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BIASED SURVEYS

Luca Gemmi
Rosen Valchev

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ABSTRACT

We find evidence suggesting that surveys of professional forecasters are biased by strategic incentives. First, we find that individual forecasts overreact to idiosyncratic information but underreact to common information. Second, we show that this bias is not present in forecasts data that is not subject to strategic incentives. We show that our evidence is consistent with a model of strategic diversification incentives in forecast reporting. Our results caution against the use of surveys of forecasts as a direct measure of expectations, as this would overestimate the likely deviations from rational expectations, the information precision and the degree of disagreement.

Luca Gemmi
University of Lausanne - HEC Lausanne
luca.gemmi@unil.ch

Rosen Valchev
Department of Economics
Boston College
140 Commonwealth Avenue
Chestnut Hill, MA 02467
and NBER
valchevr@gmail.com

1 Introduction

Expectations play a pivotal role in macroeconomic models, and as a result, the process through which agents form their expectation has been a central, and often hotly debated, topic. An important and influential recent advance in the literature is the use of data on surveys of forecasts, which hold the promise of providing direct, micro-level measurement of agent expectations. A key emerging finding of this growing body of work is a bevy of apparent violations of the full information rational expectations (FIRE) paradigm, which has otherwise been the bedrock of macroeconomic models for decades. On the one hand, Coibion and Gorodnichenko (2015) document that aggregate ("consensus") forecasts, typically defined as the mean across survey participants, are "sticky" in a way that implies that the forecasters are operating under imperfect and noisy information. On the other hand, Bordalo et al. (2020) document that individual-level forecast "overreact" to new information, indicating a violation of rational expectations.

This recent literature, however, often assumes that surveys of forecasts provide an unbiased measure of the respondents true beliefs and expectations. This is at odds with an older literature (e.g. Laster et al. (1999), Ottaviani and Sørensen (2006)) that posits the possibility of survey participants, and specifically professional forecasters, to be influenced by strategic considerations in their responses – for example a desire to "stand out" or alternatively "herd" with the crowd, depending on the broader economic environment. The macro literature's argument against this possibility has mostly centered on indirect evidence, primarily considering the possibility of strategic *coordination* across forecasters, but not the alternative of an environment where agents face strategic *diversification* incentives.

In this paper, we devise a direct empirical test of the strategic considerations hypothesis which allows for both strategic coordination and diversification incentives. Our key insight is that if strategic considerations are empirically relevant, then forecast errors will react in a systematically different way to the arrival of new "public" information that is commonly observed by all survey participants, such as the latest GDP data release, as compared to new forecaster-specific information, such as an update in the forecaster's own model. We formally show the intuitive result that if survey respondents have incentives to coordinate with one another, and thus "herd", then they would optimally overweight such common signals in their reported forecasts. On the other hand, if forecasters instead have a strategic incentive to “stand out” from the crowd, then public information will be underweighted in reported forecasts, as agents try to differentiate themselves.

Our main empirical finding is that while individual forecasters tend to overreact to new information on average (inline with the previous findings of Bordalo et al. (2020)), the reported forecasts actually *underreact* to newly released publicly available information. This finding is broadly inconsistent with various models of behavioral overextrapolation that are typically used to address the Bordalo et al. (2020) results, because in those frameworks overreaction would be uniform across all types of new information. Instead, we show that our results are consistent with a model of *strategic diversification*, where survey respondents have a strategic incentive to stand out from the crowd.

We use data from the Survey of Professional Forecasters (SPF), the most commonly used forecast survey dataset, in order to cleanly frame our new empirical results in the context of the existing literature.[1] As a first step in our analysis, we document that common noisy signals are indeed a quantitatively important feature of the information sets underlying the SPF forecasts. We do so by exploiting the fact that the methodology in Coibion and Gorodnichenko (2015) displays an omitted variable bias which attenuates the estimated coefficient in the presence of common noise terms (as also noted in their Appendix).[2] Correcting for this bias we find that it is quite significant, indicating that forecasters indeed rely substantially on noisy signals that are common across agents.[3]

Next, we present a model of strategic interactions in reporting forecasts, which encompasses both strategic settings discussed by Ottaviani and Sørensen (2006) – both settings of strategic substitutability where agents want to stand out (e.g. winner-take all games) and settings of strategic coordination (e.g. reputational games). Within our general framework, we prove analytically that for the model to be simultaneously consistent with both seminal stylized facts of underreaction in consensus forecasts (Coibion and Gorodnichenko (2015)) and the overreaction in individual forecasts (Bordalo et al. (2020)), the model must feature incentives for strategic diversification specifically. Intuitively, in that setting a

[1] The SPF is anonymous, however, its respondents also participate in many other, non-anonymous surveys. As we discuss in detail and also provide direct evidence to this effect, out of convenience the SPF respondents provide the same forecast to the SPF as they do to the other, non-anonymous outlets they participate in. Thus any strategic considerations that they face in their public interactions are also present in their SPF responses.

[2] This bias does not impact the key conclusions of Coibion and Gorodnichenko (2015), because the bias works against their main hypothesis. Hence, their estimates and conclusions are conservative.

[3] To do so, we follow an empirical methodology inspired by Goldstein (2023).

forecaster would like to be right when everyone else is wrong, and thus stand out.

This kind of optimal behavior biases the reported forecasts away from the agents' true, underlying rational beliefs. Assuming that agents have access to two types of noisy signals – a signal with idiosyncratic noise and a common noisy signal that is the same for everyone – we show that in their reported forecasts, agents optimally overweight the idiosyncratic signal at the expense of underweighting the common signal. This characteristic feature of the strategic diversification model leads to two differentiating implications.

First, the average of the reported individual forecasts (i.e. the consensus) is more accurate than the average of the true underlying rational beliefs, even though the reported forecasts of individual agents display predictable errors, and hence are suboptimal. The reason is that the reported forecasts are individually suboptimal specifically because they overweight the idiosyncratic signal and are thus overly exposed to its error. However, at the aggregation level of the consensus forecast these idiosyncratic errors wash out, which leaves the consensus with a higher dependence on the informative part of individual signals, without suffering from the higher variance due to idiosyncratic noise see also Lichtendahl et al. (2013)). This is consistent with the puzzling empirical fact that the SPF consensus is indeed a very good predictor of future macro variables, and that it is virtually impossible to beat it with objective statistical models (Kohlhas and Robertson (2022)).[4]

Second, and most characteristically, the model implies that any commonly observed ("public") signals should be underweighted by the reported forecasts. We design an empirical methodology that directly tests this implication, by augmenting the Bordalo et al. (2020) regression of individual forecast errors on individual forecast revisions with a proxy for a common, public signal. We show analytically that under mild assumptions, the regression coefficient on the public signal proxy is directly indicative of whether that signal is under- or overweighted relative to the rest of the information set of the agents.

