambda)^j\lambda\{E_i(f_{it-j,t+h}|j) - E_j[E_i(f_{it-j,t+h}|j)]\}^2. \tag{5}$$

Noticeably, due to idiosyncratic noisy signals within generations, the model generates disagreement even under full information updating $\lambda = 1$. Another important feature is that disagreement is time-varying, even when there is no time conditional heteroscedasticity in the noise, $\nu_{it}$. This comes from the differences between generations of forecasters: as the degree of disagreement depends on the difference between the new vintage of information and the previous ones, when an innovation is large compared to the average, the difference of opinion between the individuals revising and the others will also be larger than on average.

*Properties of the disagreement*: An increase in the degree of imperfect information has ambiguous effects on disagreement (see Appendix A.6 for details). Everything else being constant, (i) a decrease in $\lambda$ has two conflicting effects on the disagreement *between* generations of forecasters. It entails a greater heterogeneity between the generations, since it increases the length between information updating. However, it also increases the share of generations sticking to an old information vintage and for which the forecast horizon $(h+j)$ is very long. Within these generations, the disagreement tends to zero as, whatsoever its idiosyncratic signal, every forecaster's optimal prediction is given by the unconditional mean of the process.

Likewise, everything else being constant, (ii) an increase in any diagonal element of $\Sigma_\nu$ has also two conflicting effects on the disagreement *within* a generation of forecasters. It increases the amount of noise, thus differences of opinion within each generation of forecasters. On the other hand, because individuals know that the signal is very imprecise, they incorporate less of the news into their forecast. In the extreme case, when the signal is completely uninformative, the optimal forecast is the unconditional mean of the process for all forecasters, which implies zero disagreement.

Lastly, everything else being constant, (iii) a drop in $\lambda$ leads to a higher time variance of disagreement, since it increases the difference between the new vintage of information and the previous one, hence the impact of the size of the shock on disagreement. By contrast, (iv) an increase in any diagonal element of $\Sigma_\nu$ implies that this time variance of disagreement decays. The less informative the news, the less they are incorporated in the optimal forecast, therefore the less disagreement there is between generations of forecasters.

### *4.2. Estimation procedure*

The previous model is estimated by a Minimum Distance Estimation (MDE) procedure. The methodology amounts to minimizing the distance between first a vector of $K$ data-moments $\widehat{\mu}$, such as, in our case, the average forecast error or the disagreement computed from the SPF data, and, second corresponding model-generated moments which, in our case, are a function of the inattention parameters $\mu(\lambda, \Sigma_\nu)$. Formally, estimates of $\lambda$ and $\Sigma_\nu$ are obtained by minimizing:

$$[\widehat{\mu} - \mu(\lambda, \Sigma_\nu)]'\widehat{\Omega}^{-1}[\widehat{\mu} - \mu(\lambda, \Sigma_\nu)], \tag{6}$$

where $\widehat{\Omega}$ is a consistent estimator of the asymptotic variance of $\widehat{\mu}$ defined by $\sqrt{T}(\widehat{\mu} - \mu) \to \mathcal{N}(0, \Omega)$ when $T \to \infty$. Stacking the parameters of interest into $\theta = (\lambda, \text{vec}(\Sigma_\nu))'$, the minimum distance estimator $\widehat{\theta}$ satisfies $\sqrt{T}(\widehat{\theta} - \theta) \to \mathcal{N}[0, (D'\Omega^{-1}D)^{-1}]$ when $T \to \infty$, with $D \equiv D(\theta) = \nabla_\theta \mu(\theta)$ the Jacobian of $\mu(\theta)$ with respect to $\theta$ evaluated at $\widehat{\theta}$. An estimator of the standard deviation of $\widehat{\theta}$ is thus given by $\widehat{D}'\widehat{\Omega}^{-1}\widehat{D}$ where $\widehat{D} \equiv D(\widehat{\theta})$.

