Forecaster (Mis-)Behavior*

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Abstract

We document how professional forecasts overrespond to new information. We show that such overresponses are inconsistent with rational expectation formation with noisy information, common agency-based models of forecaster behaviour, as well as several behavioral alternatives. In place, we propose a simple model of absolute and relative overconfidence, consistent with the stylized facts. Unlike rational forecasters, overconfident forecasters are overoptimistic about the precision of their private information and believe it to be superior to that held by others. We show how this causes forecasters to misinterpret the information content of market-generated public outcomes. Consequently, forecasters not only overrespond to private information but also to observed public news. We document how the latter is a pervasive feature of the forecast data. Last, we use the model to shed light on the importance of misperceptions about public information for expectation formation.

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1 Introduction

Expectations about tomorrow matter for choices today. Because individual expectations are typically unobserved, however, it is difficult to discriminate between different models of expectation formation. One exception are professional forecasters, who regularly publish predictions

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about macroeconomic and financial variables. Recently, survey data on professional forecasts have been found to support the main hypotheses of a growing literature on rational expectation formation with imperfect information. Specifically, Coibion and Gorodnichenko (2015), Dovern *et al.* (2015) and others find that on *average* professional forecasts *underreact* to news, in the sense that their forecast revisions are too small.[1] This underresponse is, in turn, consistent with rational behavior by forecasters whose noisy private information optimally dampens individual forecast revisions.

In this paper, we study the statistical properties of *individual* professional forecasts and show how these are useful to discriminate between alternative models of expectation formation. In our empirical analysis, we find that *individual* forecasts of main macroeconomic variables from a variety of professional forecaster surveys *overreact* to news: individual forecasters revise their predictions too much. Importantly, we also find that forecasters overreact to a specific piece of public news: higher average, or 'consensus', forecasts from previous forecast rounds are associated with a larger overprediction in later forecasts. We show how our first finding of overreaction to general news contradicts standard models of rational Bayesian behavior. Moreover, our second finding of overreaction to public news also contradicts many alternative explanations that only imply overreaction to private information. A simple model of overconfident forecasters, who believe that their information is both more precise than the truth and more precise than that of their competitors, in contrast, can explain the facts both qualitatively and quantitatively. This is because overconfident forecasters misperceive endogenous public signals and infer excessive fundamental news from consensus forecasts.

Our benchmark empirical findings are based on the US survey of professional forecasters (SPF). We confirm previous evidence that upward and downward revisions of average inflation forecasts are, respectively, associated with under- and overpredictions of inflation outcomes. We then exploit the individual SPF micro-panel data to show how, in contrast to this underresponse of average forecasts, individual forecasters react too much to news. We first document that upward and downward revisions of individual inflation forecasts are, respectively, associated with over- and underpredictions of inflation outcomes. This implies that forecasters overreact to overall news they receive between forecast rounds. Second, we show how forecasters overreact to a specific piece of public news, namely consensus forecasts from previous rounds of the survey. A higher than average consensus forecast thus implies overprediction of inflation by individual forecasters in later rounds of the survey. We show how these two findings also hold true for other macroeconomic variables such as output growth and alternative definitions of inflation. They also pertain at different forecast horizons, in various subsamples, and in different forecaster surveys for the US and other countries.

[1] Coibion and Gorodnichenko (2012) and Fuhrer (2015) provide related evidence.

We show how such observed responses to private and public information can be used as a new test to choose between alternative theories of expectation formation. Specifically, the observed patterns of individual overreaction not only contradict standard models of rational Bayesian behavior but also allow us to assess several alternative theories of forecaster behavior based on strategic or behavioral departures from simple rationality. For example, forecasters might diversify their forecasts away from those of others to 'stand out' as in Laster *et al.* (1999), Ottaviani and Sørensen (2006), and Marinovic *et al.* (2013), or might try to mimic the more responsive forecasts of better informed competitors as in Ehrbeck and Waldmann (1996). We show how such hypotheses capture the observed overresponse of forecasts to overall news and the underresponse of average forecasts, but cannot explain the observed overresponse to public information.

We then show how a simple model of overconfident forecasters can explain observed reactions to both private and public signals. The key to this result is that overconfidence in private information has two implications. First, overconfident forecasters believe their private signals to be more precise than they actually are. And second, they think they have better information than others. In fact, both facets of overconfidence, respectively denoted "overprecision" and "overplacement", have been extensively documented in experimental and observational data (Moore and Healy, 2008).

Overprecision straightforwardly makes forecasts overrespond to private signals and thus overreact to news. Perhaps more surprisingly, we show how overplacement causes mis-perception of endogenous public signals that leads to overreaction. This is because forecasters who think they have better information than others fail to recognize that their competitors indeed behave in the same way as themselves. This makes previous average forecasts react more to average news than forecasters anticipate. They thus infer excessive movements in the fundamental from any observed movement in average forecasts. overreaction to consensus results. A quantitative illustration shows how this simple model of overconfident forecasters can explain the evidence at reasonable levels of signal precision. Importantly, although overreaction to private information implies unnecessary losses and more dispersed forecasts relative to the rational benchmark, this is largely offset by more informative consensus forecasts. Equilibrium forecast errors are thus similar in magnitude to those in the rational model, making it harder for individuals to detect their own overconfidence. In other words, overconfidence in private information internalizes the externality of private responses for the informativeness of public signals, and may thus be collectively, or "ecologically" rational (Gigerenzer and Brighton, 2009, Gigerenzer, 2016).

Professional forecasters are likely to differ from other economic agents in their incentives and information about the state of the economy. To the extent that the evidence we uncover speaks in favor of a widely documented behavioral bias, rather than particular strategic incentives, we think that our results should carry over to other contexts. In particular, they draw attention to the role of endogenous public signals, and their misperception, as a source of expectational biases. Such misperception may be relevant in all contexts where endogenous equilibrium quantities or prices aggregate dispersed information and the behavioral rules of market participants, or the equilibrium generating mechanism, are uncertain. For example, the overresponse to private information implied by overconfidence makes expectations more dispersed, thus increasing ex post disagreement. Investor overconfidence in private information may thus increase the level of asset prices as more dispersed views about asset payoffs raise the scope of investor sorting (as, for example, in the classical paper by Miller (1977)). overreaction to endogenous public signals may also make prices and other averages more volatile, as average behavior becomes more reactive both to fundamental news and aggregate noise. This may open room for more pronounced "Pigouvian" economic cycles in response to noise shocks without fundamental information.

Although we show how many common departures from the rational expectations model do not predict the empirical patterns we document, the simple model of overconfidence and misperception we present is not the only one that can explain them. One natural alternative hypothesis that is consistent with the observed overresponses of forecasts is, of course, general overreaction to news. One particularly promising variant of this are "diagnostic" expectations, where agents overreact to news as diagnostic, or representative, of updates with respect to prior information. In contemporaneous work, Bordalo *et al.* (2018a) show how this theory is consistent with the general over- and underreaction patterns of, respectively, individual and average professional forecasts across a wide variety of datasets (although the authors do not consider responses to consensus forecasts or other public signals in their data). The contrasting observable implications of overconfidence, and misperception more generally, relative to diagnostic, and generally overreactive, expectations, may, however, be exploited to identify the relative predictive power of the two theories in different contexts. For example, diagnostic expectations overreact to all public signals (while misperception only applies to endogenous public signals), and show mean reversion in expectations as prior information is used rationally every period and overreaction thus vanishes (while overconfidence does not affect the recursivity of rational expectations).

This paper is related to the literature on expectation formation, as well as to studies of the behavior and incentives of professional forecasters. It is most related to Coibion and Gorodnichenko (2015), who show that average forecasts of several key economic variables in both the US SPF and other forecaster surveys exhibit underresponses to news, in the sense that forecast revisions are positively correlated with forecast errors. Their study builds on a number of previous tests of the hypothesis of limited information rational expectations (LIRE), starting with Mankiw and Reiss (2005) who find support for a sticky-information model in both consumer expectations and SPF forecasts.[2] Our contribution is to study both individual and average SPF forecasts within a consistent framework.[3] We show that forecast revisions are negatively correlated with forecast errors at the individual level, and that there is a significant negative correlation between consensus forecasts and individual forecast errors. We argue that this can be interpreted as overreaction by forecasters to both private and public information.

Although forecaster information is sometimes acknowledged to be an upper bound of that held by the population at large (Andrade and Le Bihan, 2013), most studies that use forecaster surveys to test the LIRE hypothesis abstract from the particular characteristics that distinguish professional forecasters from the rest of the population. This has attracted criticism (for example by Lamont, 2002) and given rise to a literature that looks at the incentives to distort forecasts away from true conditional expectations of future variables. For example, forecasters might try to mimic their more able colleagues (as in Ehrbeck and Waldmann, 1996), or, more generally, change their forecasts as a function of those they anticipate from their colleagues (Lamont, 2002). Alternatively, the payoff from a correct forecast might be higher when only few competitors make the same forecast (Laster *et al.*, 1999, Ottaviani and Sørensen, 2006, and Marinovic *et al.*, 2013). This makes forecasters optimally distort their forecasts away from their posterior mean and towards their idiosyncratic signal. Our contribution is to show, in a common framework, that these and other theories of forecaster behavior may account for overresponses to private, but not to public information. We use the same framework to show how many alternatives to the LIRE assumption can also not explain such overresponse. One exception is Bordalo *et al.* (2018b), who document that survey forecasts of credit spreads feature periods of excessive optimism and, more generally, predictable errors. Based on Kahneman and Tversky's (1973) representative heuristic they explain this by 'diagnostic' expectation formation (Gennaioli and Shleifer 2010), which exaggerates the probability of future states whose likelihood has increased by recent news. Our contribution is to show how a particular well-studied departure from LIRE, overconfidence in private information, can in fact parsimoniously account for the facts we document via an implied misperception of public signals.[4]

Section 2 presents a standard framework of expectation formation with limited noisy in-

[2]See Coibion and Gorodnichenko (2015) for a detailed survey of that literature.

[3]Dovern *et al.* (2015) look at revisions of individual GDP forecasts for a broad set of countries. They argue that these are less supportive of sticky information rational expectation models (Reiss, 2006) relative to their noisy information counterpart (Woodford, 2001)

[4]There is ample evidence for overconfidence also in non-experimental data. For example, Ben-David et al (2003), show how executives are on average overconfident in their ability to predict stock returns, and that this overconfidence correlates with corporate policies (as also shown by Malmendier et al, 2005).

formation, and shows how this implies underreaction of average expectations to news. Section 3 uses US SPF data to show how there is indeed underreaction of average forecasts to average news, as found in Coibion and Gorodnichenko (2015). Individual inflation forecasts, in contrast, overreact to idiosyncratic news. They also overreact to public news contained in consensus forecasts. Moreover, these overreactions are robust to changes in the estimation sample, and found in forecasts for a number of other macroeconomic data and alternative data sources, as we document in an Appendix. Section 4 shows how many standard alternative models do not explain the observed patterns. Section 5 presents an alternative explanation, based on overconfidence and misperception of public signals, that does. Section 6 compares the overconfidence model and its implications to alternatives, including the model of diagnostic expectations. An appendix contains further empirical results and all proofs.

2 A Baseline Model

This section presents a simple model of rational forecasting with dispersed information. We use this framework as a benchmark, both for the empirical results and for the alternative models considered later in the paper.