In our benchmark specification, we use the consensus forecast from the previous round of the survey as our proxy for a commonly observed signal. The quarter $t-1$ survey is first available to the forecasters when they are surveyed again in quarter t. The lagged survey is also highly informative about the future realization of the variable being forecasted, thus it is both a new signal available to all forecasters, and also one that is very salient and

[4] Furthermore, Juodis and Kučinskas (2023) document that the high precision of the consensus is exactly achieved by averaging out the large amount of idiosyncratic noise in SPF forecasts. This is consistent with our theory, which effective implies individual forecasts are overly subject to idiosyncratic noise.

informative.

Our key finding is that indeed, the individual forecasts in the SPF *underweight* the lagged consensus forecast, while they *overweight* the rest of their information set, indicating that forecasts underweight public signals. This finding is not consistent with typical behavioral models that would imply either over- or underreaction to all new information, but is consistent with the motive of strategic diversification.

Furthermore, we present two additional pieces of evidence that support the strategic diversification theory. First, we run the same regression on the projections published in the Federal Reserve's Greenbook, which forecast the same set of variables as the SPF. However, the Federal Reserve's forecasts are made for internal monetary policy purposes and are only released with a 5 year lag, and thus are arguably not subject to the same strategic forces that arise among the SPF participants due to them competing with one another in the marketplace. As such, we would expect that the Fed's Greenbook forecasts do not exhibit the same predictable errors and biases, and indeed we find no evidence of under or overreaction to any kind of information in the Greenbook.

Second, we leverage the observation that the lagged consensus is a special kind of public signal. It is not just a commonly observed signal about the future realization of the variable being forecasted, but is also a direct estimate of everyone else's recent beliefs. As such, strategic diversification incentives imply that agents would optimally underweight the lagged consensus more than alternative common signals that do not also directly speak to the forecasts of others. With this in mind, we also consider another type of commonly available information, the past realization of the macroeconomic variable being forecasted (e.g. lagged inflation), as an additional common signal proxy. And indeed, we find that the reported forecasts underreact *more* to the lagged consensus, even though they are also underreacting to macro data releases, as is also expected under our model.

Lastly, we estimate a quantitative version of the model and use it to recover the true underlying beliefs of the agents. This structural analysis showcases that strategic incentives also greatly influence estimates of the degree of information imperfection and dispersion (e.g. Coibion and Gorodnichenko (2015)). Using our model to back out the true underlying individual beliefs, we find that the degree of information rigidity is 30% higher than previously estimated, while the true dispersion in beliefs is 20-80% lower than in the raw data. Furthermore, we also show that the strategic incentives increase the precision of the consensus forecast by 30-100%, as compared to the precision of the true beliefs.

Overall, we conclude that strategic incentives are a likely rational explanation of a number of "puzzles" in survey data. An important broader implication is that surveys cannot be taken as direct proxies of economic agents' expectations. Specifically, survey-based estimates of information imperfection are in fact likely to be significantly understated, while survey-based measures of disagreement are overstated.

Related literature This paper relates to three strands of the literature. First, are the papers using surveys of professional forecasters to test the full information hypothesis. A common finding in this literature is consensus underreaction, meaning a positive relation between consensus forecast errors and consensus forecast revisions (Crowe, 2010; Coibion and Gorodnichenko, 2012, 2015). Similar to Goldstein (2023), we highlight how public information biases the information rigidity estimates in this literature downward and use a similar method to quantify this bias. Our main contribution is to document that strategic incentives are likely making reported forecasts an imperfect and biased proxy of the true beliefs of agents, which among other things, also further biases information rigidity estimates. To account for this, we use a structural model to estimate the actual information rigidity of the true underlying beliefs.

Another strand of the literature uses surveys to test the rational expectations hypothesis. In particular, Bordalo et al. (2020) documents individual overreaction, meaning a negative relation between individual forecast errors and individual forecast revisions. As individual forecast errors should not be predictable using current information, the authors interpret this predictability as evidence of behavioral biases in belief formation. Instead, we show that this evidence can be explained by a departure from truthful revelation while preserving rational expectations. Moreover, we document underreaction to public information, which is consistent with a strategic incentive model but not with typical models of extrapolative beliefs. In a recent paper, Broer and Kohlhas (2022) also use a public signal proxy to build on existing tests of RE, but they find mixed results in terms of under and over-reaction. One key difference is that in our empirical approach, we isolate the *surprise* component of public signals, which (as we show formally) is what actually enters the expectations updating equation, and is thus the theoretically correct term to include in the regressions. Consequently, we obtain sharp results that are highly statistically significant and also consistently point to *underreaction* to public info across many different types of forecasted variables. Lastly, our notion of over and underreaction is conceptually different than that used in Kučinskas and Peters (2022), as we measure deviations from rational expectations, while they measure deviations from the joint hypothesis of full information and rational expectations.

A third group of papers analyzes the potential for strategic incentives in forecasters behavior (see Marinovic et al. 2013 for a review). This literature has been mostly theoretical, focusing on qualitative results and indirect evidence, while our main contribution is in providing a direct empirical test of the hypothesis. Papers like Laster et al. (1999) and Ottaviani and Sørensen (2006) present several different models of competition between forecasters, to demonstrate the theoretical possibility of both strategic coordination and strategic diversification forces. Instead, we employ a general Morris and Shin (2002)-type of framework that simultaneously allows for both possibilities. We use that framework to derive general and direct testable implications, and take them to the data finding results that strategic substitutability is the relevant case in practice. Moreover, we estimate a quantitative, fully dynamic version of the model and use it recover the underlying true expectations.

Overall, our results also speak to the fact that imperfect and noisy information is the dominant paradigm in the data, supporting earlier results on the importance of information rigidities in the expectation formation process, such as Kiley (2007), Klenow and Willis (2007), Korenok (2008), Dupor et al. (2010), Knotek II (2010), Coibion and Gorodnichenko (2012), and Coibion and Gorodnichenko (2015). In contrast to this literature, however, we also specifically identify and quantify the contribution of common noise components in the (imperfect) information sets of agents, and of the biasing effects of strategic incentives survey responders face when reporting expectations.

2 Data

Forecasts. We use data on forecasts from the Survey of Professional Forecasters (SPF), maintained by the Federal Reserve Bank of Philadelphia. In each quarter around 40 professional forecasters contribute to the SPF with forecasts for outcomes in the current quarter and the next four quarters. Individual forecasts are collected at the end of the second month of each quarter, and cover both macroeconomic and financial variables, including GDP, price indices, consumption, investment, unemployment, government consumption, and yields on government bonds and corporate bonds.