In addition to estimating parameters, MDE also allows for testing over-identifying restrictions, *i.e.* the null hypothesis that the set of $K$ moments $\mu$ can accurately be described with the $P$ parameters to be estimated, *i.e.* in our case $\lambda$ and $\Sigma_\nu$. The test statistic is $[\widehat{\mu} - \mu(\lambda, \Sigma_\nu)]'\widehat{\Omega}^{-1}[\widehat{\mu} - \mu(\lambda, \Sigma_\nu)]$. Here, rather than relying on the asymptotic Chi-square distribution, Monte Carlo simulations of the model are used to approximate the exact small sample distribution of the test statistics.

The moments selected to estimate the model are related to the forecast errors and disagreement. These are two key features of expectations that imperfect information models try to rationalize and which, in our model, are functions of the attention rate and the variance of the noise parameters. More precisely, four moments are selected. Two moments relate to the average forecast errors: the mean square of forecast errors (MSEs), $E[(e^x_{t,t+h})^2]$ and its first-order autocorrelation, $\rho^x_e(1)$; and two moments are associated with disagreement: its average level, $E(\sigma_{t,h})$ and its time variance, $V(\sigma_{t,h})$. This latter moment is particularly crucial in order to entail the econometric identification of the model. Indeed an increase in both types of inattention (lower $\lambda$, higher diagonal components of $\Sigma_\nu$) often impacts the first three moments in the same direction. By contrast, a lower frequency of updating increases the time variance of disagreement, while a large variance of the noise in information lowers it.

The estimation involves four steps. First, an auxiliary model VAR model is estimated; specifically, a VAR model for the year-on-year inflation rate, change in unemployment rate, and real GDP growth. The VAR includes 4 lags of the vector of observations $X = (\pi\ u\ \Delta y)'$ with all variables centered prior to estimation. In our baseline estimation, quarterly euro area data over the 1987Q1–2008Q2 period are used.[16] The choice of the sample period reflects a trade-off between conflicting objectives: first, having a sufficiently long time series and second, considering an homogenous period in terms of monetary policy and the inflation regime. Second, taking the VAR parameters as given, and for a given set of structural parameters

[16] Data sources are detailed in Appendix A.1. A larger estimation sample ending in 2012Q4 is also considered.

**Table 4**
Minimum distance estimation.
The table gives the minimum distance estimation results of the two parameters characterizing the sticky/noisy expectation model described in Section 4. More specifically, $\widehat{\lambda}$ is the estimated frequency of updating one's information set and $\widehat{\sigma}$ the estimated variance of the noise in the signal. Targeted moments are the mean squared forecast error Mean($e_t^2$), the first-order autocorrelation of the forecast error $\rho_e(1)$, the average disagreement Mean($\sigma_t$), and the time variance of the disagreement V($\sigma_t$), of either the euro area inflation rate (INF), or the euro area real GDP growth rate (GDP), or both. All moments are calculated with 1-year horizon forecasts. Two samples are considered: a pre-crisis sample that goes from 1999Q1 to 2008Q3, and a sample including the Great Recession that covers 1999Q1 to 2012Q4. $p$-Values of the J-stat (over-identification test) are obtained by Monte-Carlo simulations.

| MDE—results | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| Specification | | | | |
| Sample | Pre-crisis | Pre-crisis | Pre-crisis | Incl.-crisis |
| Moments | INF | GDP | INF/GDP | INF/GDP |
| Parameter estimates | | | | |
| $\widehat{\lambda}$ | .340 (.629) | .352 (.081) | .180 (.016) | .060 (.352) |
| $\widehat{\sigma}_v$ | .325 (.099) | .785 (.011) | .832 (.006) | 1.193 (.151) |
| Specification test (j-stat) | | | | |
| $p$-Value | .018 | .956 | .059 | .006 |

$(\lambda, \Sigma_v)$, the targeted moments are simulated using the Kalman filter and the hybrid model. Third, the distance between these simulated moments and the actual ones is computed. Fourth, the objective function is minimized over the space of parameters using a numerical routine.