There is a continuum of measure one of forecasters, indexed by $i \in [0, 1]$. Forecasters minimize the mean-squared error of their forecasts f_i of the random variable θ. All forecasters have the prior belief $\theta \sim N(\mu_i, \tau_\theta^{-1})$ and observe two types of information. Their own private information, summarized by the *private signal*

$$x_i = \theta + \epsilon_i, \tag{2.1}$$

where the noise terms $\epsilon_i \sim \mathcal{N}(0, \tau_x^{-1})$ are independent of θ and $\mathbb{E}[\epsilon_i \epsilon_j] = 0$ for all $j \neq i$. The private signal of one forecaster is not observed by any other forecaster. In addition to their private information, all forecasters observe the realization of the *public signal*

$$y = \theta + \xi, \tag{2.2}$$

where $\xi \sim \mathcal{N}(0, \tau_y^{-1})$ is independent of θ and ϵ_i for all $i \in [0, 1]$. The signal y is public in the sense that its realization is common knowledge among all forecasters.

Below, we focus on three implications of rational expectations with mean-squared error preferences and dispersed information.[5]

[5]Apart from those discussed below, several broad aspects of survey forecasts are clearly consistent with noisy rational expectations. First, survey forecasts are dispersed and differ across forecasters (Zarnowitz, 1985). Second, forecasts are often smoother, with lower volatility, than the variable that is being forecasted (Ottaviani and Sørensen, 2006). In fact, one of Muth's (1961) aims in proposing the rational expectations

Average Forecasts (Implication 1): Consider the problem faced by individual i. Based on both private and public information, the optimal forecast of θ is

$$f_i = \mathbb{E}\left[\theta \mid \mu_i, x_i, y\right] = \mu_i + k\left(\mathbb{E}\left[\theta \mid x_i, y\right] - \mu_i\right), \tag{2.3}$$

where $k = \frac{\tau_x + \tau_y}{\tau_\theta + \tau_x + \tau_y} \in (0, 1)$ denotes the combined weight on new information, x_i and y.[6] Averaging (2.3) across all $i \in [0, 1]$ and rearranging we arrive at

$$\theta - f = \frac{1-k}{k}\left(f - \mu\right) - c\xi,$$

where $f = \int_0^1 f_i di$ denotes the average forecast, $\mu = \int_0^1 \mu_i di$ the average prior expectation, $c = \frac{\tau_y}{\tau_x + \tau_y}$ and $\int_0^1 \epsilon_i di = 0$ since the noise in forecasters' private signals cancels on average.

In a regression of mean forecast errors $\theta - f$ on mean forecast revisions $f - \mu$,

$$\theta - f = a + b\left(f - \mu\right) + \nu, \tag{2.4}$$

where a and ν denote constant and error terms, respectively, the estimates of the slope b will therefore be positive and measure the extent of information frictions ($k < 1$). That is, estimates of $b > 0$ will measure the extent to which forecasters' information (x_i and y) accurately reflect the fundamental θ.

Because of the presence of private information, individuals, on average, underrespond to new information in (2.4), as captured by the average forecast revision. Forecasters down-weigh their own information to account for its noisiness $k < 1$. But since the private noise terms cancel on average, this down-weighing of information leads to an underresponse to the average new information observed, and hence to a positive correlation between the mean-forecast error, on the one hand, and the mean-forecast revision, on the other hand.

Indeed, as shown by Coibion and Gorodnichenko (2015), the correlation of errors and revisions is generically positive for average forecasts across a wide-variety of information structures when forecasters are in possession of private information. The mean forecast, in essence, encodes more precise information than used by individual forecasters because of the presence of private information. This, in turn, causes the average forecast revision to underrespond to average new information. The averaging of private informations also renders the average forecast more precise (Zarnowitz and Lambros, 1987).

Individual Forecasts (Implication 2 and 3): A well-known consequence of conditional

hypothesis was to explain these two stylized facts observed using survey data (p. 361 in Muth, 1961).

[6] As discussed in e.g. Bhattacharya and Pfleiderer (1985) conditional expectations do not only correspond to optimal predictors for mean-squared error loss functions but indeed for any symmetric loss function.

expectation forecasts is that individual forecast errors $\theta - f_i$ are uncorrelated with convex combinations of the elements in forecasters' information set (Granger, 1969).

Let z denote any linear combination of x_i, y and μ_i. Then,

$$\mathbb{E}\left[\theta - f_i \mid z\right] = \mathbb{E}\left[\theta \mid z\right] - \mathbb{E}\left[\mathbb{E}\left[\theta \mid x_i, y, \mu_i\right] \mid z\right] = 0, \tag{2.5}$$

since $\mathbb{E}\left[\mathbb{E}\left[\theta \mid x_i, y, \mu_i\right] \mid z\right] = \mathbb{E}\left[\theta \mid z\right]$ by the *Law of Iterated Expectations.*

Equation (2.5) has two important consequences. First, estimates of the slope in (2.4) at the individual level should be zero. That is, estimates of β in the regression

$$\theta - f_i = \alpha + \beta\left(f_i - \mu_i\right) + \nu_i, \tag{2.6}$$

should be undistinguishable from zero, in contrast to at the average level where the slope coefficient is positive ($b > 0$). Individual forecast errors $\theta - f_i$ cannot be correlated with individual forecast revisions $f_i - \mu_i$, themselves a combination of x, y and μ_i. If they were, forecasters would be able exploit this correlation to improve their forecasts, contradicting the assumption that their forecasts were the conditional expectation to start with.

Second, by similar logic, (2.3) also dictates that individual forecast errors should be uncorrelated with any public information y that forecast revisions are in part based on. The estimate of δ in the regression

$$\theta - f_i = \alpha + \delta y + \nu_i. \tag{2.7}$$

should thus also equal zero, since any non-zero coefficient would contradict the assumption that forecasts correspond to conditional expectations.

We summarize these implications of noisy rational expectations in Proposition 1.

Proposition 1. *With rational expectations and private information, individual forecast revisions and public information do not predict individual forecast errors ($\beta = 0$ and $\delta = 0$). Mean forecast errors are, however, positively correlated with mean forecast revisions ($b > 0$) .*

Because of the potential for heterogenous priors $\mu_i \neq \mu_j$ for $i \neq j$, Proposition 1 covers the important case in which θ itself evolves dynamically across time, in accordance with for example an $AR(1)$. When new information is observed in each period, forecasts in (2.3) then correspond to those that arise from the Kalman Filter (Anderson and Moore, 1979).[7]

[7] Furthermore, because the last two implications in Proposition 1 ($\beta = 0$ and $\delta = 0$) derive from the Law of Iterated Expectations, they extend to economies in which shocks are non-normal. The first implication, $b > 0$, carries directly over to other affine prior-likelihood combinations, such as beta-binomial, gamma-poisson, and when observations are negative binomial, gamma, or exponential with natural conjugate priors (Ericson, 1969).

3 Empirical Evidence

In this section, we compare the implications of noisy rational expectations, listed in Proposition 1, to key features of US inflation forecasts. We document how professional forecasters on average underrespond to new information ($b > 0$). We then show how the same forecasters at the individual level in contrast overrespond to their own forecast revision ($\beta < 0$) as well as to observed public information ($\delta < 0$). Appendix A shows how these results carry over to other forecast variables, such as output, alternative estimation periods and samples, and other datasets.

Data: We focus on forecasts of US inflation from the *Survey of Professional Forecasters* (SPF).[8] At the start of each quarter, the SPF asks its respondents for their forecasts of a number of key macroeconomic and financial variables, and publishes them, in anonymous format but with personal identifiers, shortly after.[9] We study SPF forecasts of the year-on-year percentage change in the GNP/GDP deflator, for which the survey includes consistent forecasts over the six quarters following the survey quarter. We focus on inflation forecasts for three reasons. First, because inflation expectations play a central role in the economy as determinants of wages, as well as goods and asset prices. Second, to compare our estimates with those from previous studies, which focus disproportionally on inflation expectations. Last, because data are available for a substantially longer time-span for inflation forecasts than for other variables, such as output. Throughout, we consider first-release realizations of inflation to most accurately capture the precise definition of the variable being forecasted (Croushore and Stark, 2001). Importantly for our purposes, although the precise schedule over the quarter has changed over time, the administrators of the SPF have consistently and publicly published the survey results well before sending out the following questionnaire to their respondents.[10] We therefore assume from now on that the information set of respondents includes the consensus (or average) forecast from the previous quarter.

Average Forecasts: We first study the properties of average inflation forecasts. We denote

[8]The SPF is the oldest quarterly survey of individual, macroeconomic forecasts in the US, dating back to 1968. The SPF was initiated under the leadership of Arnold Zarnowitz at the American Statistical Association and the National Bureau of Economic Research, which is why it is also still occasionally referred to as the the ASA-NBER Quarterly Economic Outlook Survey (Croushore, 1993).

[9]The number of respondents (professional forecasters from financial institutions, large industrial firms, and independent forecasting enterprises) fell from over 80 to around 20 by 1990. The Federal Reserve Bank of Philadelphia then took over the administration of the survey. The number of surveyed forecasters has fluctuated between 40 and 60 since then. See https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf?la=en for more details.

[10]See p.8 in the documentation: https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf.

individual i's forecast made in period t of the variable π in period $t+h$ as $f_{it|t+h}$. We then calculate the average as $f_{t|t+h} = \frac{1}{N_t}\sum_{i=1,..N_t} f_{it|t+h}$, where N_t denotes the number of forecasters in period t, and estimate the following regression equation

$$\pi_{t+h} - f_{t|t+h} = a + b\left(f_{t|t+h} - f_{t-1|t+h}\right) + \nu_t, \tag{3.1}$$

where ν_t once more denotes an error term. We thus estimate (2.4) when θ corresponds to inflation h periods ahead.[11]

Table I presents the results for one-year ahead inflation forecasts, $h = 4$. Average forecasts revisions are positively correlated with average forecast errors ($b > 0$). This effect is strong and highly significant, in accordance with the results in Coibion and Gorodnichenko (2015), Andrade and Le Bihan (2013), Dovern *et al.* (2015), and Bordalo *et al.* (2018a). Consistent with noisy rational expectations, professional forecasters on average underrespond to the new information that they observe between two forecast rounds, leading to a positive correlation between the average forecast error, on the one hand, and the average forecast revision, on the other hand. Furthermore, consistent with the averaging out of noise in private information, average forecasts across our sample are also more precise than individual forecasts on average. This corroborates the empirical findings of Zarnowitz and Lambros (1987).

Individual Forecasts: We now turn to our main empirical results, describing the statistical properties of individual inflation forecasts. In particular, we test the implication of noisy rational expectations, detailed in Proposition 1, that forecast errors are orthogonal to any information, be it public or private, available to the individual forecaster at the time of the forecast. Figure 3 shows that this implication is *prima facie* not borne out by the data. The conditional means of individual forecast errors are negatively associated with the means of individual forecast revisions (left panel). They are also negatively associated with consensus forecasts for the same period from the previous wave of the survey (right panel).