While most macro forecasts in the SPF are of the level of a given variable, we follow Bordalo et al. (2020) (henceforth BGMS) and Coibion and Gorodnichenko (2015) (henceforth CG) in transforming most series into implied growth rates h periods ahead. We apply this method to GDP, price indices, consumption, investment and government consumption, while we keep the forecasts in level for unemployment and financial variables.

Lastly, the SPF is known to suffer from outliers, hence as in BGMS, we winsorize the data by removing forecasts are more than 5 interquartile ranges away from the median of each horizon in each quarter. We also only keep individual forecasters if they report at least 10 periods of forecasts. Appendix A provides a full description of variable construction.

Forecasted variables. Macroeconomic data is released quarterly, but is subsequently revised. At the time of the survey (second month of a given quarter t), the forecasters only know the initial release of the previous quarter's macroeconomic variables. Thus, following Bordalo et al. (2020), we construct implied forecasted growth rates between the forecast for quarter $t + h$ and the *initial* release of the macroeconomic variable for quarter $t - 1$, using the Philadelphia Fed's Real-Time Data Set for Macroeconomics. Financial variables are not revised, so we use historical data from the Federal Reserve Bank of St. Louis.

We label the realizations of forecasted variables as x_t, and denote the time t forecast by forecaster i as $\widetilde{E}_t^{(i)}[x_{t+h}]$. We use the tilde notation to be explicit about the fact that these forecasts do not necessarily correspond to optimal expectations, i.e. $\widetilde{E}_t^{(i)} \neq \mathbb{E}_t^{(i)}$, where $\mathbb{E}_t^{(i)}$ is the rational expectations operator conditional on the time t information of agent i.

It is useful to also define notation for the implied forecast error

$$fe_{t+h,t}^{(i)} = x_{t+h} - \widetilde{E}_t^{(i)}[x_{t+h}]$$

and also the time t revision in the forecast of x_{t+h} as

$$fr_{t+h,t}^{(i)} = \widetilde{E}_t^{(i)}[x_{t+h}] - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]$$

Following the literature, we also define the *consensus* forecast as the average forecast across all participating forecasters i:

$$\overline{E}_t[x_{t+h}] = \int_i \widetilde{E}_t^{(i)}[x_{t+h}]di,$$

and the consensus forecast error and revision, $\overline{fe}_{t+h,t} = \int_i fe^{(i)}_{t+h,t}di$ and $\overline{fr}_{t+h,t} = \int_i fr^{(i)}_{t+h,t}di$

Summary Statistics. Table 1 presents summary statistics for the key data series. Columns 1-5 report statistics for the consensus errors and revisions. Average forecast errors are statistically indistinguishable from zero for most series, except most notably for interest rates, for which the forecasts are systematically above realizations. As argued by BGMS, this is likely due to the downward secular trend in interest rates.

Columns 6-8 reports the summary statistics of the individual forecasts, including forecasts dispersion, share of forecasts with no meaningful revisions and the probability that less than 80 percent of forecasters revise in the same direction.[5] The large dispersion of forecasts (column (6)) and the fact that forecast revisions often go in different directions (column (8)) suggest a role for dispersed information among forecasters, which (as is standard) we allow for in our conceptual framework below. The share of not meaningful revisions is also often quite small, suggesting that forecasts are not "stale".

2.1 Motivational Evidence

The paper is motivated by two famous stylized facts of this survey data. First, the "underreaction" to new information in the *average* forecast, documented by CG. Second, the "overreaction" to new information documented at the individual level by BGMS.

Conceptual framework To help structure the discussion, and provide a formal definition of "under-" and "over-" reaction, we organize our analysis in the context of the following general framework of beliefs updating which allows for both dispersed and imperfect information. The framework generalizes the settings typically considered by the prior literature, and in particular the specific settings of BGMS and CG are special cases of our framework.

At time t agents provide a forecast of the h period ahead realization of a random variable x_{t+h} (e.g. GDP growth rate, inflation and etc.). We impose very limited restrictions on the time series process for x_t, assuming only that it is a stationary, linear Gaussian process

[5] We follow BGMS and denote a forecast as not a meaningful revision if its quarterly change is less than 0.01%.

Table 1: Summary Statistics

	Consensus					Individual		
	Errors			Revisions		Forecast dispersion	Nonrev share	Pr(< 80% revise same direction)
	Mean	SD	SE	Mean	SD			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.26	1.69	0.19	-0.14	0.68	1.00	0.02	0.80
GDP price index inflation	-0.28	0.58	0.08	-0.08	0.25	0.49	0.07	0.85
Real GDP	-0.26	1.64	0.19	-0.16	0.58	0.78	0.02	0.74
Consumer Price Index	-0.08	1.04	0.15	-0.11	0.68	0.54	0.06	0.66
Industrial production	-0.83	3.94	0.46	-0.49	1.19	1.57	0.01	0.72
Housing Start	-3.36	17.79	2.20	-2.31	5.93	8.34	0.00	0.68
Real Consumption	0.32	1.10	0.15	-0.06	0.41	0.61	0.03	0.78
Real residential investment	-0.46	8.32	1.19	-0.61	2.33	4.37	0.04	0.87
Real nonresidential investment	0.20	5.60	0.79	-0.22	1.71	2.31	0.03	0.74
Real state and local government consumption	0.04	2.96	0.38	0.14	1.10	2.09	0.07	0.91
Real federal government consumption	0.02	1.10	0.15	-0.05	0.33	0.98	0.11	0.93
Unemployment rate	0.01	0.68	0.08	0.05	0.32	0.30	0.18	0.66
Three-month Treasury rate	-0.51	1.14	0.16	-0.19	0.51	0.43	0.15	0.59
Ten-year Treasury rate	-0.48	0.73	0.11	-0.12	0.36	0.37	0.11	0.55
AAA Corporate Rate Bond	-0.46	0.82	0.11	-0.11	0.38	0.49	0.09	0.66

Notes: Columns 1 to 5 show statistics for consensus forecast errors and revisions. Forecast errors are defined as actual realizations minus forecasts. Revisions are forecast provided in t minus forecasts provided in $t-1$ about the same horizon. Columns 6 to 8 show statistics for individual forecasts. Forecast dispersion is the average cross-sectional standard deviation of individual forecasts. The share of nonrevisions is the average quarterly share of instances in which forecast revision is less than 0.01 percentage points. The final column shows the fraction of quarters where less than 80 percent of the forecasters revise in the same direction.

and thus has a Wold representation with Gaussian innovations, that is

$$x_t = \mu + \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k}^x$$

where ε_{t-k}^x are i.i.d. standard normal variables and $\sum_{k=0}^{\infty} \psi_k^2 < \infty$.