### 4.3. Results

Table 4 gives the estimation results obtained for a baseline specification of the sticky/noisy information model in which the variance of the measurement error is constrained to be the same for inflation, unemployment and output growth, *i.e.* $\Sigma_v = \sigma_v^2 I_3$. Those results are qualitatively robust to more flexible versions of the estimated model (see Appendix A.7 for details on robustness checks, including noise variances that differ across variables, systematic bias in errors and recursive estimation of the auxiliary VAR).

In the baseline case, whose results are presented in Column 1, the estimation aims at matching the moments of inflation over a pre-crisis sample. One main result is that the estimated value for the attention degree, $\widehat{\lambda} = .340$, is well below the micro-estimate of around .75 obtained from the micro-data. Thus, along this first dimension, the model is at variance with the SPF micro-facts.[17] The measurement noise is $\sigma_v = .325$, which represents about one-half of the inflation variance over this period. The test for over-identifying restrictions rejects the null that the distance between the estimated moments and the observed ones is zero, with a $p$-value of .018.

Columns 2 illustrates how the results change when one tries to match the moments of real GDP, and Column 3 when one tries to match the moments of inflation and real GDP jointly. Compared to the baseline case, the results in Column 2 present a very similar estimate for the attention degree $\widehat{\lambda} = .352$ and a larger degree of noise $\widehat{\sigma}_v = .785$. Noticeably, the over-identifying restrictions are not rejected by the data (the $p$-value of the test is .956). Still this is at the cost of a frequency of updating much lower than in the micro-data. Trying to match the moments of the two variables together (Column 3) results in an attention degree, $\widehat{\lambda} = .180$, that is even lower than in the two previous cases and in a standard deviation of the idiosyncratic noise that equals $\widehat{\sigma}_v = .832$. The estimated value for $\lambda$ is thus even farther than our micro-data estimate and the model is rejected by the formal test at the 10% level, with a $p$-value of .059.

Finally, an assessment of how the crisis affects the results is provided. More precisely, Column 4 presents the results obtained when estimating the model jointly on inflation and GDP moments on a sample ending in 2012Q4. The attention degree becomes $\widehat{\lambda} = .060$, and the noise variance is substantially larger ($\widehat{\sigma}_v = 1.193$). A larger degree of information imperfection is needed in order to match the formation of expectation during the crisis. This conveys the fact that the adjustment of expectations was moderate during the crisis and that at the same time disagreement spiralled up. Interestingly, this seems at odds with the fact documented in Section 3.2 that forecasters adjusted more the forecasts than usual over the 2008–2009 period. However, it can be that at the same time, $\lambda$ increases and forecast stay unreactive if the signal becomes very noisy. However, and as the over-identifying test makes clear, such parameter estimates cannot account for the whole set of moments the procedures aims at replicating.

[17] By analogy with Carvalho (2006) in the case of the frequency of price adjustment, our estimation of the average attention rate may be prone to an aggregation effect if forecasters have heterogeneous attention rates. However, the lowest individual average frequency of updating is equal to 50%. Aggregation bias issues cannot thus close the gap between the MDE results and the micro-data estimates.

**Table 5**
Comparing data and model-based moments.
The table compares the targeted MDE moments for euro area HICP inflation, $\pi$, observed in the SPF data (column 1), obtained with the MDE parameter estimates (column 2), or under alternate parameters values (columns 3–5). Moments are the 1-year ahead mean squared forecast error Mean($e_t^2$), the first-order autocorrelation of the forecast error $\rho_e(1)$, the average disagreement Mean($\sigma_t$), and the time variance of the disagreement V($\sigma_t$).

| Moments under various configurations<br>Inflation, $\pi$<br>Pre-crisis sample | **(1)**<br>Data | **(2)**<br>$\lambda=\widehat{\lambda}$<br>$\sigma=\widehat{\sigma}$ | **(3)**<br>$\lambda=.75$<br>$\sigma=\widehat{\sigma}$ | **(4)**<br>$\lambda=\widehat{\lambda}$<br>$\sigma=1.2$ | **(5)**<br>$\lambda=.05$<br>$\sigma=\widehat{\sigma}$ |
|---|---|---|---|---|---|
| Mean($e_t^2$) | .555 | .165 | .134 | .336 | .411 |
| $\rho_e(1)$ | .799 | .739 | .656 | .883 | .897 |
| Mean($\sigma_t$) | .250 | .223 | .170 | .144 | .232 |
| V($10\times\sigma_t$) | .248 | .204 | .014 | .021 | 1.109 |