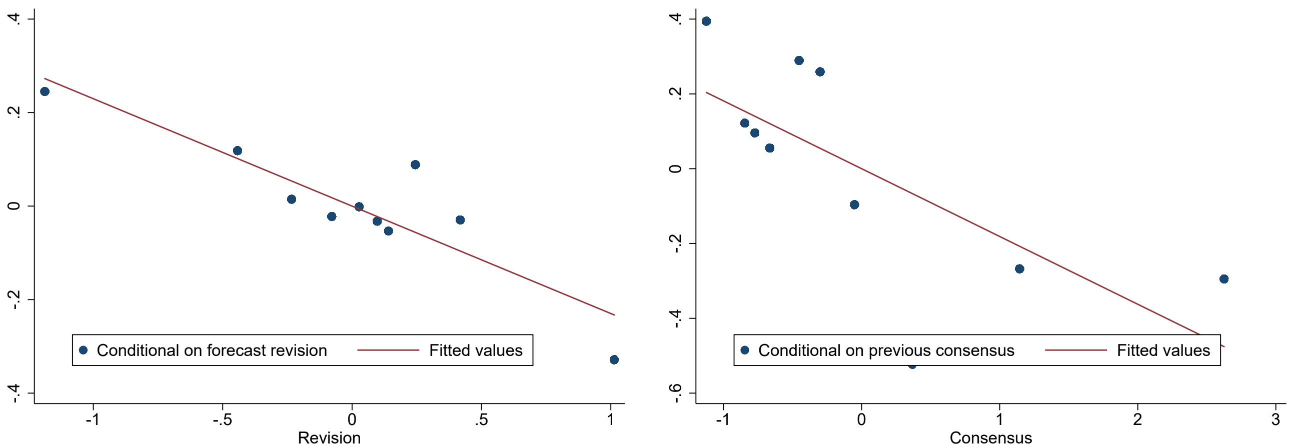
To test these implications more formally, we first estimate the equivalent of (2.6) at the individual level, using the benchmark specification

$$\pi_{t+h} - f_{it|t+h} = \alpha_i + \beta\left(f_{it|t+h} - f_{it-1|t+h}\right) + \nu_{it}, \tag{3.2}$$

where α_i denotes a forecaster specific fixed effect. Equation (3.2) thus corresponds to (2.6) when θ is once more set equal to h-period ahead inflation π_{t+h}.

[11]Notice that because of the presence of public information least-squares estimates of b in (2.4) and (3.1) are downward biased. As argued in Coibion and Gorodnichenko (2015), such downward bias, however, still entails that statistically significant findings of $b > 0$ are valid since estimates will understate the positive association.

Figure 1: Forecast Errors from the Survey of Professional Forecasters



The figure depicts the means of individual forecast errors of inflation (*vertical axis*) taken within deciles of the distributions of forecast revisions (*horizontal axis, left panel*) and consensus forecasts for the same period in the previous wave of the SPF (*horizontal axis, right panel*). All variables are demeaned by subtracting their overall mean during the sample period (1971Q2-2016Q4).

Table I: Estimates from the Survey of Professional Forecasters

	Average Forecasts	*Individual Forecasts*		
	Forecast Error	*Forecast Error*	*Forecast Error*	*Forecast Error*
Forecast Revision	1.273***	-0.195***	–	-0.199***
	(0.276)	(0.0432)		(0.0432)
Previous Consensus	–	–	-0.169***	-0.166***
			(0.0343)	(0.0446)
Constant	-0.0750	-0.0168***	0.604***	0.538***
	(0.0732)	(0.0000626)	(0.120)	(0.149)
Sample	71Q2-16Q4	71Q2-16Q4	71Q2-16Q4	71Q2-16Q4
Obs	182	5016	6722	5016
R^2	0.255	0.020	0.017	0.037

(i) Column one presents estimates of (3.1); column two and three (3.2) and (3.3).

(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

Our second test instead estimates a version of (2.7) by using a particular piece of public information that is salient to professional forecasters, namely the consensus forecast from the previous wave of the survey

$$\pi_{t+h} - f_{it|t+h} = \alpha_i + \delta f_{t-1|t+h} + \nu_{it}. \tag{3.3}$$

As argued above, and more forcefully in Ottaviani and Sørensen (2006), professional forecasters pay close attention to realizations of consensus. This is to assess how well they perform relative to their immediate competitors. Consensus estimates should therefore provide a conservative benchmark against which to test the orthogonality of individual forecast errors to public information implied by noisy rational expectations.[12]

Table I presents estimates of (3.2) and (3.3) for one-year ahead inflation forecasts, $h = 4$. Proposition 1 showed that under noisy rational expectations, we should expect estimates of the slope coefficients β and δ in both regressions to be close to zero. By contrast, the estimates in Table I are significantly negative and numerically large, inconsistent with the noisy rational expectations framework. The negative estimated value of β implies that positive individual forecast revisions are associated with negative forecast errors. Thus, forecasters on average revise their forecasts by too much, and hence overreact to the information received between subsequent survey rounds. Importantly, the negative estimate of δ implies that such overresponses also hold in reaction to a particular element of public information: Individual forecast errors are on average more negative not only when individual forecast revisions are more positive, but also when the previous consensus forecast is higher. These overresponses are corroborated in the final column of Table I, where we report the coefficient estimates of the multivariate regression, controlling both for individual forecast revisions and previous consensus realizations. Forecasters indeed overrespond both to the public information embodied in consensus forecasts and to the remaining information that they receive between forecast rounds conditional on consensus.

Robustness: These patterns documented in the SPF are remarkably stable when we consider other macroeconomic variables, forecast periods, forecast horizons, countries, as well as other types of forecasters. We summarize here the results from such alternative estimates of (3.1), (3.2), and (3.3) presented in Appendix A.

First, to complement our benchmark results using GNP/GDP inflation forecasts, we also consider forecasts of CPI inflation and real GNP/GDP growth from the SPF. The estimated coefficients for b, β, and δ all have the same sign as our benchmark results, and are all

[12] Pesaran and Weale (2006) and Fuhrer (2015) document how the orthogonality restriction of individual forecast errors to public information also fails for other variables than consensus forecasts. See also the robustness section further below for similar estimates.

statistically significant with the exception of the CPI estimate of β. Similar results hold when we restrict the sample to the period after the Federal Reserve Bank of Philadelphia took over the administration of the SPF in 1990 and substantially increased its coverage. We also document that similar results hold at a semi-annual forecast horizon (when $h = 2$).

Second, we extend beyond the United States and consider professional forecasts of inflation for another geographic area, the Euro Area, as collected by the *ECB's Survey of Professional Forecasts* (Garcia, 2003). We once more find estimates of the same sign and similar magnitudes to those from the US SPF, albeit the estimate on forecast revisions looses its statistical significance. We attribute this result to the low power of any test implied by the short estimation sample. (The ECB's Survey of Professional Forecasts only starts in 2000.)

Third, a large share of forecasters in the US and Euro Area SPF comes from financial sector institutions. We therefore also consider whether our results extend beyond financial sector forecasters. Appendix A shows how our results carry over with equal force to the non-financial sector forecasters in the US SPF, as well as to the non-financial sector forecasters that are part of the *Livingstone Survey* (Croushore, 1997).[13] The non-financial sector forecasters in the US SPF mainly come from large private sector firms and consultancies, while the Livingstone Survey covers a broader range of non-financial sector forecasters (that also include, for example, academic institutions and government entities). The Livingstone Survey estimates, in addition, show how our results extend to semi-annual forecast revisions.

Last, to supplement our benchmark results that use consensus realizations as the relevant public variable, we also consider whether individual forecast errors correlate with last period's realization of the forecasted variable. This variable, which is also publically available at the time of the forecast, is presumably also salient to individual forecasters. Consistent with the large literature that documents the phenomenon of extrapolation,[14] we find statistically significant negative estimates of δ across several different forecast variables (GNP/GDP inflation, CPI inflation, and real GDP growth). Forecasters therefore not only seem to overrespond to past realizations of consensus, but also to last period's realization of the variable that they are attempting to forecast.

Apart from these additional estimates, our confidence in the overresponse to individual forecast revisions ($\beta < 0$) is also corroborated by contemporaneous work. In their paper, Bordalo *et al.* (2018a) document a significant negative correlation between individual forecast errors and individual forecast revisions across many different economic variables in a wide variety of datasets that much extends beyond those considered in Table I and Appendix A.

[13]The Livingstone Survey is a bi-annual survey of forecaster expectations that covers many different types of forecasters. It is the oldest continuous survey of economists' expectations. The Federal Reserve Bank of Philadelphia took responsibility for the survey in 1990.

[14]See, for example, Bordalo *et al.* (2018b) and Kohlhas and Walther (2018) and the references therein.

They do not, however, study the relationship between forecast errors and public information.

Taken together, the data thus strongly suggest that average underresponses ($b > 0$) and individual overresponses ($\beta < 0$ and $\delta < 0$) occur simultaneously. Forecasters, on average, underrespond to the new information that they receive between two periods, consistent with noisy rational expectations. But, at the individual level, forecasters instead overrespond to the news that they receive. As we have argued in the introduction, and will show more formally below, several previous models of both rational and biased forecaster behavior struggle to reconcile this coincidence of over- and underresponsive forecasts. The next section makes this more explicit using the basic framework from Section 2.

4 A Common Framework for Alternative Models

A variety of explanations are consistent with the observed, simultaneous under- and overresponse of forecast revisions at the average ($b > 0$) and individual level ($\beta < 0$). On balance, these explanations can be separated into two types: First, agency-based explanations in which the assumption of mean-squared error loss is replaced, while the assumption of rational information use is maintained. And second, behavioral explanations that keep the assumption of mean-squared error loss but allow for non-rational uses of information. In this section, we show how several of the most prominent of such explanations are, nevertheless, inconsistent with the overresponse to public information ($\delta < 0$) that we also documented in the previous section.

Responses to Private Information: We start by demonstrating how additional weight on private information (relative to mean-squared optimal) can create forecasts that are consistent with the observed over- and underresponse of forecast revisions.

Consider once more individual i's forecast of θ from Section 2, $f_i = \mathbb{E}[\theta \mid \mu_i, x_i, y]$. We can alternatively write this forecast as

$$f_{i,\star} = (1 - w_\star)\, \mathbb{E}[\theta \mid \mu_i, y] + w_\star x_i, \tag{4.1}$$

where $w_\star = \frac{\tau_x}{\tau_\theta + \tau_x + \tau_y}$ denotes the mean-squared optimal weight on private information. But suppose now that the actual weight that forecasters attribute to their own private information w differs from $w_\star$. In that case, f_i can instead be characterized by

$$f_i = (1 - w)\, \mathbb{E}[\theta \mid \mu_i, y] + w x_i, \quad w \neq w_\star. \tag{4.2}$$

It then follows from (4.1) and (4.2) that[15]

$$\mathbb{C}ov\left[\theta - f_i, f_i - \mu_i\right] = -w\left(w - w_\star\right)\mathbb{E}\left[x_i - \mathbb{E}[x_i \mid \mu_i, y]\right]^2,$$

such that $\beta < 0$ when $w > w_\star$. When individuals attach more weight to private information than optimal, individuals will, on average, overrespond to the information that they receive between two periods. This, in turn, leads to a negative correlation between individual forecast errors $\theta - f_i$ and individual forecast revisions $f_i - \mu$, precisely as in the data.