We allow for the possibility that the information sets underlying the forecasts $\widetilde{E}_t^{(i)}(x_{t+h})$ contain both components with idiosyncratic errors and also components with a common error term that is correlated across forecasters. In our conceptual framework, we model this as agents having access to the following two noisy, but informative signals

$$\begin{aligned} g_t &= x_{t+h} + e_t \\ s_t^{(i)} &= x_{t+h} + \eta_t^{(i)} \end{aligned} \tag{1}$$

where $\eta_t^{(i)} \sim N(0, \tau^{-1})$ is i.i.d. across time and across agents, while $e_t \sim N(0, \nu^{-1})$ is i.i.d.

only across time, but common across agents.[6] For simplicity we assume the idiosyncratic noise has the same variance τ^{-1} across all agents, but this is not necessary. For expositional purposes, we will refer to the signal subject to idiosyncratic errors as the "private" signal, but we are not making an explicit assumptions that forecasters possess some fundamentally private or "inside" information – the source of the idiosyncratic error could also be subjective perception noise. This signal is simply meant to capture the part of the information set that makes forecaster i different from everyone else. Similarly, while it is convenient to assume that there are two separate signals, one with a purely idiosyncratic error and one with an error that is perfectly correlated across forecasters, that is not necessary – we can work with linear combinations of these signals.

We do not impose any ex-ante assumptions about whether the forecasts $\widetilde{E}_t^{(i)}[x_{t+h}]$ agents come up with based on this information is statistically optimal (i.e. rational). The only assumption we make is that each forecast is a linear combination of the previous period's forecast of x_{t+h}, that is $\widetilde{E}_{t-1}^{(i)}[x_{t+h}]$, and the two new signals g_t and s_t^i:

$$\widetilde{E}_t^{(i)}[x_{t+h}] = (1 - G_1 - G_2)\widetilde{E}_{t-1}^{(i)}[x_{t+h}] + G_1 s_t^{(i)} + G_2 g_t \tag{2}$$

where G_1 is the weight agents put on the idiosyncratic signal and G_2 is the weight put on the common signal. Rational expectations, denoted by $\mathbb{E}_t^{(i)}[x_{t+h}]$, are a special case of our general representation in (2), with the following weights: $G_1^{RE} = \frac{\tau}{\tau+\nu+1/\Sigma^{RE}}$ and $G_2^{RE} = \frac{\nu}{\tau+\nu+1/\Sigma^{RE}}$, where $\Sigma^{RE} \equiv var(x_{t+h} - \mathbb{E}_{t-1}^{(i)}[x_{t+h}])$.

Our conceptual framework is broader than the types of frameworks typically considered in the previous literature for three reasons. First, we do not assume that expectations are either optimal or suboptimal in any particular way; we only assume they are linear and keep the weights put on the different pieces of information available to the agents unrestricted. Second, we do not need to assume any particular time series process for x_t (e.g. the literature has mainly focused on AR(1) or AR(2) processes), just that it is stationary (which is a weak assumption, since in the data x_t is in growth rates). And third, we allow for the agents beliefs to be driven by informative signals with both idiosyncratic

[6] We assume that the new information arriving each period is in the form of news about the future, i.e. x_{t+h}, as opposed to information about current realizations x_t. We make this assumption for expositional convenience, as it simplifies some of the algebra below. But all results carry through if the signals are centered on x_t instead – the Kalman filter is not too different either way. Moreover, recent results in Goldstein and Gorodnichenko (2022) suggest this type of "forward" information structure is indeed the most empirically relevant.

and common errors – the previous literature has overwhelmingly focused on information structures where agents only have signals with idiosyncratic errors.

2.2 Underreaction in consensus forecasts

In a seminal contribution, Coibion and Gorodnichenko (2015) consider whether consensus forecast errors are predictable by consensus forecast revisions. Specifically, they estimate

$$\overline{fe}_{t+h,t} = \alpha + \beta_{CG}\overline{fr}_{t+h,t} + err_t \tag{3}$$

This is not a regression that tests forecast rationality, since the average forecast revision $\overline{fr}_{t+h,t}$ is not available to the forecasters when they respond to the time t survey. Hence, the fact that $\overline{fe}_{t+h,t}$ is predictable by $\overline{fr}_{t+h,t}$ does not reject rationality. Still, the CG finding of $\beta_{CG} > 0$ is often referred to as an "under-reaction" of the average forecast, since it intuitively indicates that the average forecast revision does not adjust fully to the new information arriving at time t.

Formally, the regression coefficient β_{CG} is informative about the weight put on new information in the forecasts $\widetilde{E}_t^{(i)}[x_{t+h}]$. In the context of our conceptual framework in (2), this weight is given by $G \equiv G_1 + G_2$. A finding of $\beta_{CG} > 0$ is indicative of $G < 1$, which implies that the available signals are likely noisy, as they get a weight of less than one.

There are two potential types of noise that could be present in the forecasters' information sets – idiosyncratic noise, i.e. $\eta_t^{(i)}$, and also noise that is common to all forecasters' information sets, i.e. e_t. Both of these noise terms affect the estimated G that can be inferred from the CG regression coefficient. To gain some intuition, notice that re-arranging the LHS of (2), and averaging across forecasters we get:

$$\overline{fe}_{t+h,t} = \frac{1-G}{G}\overline{fr}_{t+h,t} - \frac{G_2}{G}e_t \tag{4}$$

Since the consensus forecast revision $\overline{fr}_{t+h,t}$ is positively correlated with the time t common signal error e_t, the regression coefficient β_{CG} is in general smaller than $\frac{1-G}{G}$.

The focus of Coibion and Gorodnichenko (2015) was to estimate the potential contribution of the idiosyncratic noise $\eta_t^{(i)}$ specifically, hence in their benchmark specification they worked under the assumption that there are no common signals, which is equivalent to $\nu^{-1} = 0$ and implies $\beta_{CG} = \frac{1-G}{G}$. In that case $\frac{1}{1+\beta_{CG}}$ offers a direct measure of the weight put on new information G. Nevertheless, as explained in the Appendix to CG itself, the existence of a common noise component like e_t will bias β_{CG} downward, so that $\beta_{CG} < \frac{1-G}{G}$, which would in turn bias the estimate of G upward (implying less noise than there really is).

One can account for both the idiosyncratic and common noise terms and estimate G precisely, by using a different approach. Following Goldstein (2023), we re-arrange (2) to express the difference between *individual* and consensus forecast revisions as:

$$(fr^i_{t+h,t}) - (\overline{fr}_{t+h,t}) = G(\overline{E}_{t-1}[x_{t+h}] - \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) + G_1\eta^i_t \tag{5}$$

Standard OLS estimation of this regression provides an unbiased measure of the elasticity of forecasts to new information, G, since η^i_t is uncorrelated with $\widetilde{E}^i_{t-1}[x_{t+h}]$ and $\overline{E}_{t-1}[x_{t+h}]$.