### 4.4. *Investigating why the model fails*

Overall, these estimates and tests suggest that our flexible noisy information/sticky information model fails to quantitatively fit the data. Table 5 illustrates what lies behind the formal rejection of the model. It provides a comparison of the value of targeted moments in the SPF data for inflation (Column 1) with model based moments of inflation obtained under different values of the parameters $\lambda$ and $\sigma_v$. Column 2 reports model-based moments obtained with the estimated values of parameters. The mean squared inflation forecast error generated by the model is strikingly lower than that observed in the data. The over-identifying restriction test indicates that the differences in moments are significant. The experiment reported in Column (3) further illustrates that the model is at odds with micro-data moments by looking at the model-based moments when keeping $\sigma_v$ at its estimated value, but setting the attention degree $\lambda$ to the value observed in the micro-data $\lambda=.75$. The mean squared forecast error generated by this degree of attention becomes even lower. Moreover, the autocorrelation of the error, the level of disagreement about future inflation and, more strikingly, its time-variance are lower compared to the SPF data moments.

Results in Columns 4 and 5 illustrate to what extent an increase in the degree of imperfect information increases the model based mean squared error. Column 4 reports the results obtained with a higher variance of the noise $\sigma_v=1.2$, that is four times the values from baseline estimate, keeping $\lambda$ unchanged. As expected, the MSE of forecasts increases—to .336—and gets closer to the data values. The intuition suggests that increasing $\sigma_v$ would also increase disagreement because each forecaster typically gets a fuzzier signal of the state variable. However, another mechanism counteracts this effect: with a higher variance of the noise, forecasters tend to shrink more their estimate of the state variable and put less emphasis on the signal they perceive (see Appendix A.6 for further discussion of model properties). It turns out that, in the present case, the latter effect dominates. Indeed, disagreement decreases from .223 under MDE estimates to .144. Another gap with the data that emerges with such a high variance of the noise is that it lowers too much the time-variance of disagreement, whereas it was close to the data in the estimated values of Columns 2. Alternatively, Column 5 reports results obtained with a lower degree of attention $\lambda=.05$, keeping $\sigma_v$ unchanged. With this very low degree of the attention rate, the MSE gets closer to the data (but still below with .411) while the time variance of disagreement is extremely high compared to the micro-data.

To summarize, the sticky/noisy information model is rejected by our quantitative analysis because whenever parameters fit the level and time-variation in disagreement in the data, they then fail to generate enough variance and persistence in forecast errors.

## 5. Conclusion

The European SPF is here used to provide micro-facts that are related to the sticky and noisy imperfect information models recently introduced in the macroeconomic literature and that more generally are useful to characterize the formation of expectations. In particular, we provide an estimate for the degree of attention based on individual observations, and find that professionals are, albeit mildly, inattentive. Another key result recovered from the individual ECB SPF data is that, to a large extent, the disagreement among forecasters is similar whether they revise their forecasts or not.

A formal test rejects a model of expectations featuring both sticky and noisy information. Indeed, this model is not able to account for the strong persistence of the forecast errors together with the relatively low level of disagreement and its variability over time observed in the data. There is more stickiness in experts' expectations than the one the mere inattention is able to generate.

Several avenues for future research are worth considering. More elaborate versions of inattention models could be investigated. One could for example consider a degree of attention that varies across individuals and over forecasting horizons, two features of the SPF data highlighted in the present paper. One could also introduce noisy signals that are common to every forecasters, as a way to account for the relatively low degree of disagreement in the data. Moreover, and beyond the mere framework of inattention theories, another avenue is to investigate whether alternative forms of deviations from the perfect information rational expectation setup, for instance model uncertainty or strategic interactions between forecasters, provide a better match of the empirical patterns documented in this paper.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jmoneco.2013.08.005.

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