Furthermore, it is straightforward to show that as long as $w < 1$ in (4.2), this negative relationship coincides with an average underresponse to the average forecast revision; that is, with estimates of b that are strictly positive ($b > 0$).[16] This is because individuals still respond less to their private information in (4.2) than the optimal response to the average private signal, $\int_0^1 x_i di = \theta$.

Responses to Public Information: While an increased weight on private information is consistent with the observed under- and overresponse of forecast revisions, it nevertheless does not *per se* lead to an overresponse to public news. In fact, despite an increased use of private information when $w > w_\star$, individual forecast errors will still be uncorrelated with the public signal y.

To see this, consider an individual's forecast error based on (4.2)

$$\theta - f_i = \theta - wx_i - (1 - w)\,\mathbb{E}[\theta \mid \mu_i, y] \tag{4.3}$$

Taking conditional expectations based upon public information y then directly shows that

$$\mathbb{E}\left[\theta - f_i \mid y\right] = (1 - w)\left(\mathbb{E}\left[\theta \mid y\right] - \mathbb{E}\left\{\mathbb{E}\left[\theta \mid \mu_i, y\right] \mid y\right\}\right) = 0, \tag{4.4}$$

where the last equality follows from the *Law of Iterated Expectations*. As a result, despite the misuse of private information, forecast errors will still be uncorrelated with public news ($\delta = 0$). Overresponse to private information (relative to the mean-squared optimum) does not *per se* entail a relationship between individual forecast errors and, for example, past consensus

[15]Let $f_{i,\star}$ denote the rational forecast from (4.1). Then,

$$\begin{aligned}
\mathbb{C}ov\left[\theta - f_i, f_i - \mu_i\right] &= \mathbb{C}ov\left[\theta - f_{i,\star} + f_{i,\star} - f_i, f_i - \mu_i\right] \\
&= \mathbb{C}ov\left[f_{i,\star} - f_i, f_i\right] = \mathbb{C}ov\left[\left(w_\star - w\right)\left(x_i - \mathbb{E}[\theta \mid \mu_i, y]\right), \mathbb{E}[\theta \mid \mu_i, y] + w\left(x_i - \mathbb{E}[\theta \mid \mu_i, y]\right)\right] \\
&= -w\left(w - w_\star\right)\mathbb{E}\left[x_i - \mathbb{E}[x_i \mid \mu_i, y]\right]^2
\end{aligned}$$

since $\mathbb{E}[\theta \mid \mu_i, y] = \mathbb{E}[x_i \mid \mu_i, y]$.

[16]See the common noise model in Appendix A of Coibion and Gorodnichenko (2015). In our model, the presence of the public signal y introduces a common noise component in individual forecasts.

realizations, such as that documented in Table I.

When one considers projections of forecast errors onto public information one only considers whether those sources of information are employed to minimize forecast errors. One does not consider whether all sources of information, in general, are accurately employed. Although forecasters with $w > w_\star$ in (4.2) do not optimally use private information to minimize forecast errors, conditional on this misuse, they still utilize public information efficiently. That is why $\mathbb{E}[\theta \mid \mu_i, y]$ appears in (4.2). This, in turn, leads to a population coefficient of δ equal to zero.

We summarize the results from this subsection and the previous in Proposition 2.

Proposition 2. *Consider a forecast by individual $i \in [0,1]$ of the form*

$$f_i = (1-w)\,\mathbb{E}[\theta \mid \mu_i, y] + w x_i, \quad 1 > w > w_\star \tag{4.5}$$

Then, $b > 0$ in (2.4), $\beta < 0$ in (2.6), but $\delta = 0$ in (2.7).

Examples: A variety of models of forecaster behavior fall within the class described by Proposition 2. These models are thus consistent with an underresponse to news at the average level (and thus with $b > 0$), an overresponse at the individual level ($\beta < 0$), but inconsistent with the documented overresponse to public information (as evidenced by $\delta < 0$).

Strategic Diversification: Laster *et al.* (1999), Ottaviani and Sørensen (2006) and Marinovic *et al.* (2013) propose agency-based models of professional forecasters that fall within the class described in Proposition 2.[17] In their model, the market for professional forecasters corresponds to a winner-takes-all competition, where only the most accurate forecast is rewarded by a fixed payoff that is split equally among all winners. As a consequence, the equilibrium distribution of forecast becomes an important determinant of individual forecasts. In a symmetric equilibrium, all forecasters choose to over-emphasize private information and follow (4.5) with $w > w_\star$. To see why, consider an individual forecaster who sets $w = w_\star$. Increasing the weight on private information ($w > w_\star$) leaves the probability of winning the contest approximately unchanged (as the posterior is flat at the conditional expectation). But it strictly reduces the mass of other forecasters that makes the same forecast. In equilibrium, all forecasters therefore choose to set w such that $w \in (w_\star, 1)$. In accordance with Proposition 2, such forecasts imply a simultaneous under- and overresponse to forecast revisions ($b > 0$ and $\beta < 0$). But since public information does not diversify individual forecasts away from those of others, it is still the case that $\delta = 0$ (Appendix B).

Reputational Considerations: Ehrbeck and Waldmann (1996) propose an alternative model of

[17] See, for example, Proposition 4 in Ottaviani and Sørensen (2006) and Proposition 1 and Corollary 1 in Marinovic *et al.* (2013). Unlike these models, Proposition 2 allows for individual-specific priors.

forecaster behavior that builds on the reputational considerations faced by professional forecasters. In their model, one set of professional forecasters has access to more precise private information than another. Since forecasters are rewarded by clients according to the perceived accuracy of their forecasts, the set of forecasters that receive less precise information overrespond to their private information in an attempt to mimic their more informed competitors. Ehrbeck and Waldmann (1996) show that these less able forecasters in equilibrium follow (4.5), where $w > w_\star$, while their more informed competitors simply set $w = w_\star$.[18] Reputational considerations are thus simultaneously consistent with the documented underresponse to news at the average level ($b > 0$) as well as the overresponse at the individual level ($\beta < 0$). But since forecasters do not differ in their access to public information, conditional on private information, all forecasters still use public information efficiently ($\delta = 0$, Appendix B).[19]

Behavioral Overconfidence: A considerable literature in psychology has documented how people tend to over-emphasize their own information (see, for instance, Kahneman and Tversky, 1973). As discussed in, for example, Daniel *et al.* (1998), and more recently in Bordalo *et al.* (2018a) such inherent overconfidence could also provide the basis for the apparent overresponses to news observed in financial market forecast data, over and above that documented in the macroeconomic forecast data in Section 3. In our context, overconfident forecasters believe the precision of their private information to be higher than it actually is ($\tau_x' > \tau_x$). Their forecasts thus follow (4.5) where $w \in (w_\star, 1)$. However, as argued above, such overconfidence in private information would *in and of itself* not result in overresponses to public information since it does not also entail an amended use of public information conditional on private information. We return to how a suitably adjusted notion of behavioral overconfidence can be made consistent with the stylized facts in the next section.

Correlated Error Noise: A stark feature of the setup from Section 2 is that the errors in public and private information are uncorrelated with one another. Myatt and Wallace (2011) show that for certain prediction models, such as beauty-contest games, the outcomes of these models can depend centrally on this assumption. But suppose forecasters' private information in the setup from Section 2 takes the form $x_i = \theta + \epsilon_i + bu$, where $b \in \mathbb{R}$ and $u \sim \mathcal{N}(0, \tau_u^{-1})$, while the public signal y is $y = \theta + u + \xi$. The coefficient b here controls the correlation in the error terms. Individual forecast errors are then still given by (4.3). As a result, it still follows

[18] See the results on p. 24 of Ehrbeck and Waldmann (1996).

[19] In the spirit of Ehrbeck and Waldmann (1996), an alternative reputational model is one in which the interpretation of information is what separates forecasters. However, similar to Ehrbeck and Waldmann (1996), such a model would entail a negative relationship between the absolute size of individual forecast revisions and the absolute value of forecast errors. This is because forecasters who are better at interpreting information, and hence observe more precise signals, would revise their forecasts by more in equilibrium. As Appendix B shows, such a relationship is inconsistent with the data.

that

$$\mathbb{E}\left[\theta - f_i \mid y\right] = \mathbb{E}\left[\theta \mid y\right] - \mathbb{E}\left[\mathbb{E}\left[\theta \mid \mu_i, y\right] \mid y\right] - w\left(\mathbb{E}\left[x_i \mid y\right] - \mathbb{E}\left[\mathbb{E}\left[x_i \mid \mu_i, y\right] \mid y\right]\right)$$
$$= \mathbb{E}\left[\theta \mid y\right] - \mathbb{E}\left[\theta \mid y\right] - w\left(\mathbb{E}\left[x_i \mid y\right] - \mathbb{E}\left[x_i \mid y\right]\right) = 0, \tag{4.6}$$

so that $\delta = 0$. Intuitively, correlation among error terms does not alter that a projection of forecast errors onto public information only considers whether those sources of information are employed to minimize forecast errors. Conditional on any potential misuse of private information ($w \neq w_\star$), forecasters still efficiently use public information when we have error correlation, and as a consequence $\delta = 0$ in (4.6).

Theories Implying Underreaction: We conclude this section by mentioning that several other, prominent explanations (either agency-based or behavioral) have been proposed to describe the behavior of professional forecasters. Graham (1999), Lamont (2002), and Ottaviani and Sørensen (2006) describe different models in which forecasters all have an incentive to herd, as in Scharfstein and Stein (1990).[20] Ehrbeck and Waldmann (1996), by contrast, describe an alternative model of reputational concerns, where able forecasters have more precise prior information. Last, Hirshleifer *et al.* (1994) detail a model in which security analysts for behavioral reasons underrespond to their own private news. All of these explanations can be described within the class detailed in Proposition 2, but where $w \in (0, w_\star)$. As a result, these models cannot explain the overresponses to individual forecast revisions described in Section 3.

5 A Theory of Absolute and Relative Overconfidence

The previous section showed how several standard models of forecaster behavior are inconsistent with the documented overresponse to public information ($\delta < 0$). This is despite the ability of these models to match the simultaneous under- and overresponse of forecast revisions at the average ($b > 0$) and individual level ($\beta < 0$), respectively. In this section, we show how a simple model of *absolute and relative overconfidence* can explain our empirical results. We call "absolutely and relatively overconfident" those individuals that are not only overconfident in their own information but also wrongly think that their information is superior to that of others. We therefore merge the two related but distinct notions of overconfidence commonly used in the psychology literature (surveyed in Moore and Healy, 2008). We refer to the former type as *absolute* overconfidence, or *overprecision,* and to the latter as *relative* overconfidence, or *overplacement* (Benoît *et al.*, 2015). We show how the combination of the two, together

[20] See also, for example, Croushore (1997), Welch (2000), and the literature review in Marinovic *et al.* (2013).

with the realization that most public information reflects the endogenous choices of others, can explain our stylized facts.