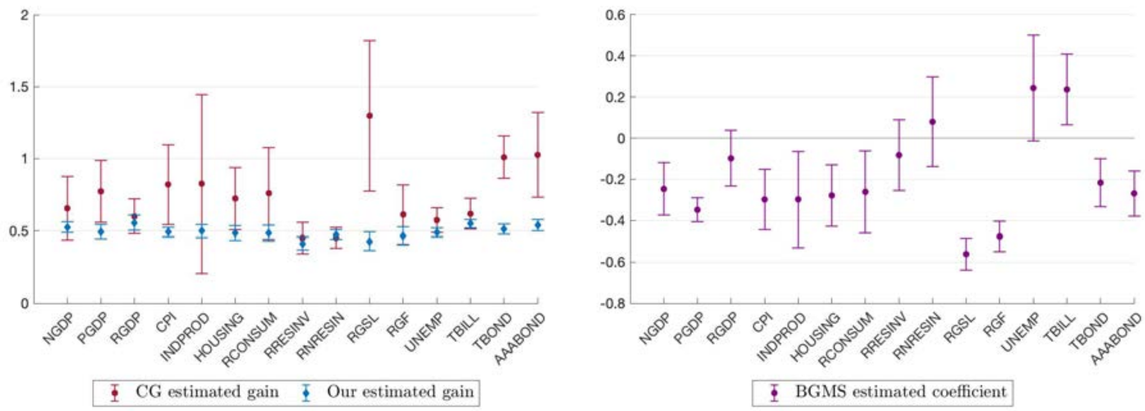
Figure 1, panel (a) reports the estimate of G from regression (5) and compares them with the estimated gains from the original CG specification, which we label $G_{CG} \equiv \frac{1}{1+\beta_{CG}}$. For the benchmark results reported in the main text we use $h = 3$ quarters, and in Appendix C.1 we reports detailed tables of the estimates for both $h = 2$ and $h = 3$. The results are very similar at both horizons.

The evidence indicates that common noise terms are in fact an important part of the information sets of the SPF forecasters. Our estimated gain is consistently lower than that implied by the CG regression across all forecasted variables, suggesting that the bias due to common noise terms plays a significant role. The differences are quite substantial – the average information gain based on the CG methodology is $G_{CG} = 0.75$, while our augmented estimate yields $G = 0.5$ on average. Thus, quantitatively, the importance of common noise terms is of roughly the same magnitude as that of idiosyncratic noise. Lastly, our estimated gains are also remarkably stable across variables and have small standard errors, while the original CG regression leads to much noisier estimates.

2.3 Overreaction in individual forecasts

In another seminal paper, Bordalo et al. (2020) directly test rational expectations by regressing forecast errors on forecast revisions at the level of *individual* forecasters

$$fe^{(i)}_{t+h,t} = \alpha_i + \beta_{BGMS} fr^{(i)}_{t+h,t} + err^{(i)}_t \tag{6}$$



(a) Estimated gains G: our measure vs CG

(b) BGMS regression coefficient

Figure 1: Under- and over- reaction in macroeconomic forecasts

Notes: Panel (a): The red circles represent the implied gain from the CG regression, i.e. $\frac{1}{1+\beta_{CG}}$. Standard errors are Newey-West (1994), with optimal bandwidth selection. The blue diamonds represent the gain estimated from (5) with individual and time fixed effects. Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level. Panel (b): Panel estimate of β_{BGMS} with forecaster fixed effects. In both panels, bars reports the 90% confidence interval for the estimated coefficients and the forecast are at horizon h=3 quarters.

If forecasters were fully rational, it should not be possible to predict forecast errors using forecast revisions, as the forecast revisions are clearly part of the forecasters' time t information sets. Thus, rational expectations predicts $\beta_{BGMS} = 0$, but to the contrary, Bordalo et al. (2020) find that for many macroeconomic series $\beta_{BGMS} < 0$. Intuitively, this implies that individual forecasts *overreact* to the arrival of new information, since the time t forecast revision was "too much", and ends up overshooting the actual realization x_{t+h}.

We replicate their results by estimating (6) as a panel with individual forecaster fixed effects, and plot the estimated β_{BGMS} in Figure 1, panel (b). Including fixed effects is important because the panel specification also exploits cross-sectional variation in addition to the time series variation, which is more information than available to the forecasters in real time (i.e. they do not know the other respondents' contemporaneously submitted forecasts). To further guard against a potential bias, we also present the median coefficients from the individual-level time series regressions in the last column of Table C.7 in Appendix C.2, which confirm the panel results. In all variations of the estimation, we confirm the fact that $\beta_{BGMS} < 0$ for the majority of forecasted series.

3 Strategic Incentives in Survey of Forecasts

The findings of under-reaction in average forecasts and the simultaneous over-reaction in individual forecasts have been important and influential in the recent macro literature, informing both the calibration of information frictions in models and also disciplining theories of behavioral expectations formation. However, that literature has generally interpreted the predictability of forecast errors based on the key assumption that the survey forecasts are *unbiased* measures of the respondents true beliefs and expectations.

This assumption is contrary to an older literature in forecasting, like Laster et al. (1999) and Ottaviani and Sørensen (2006), which argued for the existence of strategic incentives that bias survey responses away from the respondents' true, underlying expectations. Such considerations could arise from a variety of economic forces. For example, most survey respondents produce their forecasts as a byproduct of their economic consulting businesses, in which they compete with one another for customers. Other forecasters, even if nominally non-profit institutions, have reputational concerns.

The macro literature utilizing surveys has traditionally argued against the strategic reporting hypothesis by testing implications of models of strategic *coordination* incentives among forecasts. For example, Coibion and Gorodnichenko (2015) convincingly show that SPF forecasts do not display the characteristic forecast smoothing or low forecast precision that would arise if agents strategically *underutilize* information, as they would in an environment where they have incentives to "herd" together.

However, the broader hypothesis of strategic incentives, as surveyed in Marinovic et al. (2013) for example, allows for both economic settings in which forecasters have strategic incentives to herd together, and also strategic *diversification* settings in which they would actually want to stand out. Intuitively, in some strategic environments agents would optimally like to submit forecasts that shade away from their true beliefs and towards the consensus, but in others they could be incentivized to report forecasts that exaggerate the differences between their true beliefs and the consensus. The latter, which is formally a setting of strategic *diversification* incentives, has received much less attention.

In this section, we first show that indeed, one needs a model of strategic diversification, rather than strategic coordination, in order to be simultaneously consistent with both the over-reaction in individual forecasts and under-reaction in the consensus forecast. Moreover, the strategic diversification framework has the interesting implication that the consensus forecast is in fact very accurate, even though individual level forecasts are suboptimal, and this also conforms with a number of results in the literature about the apparent exceedingly high accuracy of the consensus SPF forecasts. Third, and perhaps most important, we show that the strategic diversification framework makes the further, unique prediction that while forecasts indeed overreact to idiosyncratic information, they would *underreact to public information*. This is a novel and differentiating implication that we then take to the data and confirm empirically.