5.1 A Two-period Model

Consider a two-period version of the baseline model from Section 2. We only introduce an explicit account of time in order to equate the public information that forecasters observe with the previous period's consensus estimate. At the start of each period, each forecaster $i \in [0,1]$ receives the private signal x_{it} about the random variable $\theta \sim \mathcal{N}(\mu, \tau_\theta^{-1})$,

$$x_{it} = \theta + \epsilon_{it}, \quad t = \{1, 2\},$$

where $\epsilon_{it} \sim \mathcal{N}(0, \tau_x^{-1})$ is independent of θ and $\mathbb{E}[\epsilon_{it}\epsilon_{jh}] = 0$ for all $j \neq i$ and all $t, h = \{1, 2\}$. All forecasters therefore receive private signals of the same precision, equal to τ_x. Forecasters suffer from 'absolute' overconfidence in their private information: They believe the precision of their private signals to equal $\tau_x' > \tau_x$, and thus to be greater than the truth. In addition, forecasters also exhibit 'relative' overconfidence: They believe other forecasters' private signals to have a precision smaller than their own, and equal to τ_x for simplicity.[21] The latter, relative aspect of forecasters misperceptions, often referred to as overplacement, differentiates the type of overconfidence studied here from that explored in Section 4.[22]

At the start of the second period, each forecaster also observes a noisy public signal of last period's consensus estimate

$$f = \int_0^1 f_{i1} + \xi, \tag{5.1}$$

where f_{i1} denotes i's first-period forecast and $\xi \sim \mathcal{N}\left(0, \tau_y^{-1}\right)$.[23]

5.2 Individual Forecasts

Consider forecaster i's first-period forecast

$$f_{i1} = v x_{i1} + (1 - v)\,\mu, \quad v = \frac{\tau_x'}{\tau_x' + \tau_\theta}, \tag{5.2}$$

[21] Equating forecasters beliefs about the precision of other's private information to its actual precision simplifies the derivations. But what is central for the argument below is simply that forecasters believe themselves to be superior and hence distort their interpretation of public information.

[22] Moore and Healy (2008) and Benoît *et al.* (2015) review the literature that document both overprecision and overplacement across a wide variety of experimental tasks.

[23] The reason for the introduction of the shock in (5.1) is purely technical: the important role it plays is to limit forecasters' ability to infer the true value of θ from the observation of f. The use of "non-invertibility" shocks has been standard in the noisy rational expectations literature since Hellwig (1980).

where v exceeds the mean-squared error optimal weight on private information, $v_\star = \frac{\tau_x}{\tau_x + \tau_\theta}$, because of forecasters' overconfidence in their own private information.

Let $\mu_i = f_{i1}$ denote forecaster i's prior expectation at the start of the second period with precision $\tau_\mu = \tau_\theta + \tau_x$. To derive an individual's $t = 2$ forecast, we first need to differentiate between two different consensus estimates: (i) the *realized consensus forecast* f; and (ii) the *suspected consensus forecast* f_s. The former measures the *actual* noisy signal of consensus in (5.1),

$$f = \int_0^1 f_{i1} + \xi = (1 - v)\,\mu + v\theta + \xi. \tag{5.3}$$

The latter, by contrast, measures the consensus forecast that forecasters *believe* they observe,

$$f_s = (1 - v_\star)\,\mu + v_\star\theta + \xi. \tag{5.4}$$

The variables f and f_s differ due to forecasters' misperceptions about the overconfidence of others; that is, that all forecasters attach a weight of $v > v_\star$ to their private information in (5.2).

Forecasters who observe a realized consensus forecast of f in (5.3) thus treat it *as if* it was generated by f_s in (5.4). As a result, the public signal that forecasters infer from consensus becomes

$$y = \frac{1}{v_\star}\left[f - (1 - v_\star)\,\mu\right] = \frac{v}{v_\star}\theta + \frac{v_\star - v}{v_\star}\mu + \frac{1}{v_\star}\xi. \tag{5.5}$$

Nevertheless, the signal that forecasters *believe* that they infer is

$$y_s = \theta + \frac{1}{v_\star}\xi. \tag{5.6}$$

There are two important differences between y and y_s, both of which are driven by forecasters' misperception about each other's behavior. First, the realized consensus outcome is more precise than the suspected one. Conditional on μ, the precision of y about θ is $v^2\tau_\xi$, while the precision of y_s is only $v_\star^2\tau_\xi$, where $v > v_\star$. Since all forecasters respond more to their own private information than expected by others, consensus embeds more of the truly new (private) information that forecasters can learn from each other. This increases the informativeness of the consensus estimate.

Second, and related, overconfident forecasters also over-infer movements in the fundamental from consensus. The realized consensus loads onto the fundamental with $v/v_\star > 1$ in (5.5), while the suspected consensus only loads onto the fundamental with one in (5.6). A movement of $d\theta > 0$ in the fundamental, thus, causes forecasters to all else believe in a moment equal to $(v/v_\star)\,d\theta > d\theta$, based on the observation of consensus alone. Put succinctly, the misperceptions about others inherent to our notion of overconfidence causes forecasters to both underestimate the precision of consensus as well as to over-infer movements in the fundamental from it.

We are now ready to state forecasters' second-period forecast:

$$f_{i2} = (1-w)\,\hat{\mathbb{E}}\left[\theta \mid y_s, \mu_i\right] + wx_{it}, \tag{5.7}$$

where $\hat{\mathbb{E}}\left[\theta \mid y_s, \mu_i\right] \neq \mathbb{E}\left[\theta \mid y, \mu_i\right]$ denotes the conditional expectation of θ based on μ_i and the realized public signal y being treated as if it were y_s. We note that $w = \frac{\tau_x'}{\tau_\theta + 2\tau_x' + v'^2\tau_\xi} \in (w_\star, 1)$ in (5.7) whenever $\tau_\theta \leq \tau_x$ (see Appendix C).[24]

5.3 Overreaction and Misperception

In this subsection, we derive sufficient conditions for our forecasts in (5.7) to be consistent with our empirical results from Section 3. First, because of the presence of noisy private information, on average forecasters underrespond to new information, as measured by the average forecast revision. Second, despite this underresponsiveness at the average level, at the individual level, forecasters instead overrespond due to their overconfidence in private information. And last, because of their misperception about others inherent to our notion of overconfidence, a negative relationship arises between the realized consensus estimate and individual forecast errors.

Proposition 3. *Consider individual $i \in [0,1]$'s second-period forecast*

$$f_{i2} = (1-w)\,\hat{\mathbb{E}}[\theta \mid \mu_i, y_s] + wx_i, \tag{5.8}$$

Then, if $\tau_\theta < \min\left\{\tau_x, \frac{\tau_x'}{\tau_x}v_\star^2\tau_\xi\right\}$, $b > 0$ in (2.4), $\beta < 0$ in (2.6) and $\delta < 0$ in (2.7).

Proof. The first and second result in Proposition 3 follow from Proposition 2 and that $w \in (w_\star, 1)$ and are therefore omitted here. To see how the misperceptions about other forecasters' behavior can lead to overresponses to public news, consider individual i's forecast error

$$\theta - f_{i2} = \theta - wx_i - (1-w)\,\hat{\mathbb{E}}[\theta \mid \mu_i, y_s] \tag{5.9}$$

[24] The necessary and sufficient condition for $w \in (w_\star, 1)$ in (5.7) is $\tau_\xi\tau_x^2\left(\tau_\theta - \tau_x\right) < \tau_\theta^4 + 3\tau_\theta^3\tau_x + 3\tau_\theta^2\tau_x^2 + \tau_\theta\tau_x^3 + \tau_\xi\tau_x^3 - \tau_\xi\tau_\theta\tau_x^2$. The reason for this dependence on the precision of consensus and the prior is simple: In order to have, for instance, underresponses at the average level, we need forecasters to attach sufficient weight onto their own private information, to counteract the overresponses that will occur to consensus, for example. This, in turn, requires the consensus and the prior not to be excessively informative.

Taking conditional expectations based upon *realized* public information then shows that

$$\mathbb{E}\left[\theta - f_{i2} \mid y\right] = (1-w)\left(\mathbb{E}\left[\theta \mid y\right] - \mathbb{E}\left[\hat{\mathbb{E}}\left[\theta \mid \mu_i, y_s\right] \mid y\right]\right) \tag{5.10}$$

$$= \frac{(1-w)(1-\frac{v}{v_\star})v_\star^2\tau_\xi}{\left(\frac{v}{v_\star}\right)^2 v_\star^2\tau_\xi + \tau_\mu}\left[\frac{v}{v_\star} + \left(1+\frac{v}{v_\star}\right)\frac{\tau_\mu}{\tau_\mu + v_\star^2\tau_\xi}\frac{\frac{v}{v_\star}(1-\frac{v}{v_\star})v_\star^2\tau_\xi - \tau_\theta}{\left(\frac{v}{v_\star}\right)^2 v_\star^2\tau_\xi + \tau_\theta}\right]y. \tag{5.11}$$

Thus, $\delta < 0$ when $\tau_\theta < \min\left\{\tau_x, \frac{\tau_x'}{\tau_x}v_\star^2\tau_\xi\right\}$ since $v/v_\star > 1$ and the term inside the bracket in (5.11) is positive. □

Unlike in (4.4) above, the Law of Iterated Expectations in (5.8) no longer implies orthogonality between individual forecast errors and public information. This is because $\mathbb{E}\left\{\hat{\mathbb{E}}\left[\theta \mid \mu_i, y_s\right] \mid y\right\} \neq \mathbb{E}\left[\theta \mid y\right]$ when $y_s \neq y$. A relationship therefore arises between individual forecast errors and consensus realizations, $\delta \neq 0$. Combined, the misperceptions about others at the heart of our notion of overconfidence and the presence of endogenous public information breaks the implication of the LIE that forecast errors are orthogonal to public news. As a consequence, an overresponse to public information can arise in conjunction with an under- and overresponse of forecast revisions at the average and individual level, respectively.

A Simplified Case: To connect this overresponse to public information to the misperception about others inherent to (5.7), it is helpful to consider a special case. A similar argument extends to the more general case covered in Proposition 3.

Suppose forecasters do not receive any additional private information in the second period and that their first-period priors are all equal to zero, $\mu_i = 0$, for all $i \in [0, 1]$. Then, it immediately follows that

$$\mathbb{E}\left[\theta - f_i \mid y\right] = \mathbb{E}\left\{\theta - \hat{\mathbb{E}}\left[\theta \mid \mu_i, y_s\right] \mid y\right\}$$

$$= \mathbb{E}\left\{\mathbb{E}\left[\theta \mid \mu_i, y\right] - \hat{\mathbb{E}}\left[\theta \mid \mu_i, y_s\right] \mid y\right\}, \tag{5.12}$$

in which the forecast in (5.12) based on y is

$$\mathbb{E}\left[\theta \mid \mu_i, y\right] = \kappa_\star y, \quad \kappa_\star = \frac{\nu^2\tau_\xi}{\tau_\mu + \nu^2\tau_\xi} \times \frac{v_\star}{v} \tag{5.13}$$

while the overconfident forecast based on y_s is

$$\hat{\mathbb{E}}\left[\theta \mid \mu_i, y_s\right] = \kappa y, \quad \kappa = \frac{\nu_\star^2\tau_\xi}{\tau_\mu + \nu_\star^2\tau_\xi} \times 1 \tag{5.14}$$

so that δ from (5.12) equals the simple difference between κ and $\kappa_\star$ ($\delta = \kappa\prime_\star - \kappa$).

As argued above, there are two important differences between the public information that forecasters observe and what they believe they observe. These two differences, in turn, map into two counteracting forces that determine the relative weights on public information in (5.13) and (5.14).