3.1 A Simple Analytical Model of Strategic Incentives

To derive the key intuition, we present a tractable model that subsumes the several different strategic settings considered in Ottaviani and Sørensen (2006), within a single global games framework a-la Morris and Shin (2002) that allows for both strategic coordination and strategic diversification incentives. For the analytical results of this section we make the simplifying assumption that x_t is an i.i.d., white noise process. This greatly simplifies the solution to the strategic interaction game, which necessitates finding a fixed point. Nevertheless, in Section 4 below we generalize this analysis to the case of a AR(1) x_t that we solve numerically, and estimate to the data. Moreover, when we design the reduced form empirical tests in Section 3.2 we again work in the general setting of an unrestricted, stationary process for x_t. The i.i.d. assumption we make here is just for analytical and expositional convenience.

Agents are rational and have access to the two signals, g_t and $s_t^{(i)}$, defined in (1). In the spirit of Morris and Shin (2002), the forecasters' problem is to submit a forecast $\widetilde{E}_t^{(i)}[x_{t+h}]$ that minimizes the weighted average of the expected squared forecast error and the expected distance from the average forecast:

$$\min_{\widetilde{E}_t^{(i)}[x_{t+h}]} \mathbb{E}\left[(\widetilde{E}_t^{(i)}[x_{t+h}] - x_{t+h})^2 - \lambda(\widetilde{E}_t^{(i)}[x_{t+h}] - \overline{E}_t[x_{t+h}])^2 \middle| g_t, s_t^{(i)} \right] \tag{7}$$

The strategic interactions incentives are controlled by the single parameter $\lambda \in (-1, 1)$, where $\lambda > 0$ indicates a game of strategic substitutability (i.e. where agents want to stand-out from the crowd, as in the prize-winning context of Ottaviani and Sørensen (2006)), while $\lambda < 0$ indicates a game of strategic coordination (i.e. where agents want to herd together, as in the reputational concern setting of Ottaviani and Sørensen (2006)))

The first order condition is:

$$\widetilde{E}_t^{(i)}[x_{t+h}] = \frac{1}{1-\lambda}\mathbb{E}(x_{t+h}\,|g_t, s_t^{(i)}) - \frac{\lambda}{1-\lambda}\mathbb{E}(\overline{E}_t[x_{t+h}]\,|g_t, s_t^{(i)}) \tag{8}$$

If $\lambda = 0$, there are no strategic incentives and agents report their true rational beliefs. Otherwise, agents shade their reported forecasts either towards or away from their expectation of the average forecast $\overline{E}_t[x_{t+h}]$, depending on the sign of λ. In the special case under consideration here, where x_t is i.i.d., the rational expectation of x_{t+h} is given by

$$\mathbb{E}[x_{t+h}\,|g_t, s_t^{(i)}] = \mu + G_1^{RE}(s_t^{(i)} - \mu) + G_2^{RE}(g_t - \mu) \tag{9}$$

with $G_1^{RE} = \frac{\tau}{\tau+\nu+\chi}$, $G_2^{RE} = \frac{\nu}{\tau+\nu+\chi}$, where $\chi = 1/Var(x_t))$.

To solve for the optimal response, $\widetilde{E}_t^{(i)}[x_{t+h}]$, we guess a linear solution

$$\widetilde{E}_t^{(i)}[x_{t+h}] = \mu + G_1(s_t^{(i)} - \mu) + G_2(g_t - \mu) \tag{10}$$

and solve the fixed point jointly defined by (8) and (10), to obtain

$$G_1 = \frac{G_1^{RE}}{(1-\lambda) + \lambda G_1^{RE}}$$

$$G_2 = \frac{(1-\lambda)G_2^{RE}}{(1-\lambda) + \lambda G_1^{RE}}$$

Thus, when agents face strategic *diversification* incentives ($\lambda > 0$), and hence want to stand out from the crowd, they overweight their idiosyncratic signals, at the expense of underweighting the common (public) signal. The opposite under- and over-weighting pattern holds when agents face strategic coordination incentives instead (i.e. $\lambda < 0$). That is, dividing the above two equations by the respective optimal weights G_1^{RE} and G_2^{RE},

$$\frac{G_1}{G_1^{RE}} > \frac{G_2}{G_2^{RE}} \iff \lambda > 0 \tag{11}$$

Now let us relate to the CG and BGMS regressions we estimated in the previous section. First, since the new information at time t, i.e. the signals g_t and $s_t^{(i)}$, is partly idiosyncratic, the model implies that when $\lambda > 0$ the new signals as a whole get overweighted relative to the prior, μ, which is common across agents (and thus is also something to shade away from). Hence, when $\lambda > 0$ there is overreaction to new information, and $\beta_{BGMS} < 0$.

On the other hand, if $\lambda < 1$, then the model implies $\beta_{CG} > 0$. The reason is two-fold. First, because there is dispersed information, the average belief is sticky and the CG regression coefficient would be positive if reported forecasts $\widetilde{E}^{(i)}_{t-1}[x_{t+h}]$ were rational, for the same reasons as in Coibion and Gorodnichenko (2015). Second, when $\lambda > 0$ the reported forecasts overreact to new information, as just explained above. However, if the desire to overweight new information is not too strong, then we would still obtain $\beta_{CG} > 0$.

Formally we have the following Proposition.

Proposition 1 *In the strategic incentives game in (7), the resulting forecasts imply*

$$\beta_{BGMS} = \frac{-\lambda\tau\chi}{([(1-\lambda)\nu+\tau]^2 + (1-\lambda)^2\nu\chi)} < 0 \iff \lambda > 0$$
$$\beta_{CG} = \frac{(1-\lambda)\tau\chi}{([(1-\lambda)\nu+\tau]^2 + [(1-\lambda)^2\nu+\tau]\chi)} \iff \lambda < 1$$

Thus, putting both of these results together, we can conclude that the case of strategic diversification, i.e. $\lambda \in (0,1)$, is in fact the one consistent with both the under-reaction in aggregate forecasts, and the over-reaction in individual forecasts.

Moreover, in addition to matching these influential stylized facts, the strategic diversification model also makes the further, differentiating prediction that forecasts should specifically overweight new *idiosyncratic* information, at the expense of new common information (see equation (11)). Intuitively, forecasters are willing to sacrifice some accuracy in order to stand out from the crowd, and they do that by tilting their reported forecast towards idiosyncratic and away from common information. Typical models of behavior overreaction that have otherwise been used to explain the BGMS overreaction results are inconsistent with this differential under- and overreaction to different kinds of signals.