First, the realized public signal y is more precise than the suspected public signal y_s. Its precision about θ is $v^2\tau_\xi$ rather than $v_\star^2\tau_\xi$ as suspected, where $v > v_\star$. This, all else equal, causes the weight on y in (5.14) to be too small relative to (5.13), $\kappa < \kappa_\star$. When forecasters are overconfident in the precision of their own information relative to others, they underestimate the extent to which consensus embeds the truly new (private) information that forecasters can learn from one another. This, in turn, causes forecasters to, all else equal, underrespond to consensus realizations, and as a result a positive correlation between individual forecast errors and past consensus estimates to arise, $\delta > 0$.

But second, because $v_\star/v < 1$, the realized public signal also has a larger loading on the fundamental than the suspected public signal. A move of $d\theta$ causes a movement of $v/v_\star d\theta > d\theta$ in y relative to $d\theta$ in y_s. This over-inference, by contrast, leads the weight on the realized public signal y in (4.5) to be too large ($\kappa > \kappa_\star$), and hence implies $\delta < 0$, all else equal. When forecasters are overconfident in their own information vis-à-vis that held by others, they underestimate the extent to which movements in consensus correctly reflect the fundamental. This, in turn, causes forecasters to over-infer values of the fundamental from consensus realizations and thus to overrespond ($\delta < 0$).

Intuitively, how forecaster respond to public information depends on their views about its precision and its interpretation. Overconfidence causes forecasters to mistake both. Specifically, the misperception about others at the core of overplacement causes forecasters to over-infer values of the fundamental from consensus realizations. This is because forecasters underestimate others' emphasis on private information. As a result, forecasters overrespond to public news in Proposition 3, $\delta < 0$, when consensus is sufficiently informative (τ_ξ small), the prior relatively uninformative (τ_θ small), and overconfidence sufficiently prevalent (τ_x'/τ_x large).

5.4 Quantitative Illustration

We have shown how our model of overconfidence is qualitatively consistent with the stylized facts about individual forecasts. Although our model is simple, in this subsection we explore the capacity of the model to quantitatively match the SPF data.

We use a simulated method of moments procedure to choose parameter values. Apart from the individual regression coefficients β and δ, we also include the standard deviation of forecast revisions among our target moments. This is to capture the volatility of forecasts at different horizons, and thus the volatility of news encountered by forecasters.[25]

The criterion we choose to minimize is

$$\Lambda(\tau) \quad = \quad [\hat{m} - m(\tau)]' W^{-1} [\hat{m} - m(\tau)],$$

where $\hat{m}$ is a vector of target moments from the data and $m(\tau)$ is the vector of simulated moments as a function of the parameter vector $\tau = (\tau_x, \tau_x', \tau_\xi, \tau_\theta)$. Throughout the calibration, we normalize the precision of the first-period prior to one and use a diagonally-weighted minimum distance procedure, corresponding to a weighting matrix that has the variances of the moments on the diagonal and is zero everywhere else.

Table II: SMM Estimation: Inflation Forecasts

	β	δ	σ_{revision}	$\sqrt{\tau_x}$	$\sqrt{\tau_\xi}$	$\sqrt{\tau_\theta}$	$\sqrt{\tau_{x'}}$
Data	-0.195	-0.169	0.980				
Naive Overc.	-0.189	-0.173	0.956	0.80	6.67	1.00	1.45

Table II presents the results for inflation, where for ease of interpretation we report the square root of the precision, the inverse of the standard deviation. Our model of overconfidence is able to capture all three data moments well. We estimate private signals to be rather noisy ($\sqrt{\tau_x} = 0.80$) and the noise in consensus to be small ($\sqrt{\tau_\xi} = 6.67$). At a level of overconfidence that increases the square-root of the perceived precision of private signals by a factor of 1.8, the model predicts well both the overresponse to individual forecast revisions and to consensus realizations. This is consistent with the results in Proposition 3, which showed how the combination of a precise consensus and meaningful overconfidence, all else equal, made overresponses more pervasive. Appendix D shows how the model also captures well the overresponses observed in forecasts of real output growth and CPI inflation (although the model does not quite capture the strong estimated response of the latter to consensus forecasts).

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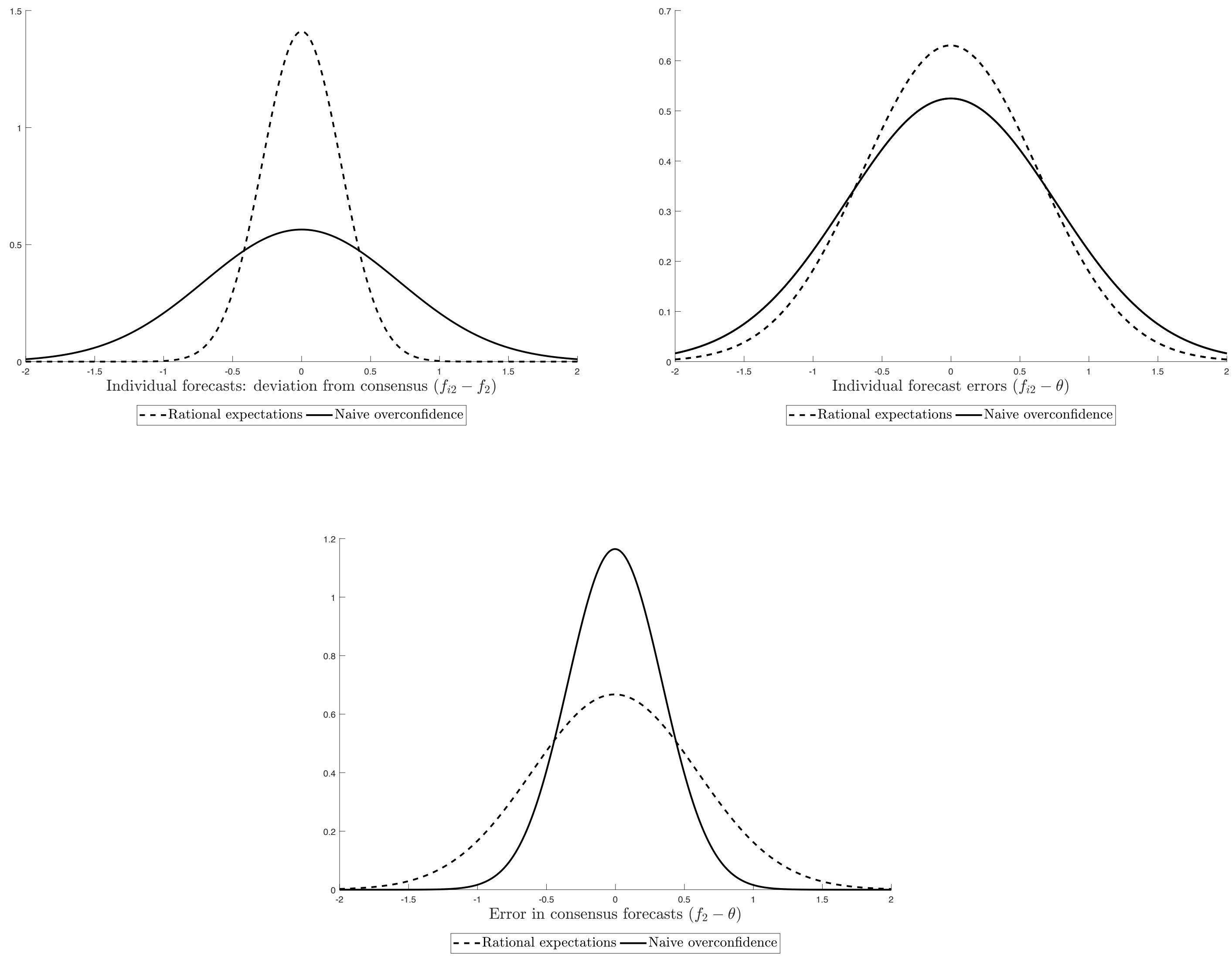
5.5 Model Implications

We conclude this section by exploring auxiliary implications of our model, using the estimates from Table II. Specifically, we show how overconfident forecasts are substantially more

[25] We calculate the standard deviation using a simple resampled bootstrap procedure with 10,000 resamples.

Figure 2: The Behavior of Calibrated Individual Forecasts



The top left-hand chart depicts the distribution of the difference between individual second-period forecasts and second-period consensus. It does so for both the overplaced overconfidence model and the corresponding mean-squared optimal, rational expectation model. In both cases, we use the parameters listed in Table II . The top right-hand chart, by contrast, shows the corresponding distribution of individual forecast errors in the two cases. The bottom chart depicts the distribution of the errors in the second-period consensus forecast.

dispersed than their mean-squared optimal counterparts. However, despite this increased dispersion, individual forecast errors from the two cases are remarkably similar. This is because overconfidence also causes consensus to be more informative. Last, we show how overconfidence amplifies the effect of 'noise shocks' on individual forecasts. This could have important implications for the role of such shocks in driving business cycle fluctuations.

The top left-hand chart in Figure 2 shows the distribution of individual second-period forecasts relative to second-period consensus. Compared to rational, mean-squared optimal forecasts, overconfident forecasts are substantially more dispersed. The standard deviation of the overconfident forecast distribution is about 1.5 times larger in the second period. This is because overconfidence causes individuals to put additional emphasis on private information. As discussed for example in Muth (1961), Mankiw *et al.* (2003), and more recently in Fuster *et al.* (2019), the amount of observed dispersion in macroeconomic forecasts is puzzling. This is especially true given the large amounts of public information that is available. Figure 2 and Table II show how our model of overconfidence can help bridge this gap: Overconfidence in the precision of private information creates, for realistic parameter, sizable amounts of forecast dispersion at the same time as relatively precise public information.

An important feature of our calibrated model is that despite the overconfidence of forecasters, individual forecast errors are remarkable close to their rational counterparts. The top right-hand chart in Figure 2 illustrates this point. In particular, it shows how the standard deviation of individual second-period forecast errors is only about slightly larger in the overconfident case. As a result, overconfident forecasters would face difficulty inferring from the precision of their own forecast alone that they were indeed overconfident.[26]

The bottom chart in Figure 2 demonstrates that the reason for this close equivalence is that the consensus signal is substantially more precise in the overconfident case. Because overconfident forecasters put more emphasis on private information, the endogenous consensus embeds more of the sum of forecasters' private information, the only truly new information that forecasters can learn from each other. In effect, overconfidence in private information counteracts the standard learning externality that exists in markets with endogenous public information, and which causes agents to attach too little weight to private information (Vives, 1997;Amador and Weill, 2010). That is why, despite the misuse and misinterpretation of information, overconfident forecasters in Figure 2 do almost as well as mean-squared optimal ones.

A core argument for rational, mean-squared optimal beliefs is that such beliefs make individuals as well-off as they can be (Brunnermeier and Parker, 2005). However, this rationale

[26]Because of mean-squared error preferences, this is equivalent to the statement that they would face difficulty inferring from their own utility alone that they were overconfident.

for rational expectations relies upon agents being strictly worse off with non-rational expectations. As Figure 2 shows, this is not necessarily the case in our model. This connects our results with those of Gigerenzer and Todd (1999), Gigerenzer and Brighton (2009), and others that attempt to find group-optimal or 'ecologically rational' explanations for individual biases in people's behavior.

Last, a substantial literature in macroeconomics has documented how noise shocks to public information can account for a substantial share of business cycle fluctuations (see, for example, Chahrour and Jurado, 2018 and the references therein). Because overconfident forecasters in our model, to match the forecaster data, attach more weight to public information than optimal, any such shocks will also have a heightened effect on individual forecasts.. Compared to the rational model, our model of overconfidence would therefore attribute a larger share of the volatility of individual forecasts to public noise. This illustrates how the overconfidence at the heart of our model could have important implications for the capacity of noise shocks to create meaningful business cycle fluctuations.

6 Comparison to Alternative Models of Overresponses

The previous section showed how a parsimonious model of overconfidence captures salient features of professional forecasts. The model, in particular, relied on three well-documented features: Absolute overconfidence (or overprecison) in private information, relative overconfidence in private information (or overplacement), and the endogeneity of public news. We have shown these features combine to make forecasters not only overrespond to private information but also endogenous public news.

A natural alternative explanation is one which assumes overresponses to all information (be it public or private) as a primitive of the model. Such models of generalized overresponses have recently been proposed in, for example, Bordalo *et al.* (2018b) in their theory of diagnostic expectations. In their model, forecasters overrespond to all news as diagnostic (or representative) of updates relative to prior information. In fact, in contemporaneous work, Bordalo *et al.* (2018a) document the same simultaneous under- and overresponse of forecast revisions that we document in Section 3 across a wide variety of datasets, and show how they are consistent with diagnostic expectation formation. The authors do not, however, consider the simultaneous overresponses to public information, such as consensus outcome.

We view the model of overconfidence in the previous section as complementary to the theory of diagnostic expectations. Unlike models of generalized overresponses, it draws attention to the role of endogenous public signals, and their possible misinterpretation, as a source of expectational biases. Specifically, Proposition 3 shows how mere overconfidence in private information can result in an overresponse to endogenous public news. The model, however, does not predict overresponses to purely exogenous public signals about underlying fundamentals. Diagnostic expectations, in contrast, predict overreaction to both signals in the same fashion. This contrasting implication is, however, difficult to test using macroeconomic forecasts, since most relevant public signals that are relevant in this context are also endogenous outcomes of individual actions and their expectation formation.

A second important difference between the two theories is that diagnostic expectations are not recursive, unlike those in Proposition 3 that inherit the recursivity of the rational model. Specifically, Bordalo *et al.* (2018a) assume that previous information enters expectations in the form of a rational prior every period. This makes the timing of news important: current expectations, and thus forecasts, overreact to current news, but the effect vanishes in the next forecast when priors are reset to their rational values. This implies "mean reversion" in forecasts, or negative serial correlation in forecast revisions, and stronger overreaction to more recent news.[27]

We conclude this section with a brief comment about the alternative, rational models discussed in Section 4. In principle, such rational models of overresponses to private information could also be made consistent with the documented overresponses to public news, if we in addition assume that forecasters underestimate the overresponses of others. However, such underestimation is often difficult to motivate within the context of rational models of strategic behavior. For example, the correct perception about other forecasters' behavior is at the center of theories of strategic forecaster diversification. We think that an appealing feature of our model of overconfidence is that it implies both overresponses to private and public information through one empirically-plausible behavioral friction.[28]

7 Conclusion

Expectations are a central determinant of economic allocations. In part because of this central role, a considerable debate has arisen since Muth's (1961) seminal contribution about the best model of expectation formation.

[27]At the danger of overinterpreting their model, to the extent that SPF consensus forecasts are published early in the quarterly forecast cycle (between 2 to 4 weeks after individual forecasts are collected), we might expect a weaker overreaction to consensus forecasts than to other information. Our benchmark estimates in Table I show overresponses of similar magnitude.

[28]An alternative reason for mis-perception is of course "non-perception" of public information (such that $y_s \neq y$), either by forecasters (who may not be aware of all public information), or by researchers (whose dataset may not include all public information available at the time forecasts are made). Our empirical framework rules this out, however, by testing overreaction to a specific piece of public information, consensus forecasts, that is accurately measured and not revised, publicly available at the time forecasts are made and presumably also salient to forecasters as a key input to their business.

Recently, influential evidence has shown that *average forecasts* across a wide variety of surveys are consistent with models of dispersed, imperfect information and rational information use (Coibion and Gorodnichenko, 2015, Dovern *et al.*, 2015, and others). In this paper, we in contrast have explored the implications of such models for *individual,* rather than average, professional forecasts .

We have documented how the statistical properties of individual inflation forecasts contradict simple versions of noisy rational expectations. Specifically, individual forecasts overrespond to overall new information received between forecast roudns and, in particular, to readily available public signals, such as previous consensus forecasts. We have shown how such overresponses violate a basic tenet of noisy rational expectations, the Law of Iterated Expectation. Importantly, we havedocumented such overresponses for other variables than inflation, at different forecast horizons, and in other forecaster surveys for the US and other countries.

Several common theories of forecaster behaviour are consistent with the documented overresponses to new information at the individual level, and the underresponse of average forecasts implied by noisy rational expectations. But as we have documented above, such models are also often inconsistent with the simultaneous overresponse to readily available endogenous public signals, such as consensus outcomes. In place, we have above proposed a new model of overconfident forecasters consistent with the stylized facts.

We have called overconfident those forecasters that believe that their information is not only better than it truthfully is but also better than that available to their competitors. These biases of, respectively, “overprecision” and “overplacement”, have been extensively documented in both experimental and other contexts (Moore and Healy, 2008). Combined, they entail that forecasters interpret a specific change in public information as an average of weak responses to news by poorly informed forecasters, while in fact it results from forceful responses by overconfident forecasters to a small movement in fundamentals. We showed how this model can rationalize the observed forecast data both qualitatively and quantitatively.

Morover, for realistic parameters, the resulting individual forecasts are close to “ecologically rational”. Because overprecision counteracts the standard learning externality that exists in markets with endogenous public information, the mean-squared error of individual forecasts are close to their mean-squared error optimal counterpart. This connects our results with those of Gigerenzer and Todd (1999); Gigerenzer and Brighton (2009), and others that attempt to find group-optimal explanations for individual biases.

Last, our results entail specific opportunities for further research. First, it seems worthwhile to explore the extent to which our empirical results vary across forecasters. In contemporaneous work, Bordalo *et al.* (2018a) indeed document similar overresponses to new information on average across a wide range of forecasters. But it would seem central for a theory of overconfidence to also document whether (and by how much) such overresponses extend to specific pieces of endogenous public information. Second, Kohlhas and Walther (2018) show how apparent overresponses to public information can also arise rationally, as the outcome of forecasters' optimal information choice under dispersed information. Attempting to disentangle the extent to which measured overresponses to public information arise from behavioural overconfidence or optimal information choice seems a natural next step.

References

Amador, M. and Weill, P.-O. (2010). Learning from prices: Public communication and welfare. *Journal of Political Economy*, **118** (5), 866–907.

Anderson, B. D. and Moore, J. B. (1979). Optimal filtering. *Englewood Cliffs*, **21**, 22–95.

Andrade, P. and Le Bihan, H. (2013). Inattentive professional forecasters. *Journal of Monetary Economics*, **60** (8), 967–982.

Benoît, J.-P., Dubra, J. and Moore, D. A. (2015). Does the better-than-average effect show that people are overconfident?: Two experiments. *Journal of the European Economic Association*, **13** (2), 293–329.

Bhattacharya, S. and Pfleiderer, P. (1985). Delegated portfolio management. *Journal of Economic Theory*, **36** (1), 1–25.

Bordalo, P., Gennaioli, N., Ma, Y. and Shleifer, A. (2018a). Overreaction in macroeconomic expectations.

—, — and Shleifer, A. (2018b). Diagnostic expectations and credit cycles. *The Journal of Finance*, **73** (1), 199–227.

Brunnermeier, M. K. and Parker, J. A. (2005). Optimal expectations. *American Economic Review*, **95** (4), 1092–1118.

Chahrour, R. and Jurado, K. (2018). News or noise? the missing link. *American Economic Review*, **108** (7), 1702–36.

Coibion, O. and Gorodnichenko, Y. (2012). What can survey forecasts tell us about information rigidities? *Journal of Political Economy*, **120** (1), 116–159.

— and — (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, **105** (8), 2644–78.

Croushore, D. and Stark, T. (2001). A real-time data set for macroeconomists. *Journal of econometrics*, **105** (1), 111–130.

Croushore, D. D. (1993). Introducing: the survey of professional forecasters. *Business Review-Federal Reserve Bank of Philadelphia*, **6**, 3.

— (1997). The livingston survey: still useful after all these years. *Business Review-Federal Reserve Bank of Philadelphia*, **2**, 1.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *the Journal of Finance*, **53** (6), 1839–1885.

Dovern, J., Fritsche, U., Loungani, P. and Tamirisa, N. (2015). Information rigidities: Comparing average and individual forecasts for a large international panel. *International Journal of Forecasting*, **31** (1), 144–154.

Ehrbeck, T. and Waldmann, R. (1996). Why are professional forecasters biased? agency versus behavioral explanations. *The Quarterly Journal of Economics*, **111** (1), 21–40.

Ericson, W. A. (1969). A note on the posterior mean of a population mean. *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 332–334.

Fuhrer, J. C. (2015). Expectations as a source of macroeconomic persistence: an exploration of firms' and households' expectation formation.

Fuster, A., Perez-Truglia, R., Wiederholt, M. and Zafar, B. (2019). Expectations with endogenous information acquisition: An experimental investigation.

Garcia, J. A. (2003). An introduction to the ecb's survey of professional forecasters.

Gigerenzer, G. (2016). Towards a rational theory of heuristics. In *minds, models and milieux*, Springer, pp. 34–59.

— and Brighton, H. (2009). Homo heuristicus: Why biased minds make better inferences. *Topics in cognitive science*, **1** (1), 107–143.

— and Todd, P. M. (1999). *Simple heuristics that make us smart.* Evolution and Cognition (Paper.

Graham, J. R. (1999). Herding among investment newsletters: Theory and evidence. *The Journal of Finance*, **54** (1), 237–268.

Granger, C. W. (1969). Prediction with a generalized cost of error function. *Journal of the Operational Research Society*, **20** (2), 199–207.

Hellwig, M. F. (1980). On the aggregation of information in competitive markets. *Journal of economic theory*, **22** (3), 477–498.

Hirshleifer, D., Subrahmanyam, A. and Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance*, **49** (5), 1665–1698.

Kahneman, D. and Tversky, A. (1973). On the psychology of prediction. *Psychological review*, **80** (4), 237.

Kohlhas, A. N. and Walther, A. (2018). Asymmetric attention.

Lamont, O. A. (2002). Macroeconomic forecasts and microeconomic forecasters. *Journal of economic behavior & organization*, **48** (3), 265–280.

Laster, D., Bennett, P. and Geoum, I. S. (1999). Rational bias in macroeconomic forecasts. *The Quarterly Journal of Economics*, **114** (1), 293–318.

Mankiw, N. G., Reis, R. and Wolfers, J. (2003). Disagreement about inflation expectations. *NBER macroeconomics annual*, **18**, 209–248.

Marinovic, I., Ottaviani, M. and Sorensen, P. (2013). Forecasters objectives and strategies. *Handbook of economic forecasting*, **2**, 690–720.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance*, **32** (4), 1151–68.

Moore, D. A. and Healy, P. J. (2008). The trouble with overconfidence. *Psychological review*, **115** (2), 502.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, pp. 315–335.