In the next section, we test this implication in the data directly. But before we turn to that, we also want to note that this characteristic under and overweighting of common and idiosyncratic signals further implies that the resulting consensus forecast $\overline{E}_t(x_{t+h})$ is in fact more accurate than the average of the true rational individual beliefs (i.e. $\overline{\mathbb{E}}_t[x_{t+h}]$). The reason for this counter-intuitive finding is that while individual forecasts deviate from optimality, they do so by overweighting the idiosyncratic signals at the expense of the common signals. Intuitively, this makes the individual forecasts suboptimal as they are now overly exposed to the idiosyncratic errors $\eta_t^{(i)}$ relative to the common error e_t. But the idiosyncratic errors *wash out* when we aggregate to the consensus forecast $\overline{E}_t[x_{t+h}]$, which actually ends up leaving the consensus forecast less affected by the common error than the average of the true beliefs $\mathbb{E}_t[x_{t+h}]$, making the consensus surprisingly accurate. Formally, we can show the following relationship holds between the mean squared errors of the consensus forecast with and without strategic incentives biasing the reported forecasts.

Proposition 2 *In the strategic incentives game in (7) with $\lambda \in (0,1)$,*

$$Var(x_{t+h} - \overline{E}_t(x_{t+h})) = \frac{(1-\lambda)^2}{(1-\lambda+\lambda G_2^{RE})^2} Var(x_{t+h} - \overline{\mathbb{E}}_t(x_{t+h})) < Var(x_{t+h} - \overline{\mathbb{E}}_t(x_{t+h}))$$

This is an interesting and differentiating implication that is consistent with the puzzling empirical finding that while individual forecasts display predictable errors and other biases, the consensus forecasts have in fact proven to be surprisingly accurate, and virtually impossible to beat (see for example Kohlhas and Robertson (2022)).

3.2 Under-reaction to public information in the data

We propose a new empirical methodology that allows us to directly test for the relative underweighting of common signals. The methodology works under the mild assumptions that x_t follows an arbitrary stationary process and that the reported forecasts follow a linear structure as in (2). To see the key intuition behind our approach, note that by manipulating (2) we can express individual forecast errors as:

$$fe_{t+h,t}^{(i)} = \frac{1-G_1}{G_1}(\widetilde{E}_t^{(i)}[x_{t+h}] - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) - \frac{G_2}{G_1}(g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) - \eta_t^{(i)} \tag{12}$$

We could then use an empirical proxy for the public signal g_t to run the following multivariate regression

$$fe_{t+h,t}^{(i)} = \alpha + \beta_1 fr_{t+h,t}^{(i)} + \beta_2 pi_{t+h,t}^{(i)} + err_t^{(i)} \tag{13}$$

where $pi_{t+h,t}^{(i)} = g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]$ is the deviation of the public signal from agent i's previous period forecast. Loosely speaking, this is the individual-level "surprise" in the public signal, although we stress that $\widetilde{E}_{t-1}^{(i)}[x_{t+h}]$ is not necessarily the true expectation of agent i, just the reported forecast.

Clearly, if forecasts are rational then forecast errors are not predictable and hence $\beta_1 = \beta_2 = 0$. However, when forecasts deviate from optimality then the β_1 coefficient speaks to deviations from optimality in terms of the idiosyncratic signal and β_2 is informative about the differential under- and over-weighting of the common signal. Formally, we can derive the following Proposition regarding these regression coefficients.

Proposition 3 *If agents forecasts follow (2), then for any stationary process x_t*

$$\beta_1 < 0 \iff G_1 > \frac{G_1^{RE}}{G^{RE} + \frac{\Sigma^{RE}}{\widetilde{\Sigma}}(1 - G^{RE})}$$

$$\beta_2 > 0 \iff \frac{G_1}{G_1^{RE}} > \frac{G_2}{G_2^{RE}}$$

where $\widetilde{\Sigma} \equiv var(x_t - \widetilde{E}_{t-1}^{(i)}[x_t])$ *and* $\Sigma^{RE} \equiv var(x_{t+h} - \mathbb{E}_{t-1}^{(i)}[x_{t+h}])$.

Intuitively, $\beta_2 > 0$ implies that the common signal, g_t, is underweighted relative to the idiosyncratic signal, $\eta_t^{(i)}$, while a $\beta_1 < 0$ implies an overreaction to the idiosyncratic signal – specifically, since $G^{RE} + \frac{\Sigma^{RE}}{\widetilde{\Sigma}}(1 - G^{RE}) < 1$, finding $\beta_1 < 0$ implies that $G_1 > G_1^{RE}$.

To implement regression (13) in the data, we use the lagged consensus forecast $\overline{E}_{t-1}(x_{t+h})$ – namely the average of the individual forecasts provided in the previous quarter about the same future date $t + h$ – as a proxy for the public signal g_t. This is a time t signal, because the time $t - 1$ vintage of the survey is published after all $t - 1$ forecasts are submitted, hence the first time this information is available is for the time t vintage of the forecasts. Second, this is a public signal because the SPF is commonly available to everyone. And third, this is indeed a highly informative signal, since it is well known that the consensus of the SPF survey is indeed a very good forecast that receives a lot of attention (e.g. Kohlhas and Robertson (2022)). As a very informative and commonly available signal, it is thus reasonable to expect it is a component of all forecasters' information sets.

In Table 2 we report both the panel regression estimates of (13) (with individual fixed effects) and the median from individual forecaster regressions. Both specifications display a consistent finding of $\beta_1 < 0$ and $\beta_2 > 0$ across variables, with very few exceptions. Figure 2 also provide a graphical representation of our panel estimates. In particular, our key regression coefficient, β_2, is clearly positive and statistically different from zero for all forecasted series.

Table 2: Private and public information

Panel A: 3 quarters horizon

	Revision				Public signal			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.54	0.12	0.00	-0.44	0.75	0.07	0.00	0.76
GDP price index inflation	-0.68	0.05	0.00	-0.64	0.81	0.04	0.00	0.83
Real GDP	-0.34	0.12	0.01	-0.18	0.57	0.08	0.00	0.61
Consumer Price Index	-0.48	0.11	0.00	-0.46	0.68	0.08	0.00	0.69
Industrial production	-0.59	0.15	0.00	-0.60	0.79	0.08	0.00	0.78
Housing Start	-0.58	0.11	0.00	-0.53	0.78	0.05	0.00	0.71
Real Consumption	-0.57	0.16	0.00	-0.58	0.81	0.08	0.00	0.81
Real residential investment	-0.38	0.15	0.01	-0.39	0.73	0.08	0.00	0.66
Real nonresidential investment	-0.12	0.18	0.50	-0.10	0.65	0.10	0.00	0.51
Real state and local government consumption	-0.83	0.04	0.00	-0.81	0.93	0.03	0.00	0.89
Real federal government consumption	-0.84	0.03	0.00	-0.77	0.91	0.03	0.00	0.87
Unemployment rate	0.11	0.21	0.61	-0.02	0.44	0.11	0.00	0.42
Three-month Treasury rate	0.06	0.15	0.68	0.11	0.52	0.11	0.00	0.38
Ten-year Treasury rate	-0.47	0.09	0.00	-0.40	0.76	0.04	0.00	0.83
AAA Corporate Rate Bond	-0.61	0.09	0.00	-0.67	0.83	0.06	0.00	0.87