Myatt, D. P. and Wallace, C. (2011). Endogenous information acquisition in coordination games. *The Review of Economic Studies*, **79** (1), 340–374.

Ottaviani, M. and Sørensen, P. N. (2006). The strategy of professional forecasting. *Journal of Financial Economics*, **81** (2), 441–466.

Pesaran, M. H. and Weale, M. (2006). Survey expectations. *Handbook of economic forecasting*, **1**, 715–776.

Scharfstein, D. S. and Stein, J. C. (1990). Herd behavior and investment. *The American Economic Review*, pp. 465–479.

Vives, X. (1997). Learning from others: a welfare analysis. *Games and Economic Behavior*, **20** (2), 177–200.

Welch, I. (2000). Herding among security analysts. *Journal of Financial economics*, **58** (3), 369–396.

Zarnowitz, V. (1985). Rational expectations and macroeconomic forecasts. *Journal of Business & Economic Statistics*, **3** (4), 293–311.

— and Lambros, L. A. (1987). Consensus and uncertainty in economic prediction. *Journal of Political economy*, **95** (3), 591–621.

Appendix A: Robustness

This Appendix presents estimates of our three estimation equations, restated below for convenience,

$$\pi_{t+h} - f_{t|t+h} = a + b\left(f_{t|t+h} - f_{t-1|t+h}\right) + v_t \tag{1}$$

$$\pi_{t+h} - f_{it|t+h} = \alpha_i + \beta_i\left(f_{it|t+h} - f_{it-1|t+h}\right) + v_{it} \tag{2}$$

$$\pi_{t+h} - f_{it|t+h} = \alpha_i + \delta f_{t-1|t+h} + v_{it} \tag{3}$$

based on alternative forecast variables to GNP/GDP inflation, alternative data sets, as well as using alternative specifications. Table 1 presents estimates using SPF forecasts of consumer price inflation (CPI). Table 2 reports similar estimates for output growth (GNP/GDP). Table 3 presents estimates of (2) and (3) for alternative sample periods, and Table 4 estimates for two-quarter ahead forecasts (compared to the four-quarter ahead horizon in our benchmark specification). Table 6 reports results for forecasters working in financial services and those working in other industries.[1] Table 7 presents the coefficient estimates from a regression of forecast errors on the most recently observed outcome of the forecasted variable. Table 5 presents estimates using HICP inflation and real GDP growth from the *Euro Area Survey of Professional Forecasters (*EUSPF*)*, conducted quarterly since January 2000 by the ECB (Garcia, 2003). Finally, Table 8 shows how all our results also hold when estimating (1), (2), and (3), using CPI inflation forecasts from the Livingstone Survey.[2]

Table 1: CPI Estimates from the Survey of Professional Forecasters

	Average Forecasts	*Individual Forecasts*		
	Forecast Error	*Forecast Error*	*Forecast Error*	*Forecast Error*
Forecast Revision	0.250	-0.262***		-0.290***
	(0.252)	(0.0319)		(0.0305)
Previous Consensus			-0.371***	-0.425***
			(0.0510)	(0.0491)
Constant	-0.144	-0.202***	0.858***	0.965***
	(0.0991)	(0.00343)	(0.143)	(0.134)
Sample	04/82:10/16	04/82:10/16	04/82:10/16	04/82:10/16
Obs	133	3511	4542	3511
R^2	0.011	0.023	0.029	0.058

(i) Column one presents estimates of b; column two and three β and δ, using SPF forecasts for CPI inflation.

(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

[1] The US SPF classifies the sectors where forecasters work into financial services and others. The industry split is only available since the first quarter of 1990 .

[2] See https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/livingston-survey/livingston-documentation.pdf?la=en for more information on the Livingstone Survey.

Table 2: GDP Estimates from the Survey of Professional Forecasters

	Average Forecasts	*Individual Forecasts*		
	Forecast Error	*Forecast Error*	*Forecast Error*	*Forecast Error*
Forecast Revision	0.629**	-0.0807*		-0.218***
	(0.273)	(0.0464)		(0.0409)
Previous Consensus			-0.202***	0.203***
			(0.0599)	(0.0518)
Constant	-0.0762	-0.176***	0.376**	-0.886***
	(0.116)	(0.00669)	(0.167)	(0.158)
Sample	07/81:10/16	07/81:10/16	07/81:10/16	07/81:10/16
Obs	142	3806	4967	5045
R^2	0.059	0.002	0.007	0.028

(i) Column one presents estimates of b; column two and three β and δ, using SPF forecasts for output growth.

(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

(iii) GNP forecasts until 1991 and GDP thereafter. GNP was calculated from nominal forecasts using the GNP deflator until 1981Q2. We exclude periods where GNP was calculated from nominal output and inflation forecasts to avoid importing the properties of inflation forecasts into those for real output. This yields the starting period 1981Q3.

Table 3: Sub-sample Estimates from the Survey of Professional Forecasters

	(1)	(2)	(3)	(4)	(5)	(6)
	PGDP	*PGDP*	*CPI*	*CPI*	*GDP*	*GDP*
Forecast Revision	-0.371***		-0.280***		-0.100**	
	(0.0228)		(0.0403)		(0.0502)	
Previous Consensus		-0.340***		-0.521***		-0.475***
		(0.0411)		(0.0479)		(0.0472)
Constant	-0.337***	0.436***	-0.162***	1.169***	-0.173***	1.145***
	(0.00154)	(0.0909)	(0.00330)	(0.121)	(0.00686)	(0.128)
Sample	91Q2-16Q4		91Q2-16Q4		91Q2-16Q4	
Obs	3056	3837	3067	3877	3166	3989
R^2	0.084	0.046	0.022	0.044	0.003	0.044

(i) Column one, three, and five present estimates of β, columns two, four, and six of δ, using SPF forecasts for 12-month ahead GDP deflator inflation (PGDP), consumer price inflation (CPI) and real GDP growth (GDP).

(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Estimates from the Euro Area Survey of Professional Forecasters

	Average Forecasts		*Individual Forecasts*	
	Forecast Error	*Forecast Error*	*Forecast Error*	*Forecast Error*
Forecast Revision	0.800***	-0.0672		-0.0770
	(0.0564)	(0.0580)		(0.0599)
Previous Consensus			-0.535***	-0.546***
			(0.127)	(0.133)
Constant	0.195***	0.132***	1.081***	1.093***
	(0.0157)	(0.00520)	(0.224)	(0.231)
Sample	00Q4:17Q1	00Q4:17Q1	00Q4:17Q1	00Q4:17Q1
Obs	3780	2391	2391	2391
R^2	0.060	0.001	0.008	0.010

(i) Column one presents estimates of b; column two and three β and δ, using Euro Area SPF forecasts for 12-month ahead growth rates in the Harmonised Index of Consumer Prices (HICP).

(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Estimates from the Survey of Professional Forecasters with $h = 2$

	Average Forecasts		*Individual Forecasts*	
	Forecast Error	*Forecast Error*	*Forecast Error*	*Forecast Error*
Forecast Revision	1.095***	-0.257***		-0.257***
	(0.303)	(0.0379)		(0.0379)
Previous Consensus			-0.0398	-0.0494
			(0.0315)	(0.0411)
Constant	-0.0570	-0.0177***	0.151	0.148
	(0.0836)	(0.0000290)	(0.111)	(0.138)
Sample	71Q1-16Q4	71Q1-16Q4	71Q1-16Q4	71Q1-16Q4
Obs	184	5187	6843	5187
R^2 0.168	0.040	0.001	0.042	

(i) Column one presents estimates of b; column two and three β and δ, using 6-month ahead GDP deflator forecasts.

(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Forecasters in Financial Services vs. Others

	(1) *Financial*	(2) *Financial*	(3) *Non-financial*	(4) *Non-financial*
Individual Forecast Revision	-0.370***		-0.366***	
	(0.0416)		(0.0310)	
Previous Consensus		-0.322***		-0.300***
		(0.0607)		(0.0661)
Constant	-0.290***	0.437***	-0.364***	0.319**
	(0.00257)	(0.135)	(0.00207)	(0.146)
Sample	90Q3-16Q4	90Q3-16Q4	90Q3-16Q4	90Q3-16Q4
Obs	1180	1539	1689	2067
R^2	0.068	0.059	0.087	0.027

(i) Column one and three present estimates of β, column two and four of δ, using SPF forecasts for 12-month ahead GDP deflator inflation. Column one and two (three and four) use data from financial (non-financial) sector forecasters.
(ii) HAC standard errors used. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Alternative Public Variable: The Most Recent Observed Outcome

	(1) *PGDP*	(2) *CPI*	(3) *GDP*
Most Recent Observed Outcome	-0.169***	-0.113***	-0.226***
	(0.0264)	(0.0168)	(0.0142)
Constant	0.636***	0.122***	0.251***
	(0.0967)	(0.0457)	(0.0343)
Sample	71Q2-16Q4	83Q4-16Q4	81Q3-16Q4
Obs	6822	4542	6845
R^2	0.036	0.013	0.069

(i) The table presents the results from a regression of forecast errors on the most recently observed outcome, for 12-month growth rates in the GDP deflator (PGDP), consumer price inflation (CPI) and real GDP growth (GDP).
(ii) * $p < .1$, ** $p < .05$, *** $p < .01$

Table 8: CPI Estimates from the Livingstone Survey

	Average Forecasts	*Individual Forecasts*		
	Forecast Error	*Forecast Error*	*Forecast Error*	*Forecast Error*
Forecast Revision	-0.455*	-0.440***		-0.436***
	(0.250)	(0.0588)		(0.0551)
Previous Consensus			-0.513***	-0.630***
			(0.0650)	(0.0555)
Constant	-0.458**	-0.461***	1.170***	1.365***
	(0.187)	(0.0166)	(0.189)	(0.164)
R^2	0.041	0.111	0.020	0.142
Obs.	49	1364	1772	1364

(i) Column one presents estimates of b; column two and three β and δ, using 6-month ahead forecast revisions and 12-month ahead forecasts of CPI inflation.

(ii) HAC standard errors used. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix B: Alternative Explanations

Appendix B.1 Empirics

Table 9: Revisions and Errors in Inflation

	(1) Absolute Forecast Error
Absolute Forecast Revision	0.264***
	(0.0377)
Constant	0.850***
	(0.0195)
R^2	0.039
N	5016

HAC standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

To Come...

Appendix C: A Model of Overconfidence

To Come...

Appendix D: Quantitative Illustration

Table 10: SMM Estimation: GDP Forecasts

	β	δ	σ_{revision}	$\sqrt{\tau_x}$	$\sqrt{\tau_\xi}$	$\sqrt{\tau_\theta}$	$\sqrt{\tau_{x'}}$
Data	-0.0807	-0.2020	0.8527				
Naive Overc.	-0.0729	-0.1837	0.8377	1.00	10.0	1.00	4.00

Table 11: SMM Estimation: CPI Forecasts

	β	δ	σ_{revision}	$\sqrt{\tau_x}$	$\sqrt{\tau_\xi}$	$\sqrt{\tau_\theta}$	$\sqrt{\tau_{x'}}$
Data	-0.2620	-0.3700	0.6677				
Naive Overc.	-0.2320	-0.1660	0.6741	1.67s	100.0	1.00	11.11