Panel B: 2 quarters horizon

	Revision				Public signal			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.35	0.09	0.00	-0.27	0.62	0.06	0.00	0.63
GDP price index inflation	-0.55	0.06	0.00	-0.50	0.70	0.04	0.00	0.66
Real GDP	-0.26	0.13	0.05	-0.14	0.54	0.08	0.00	0.54
Consumer Price Index	-0.38	0.09	0.00	-0.36	0.52	0.08	0.00	0.52
Industrial production	-0.16	0.12	0.19	-0.14	0.49	0.08	0.00	0.50
Housing Start	-0.15	0.08	0.08	-0.15	0.54	0.05	0.00	0.56
Real Consumption	-0.37	0.11	0.00	-0.29	0.64	0.07	0.00	0.69
Real residential investment	-0.13	0.11	0.23	-0.16	0.49	0.07	0.00	0.43
Real nonresidential investment	-0.02	0.10	0.81	-0.04	0.41	0.07	0.00	0.44
Real state and local government consumption	-0.63	0.08	0.00	-0.51	0.79	0.04	0.00	0.72
Real federal government consumption	-0.71	0.06	0.00	-0.64	0.80	0.04	0.00	0.74
Unemployment rate	0.09	0.15	0.57	0.03	0.39	0.10	0.00	0.37
Three-month Treasury rate	0.02	0.11	0.89	0.10	0.48	0.10	0.00	0.39
Ten-year Treasury rate	-0.46	0.11	0.00	-0.45	0.71	0.07	0.00	0.67
AAA Corporate Rate Bond	-0.49	0.08	0.00	-0.52	0.70	0.06	0.00	0.71

Notes: this table reports the coefficients of regression (13) (individual forecast errors on individual revisions and public information). Columns 1 to 3 show coefficient β_1 (forecast revision) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by time and forecaster. Column 4 shows the median coefficient of the same regression at the individual level. Columns 5 to 7 show coefficient β_2 (public information) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by time and forecaster. Column 8 shows the median coefficient of the same regression at the individual level. Panel A uses forecast at 3 quarters horizon and panel B uses forecast at 2 quarters horizon.

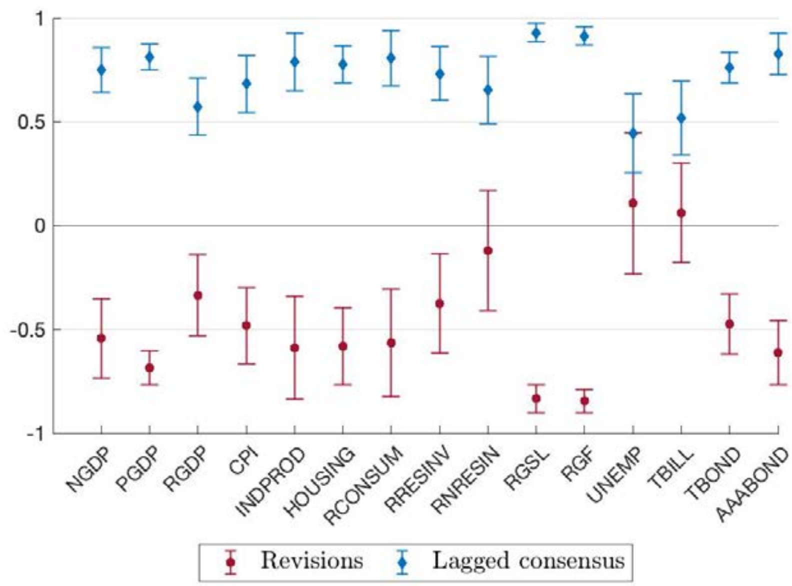


Figure 2: Forecast errors on forecast revisions and public information

Notes: this figure plots the coefficients from the panel regression (13) with individual fixed effect and horizon h=3. The red circles represent the coefficient β_1 while the blue diamonds represent the coefficient β_2. Bars reports the 90% confidence interval for the estimated coefficients. Standard errors are robust and clustered at both time and individual forecaster level.

This means that while idiosyncratic signals are indeed overreacted to (as we might expect from the BGMS findings), there is in fact a relative *underreaction* to common signals. These results speak in favor of the model of strategic diversification incentives presented in the previous section, but are inconsistent with typical behavior models of overreaction and overextrapolation that have otherwise been used to address the BGMS findings, as these behavioral models would suggest that all sources of new information are similarly overweighted.

Thus, on the one hand, deviations from rationality are not necessarily needed to explain the puzzling behavior of surveys of forecasts. On the other hand, more generally our refined estimates of what sources of information are overreacted to, and what are actually underreacted to, provide new important moments for the literature to take into account and inform models with.

Lastly, econometrically, it is also interesting to observe that the point estimates of β_1 and β_2 are very consistent across variables and are also tightly estimated, unlike the BGMS coefficients which are significantly noisier (see Figure 2). Moreover, our β_1 estimate is consistently more negative than the corresponding β_{BGMS} estimates. Thus, once we separately identify the overreaction to idiosyncratic information in particular, we find that it is much stronger than the overall overreaction that BGMS estimate. Thus, controlling separately for the public signal on the right hand side of the forecast error predictability regressions is useful even just for limiting estimation noise, as otherwise the differential under- and over-weighting of the different types of signals is averaged out in the BGMS regression.

3.3 Additional Tests

While the differential under- and overreaction to common relative to idiosyncratic information is inconsistent with behavioral models where agents overreact to all new information, it can be consistent with models where agents do not update beliefs rationally because they overestimate the actual precision of their idiosyncratic signals relative to public signals (e.g. Daniel et al. (1998); Eyster et al. (2019); Broer and Kohlhas (2022)).

In the following sections we provide further empirical evidence that specifically supports the strategic diversification theory against such alternative behavioral theories. First, we observe that strategic considerations are likely to mainly apply to professional forecasters which compete with one another in the market place, but should not apply to forecasts produced by policy makers. In line with this, we show that Federal Reserve forecasts do not exhibit any of the biases documented in the forecasts of professional forecasters. Second, we show that professional forecasters underweight lagged consensus forecasts substantially more than other commonly observed sources of information, suggesting that the forecasters are especially sensitive to differentiating themselves from the consensus.

3.3.1 Comparison between professional and government forecast

In this section we distinguish between behavioral and strategic diversification theories by comparing the Survey of Professional Forecasters with the Tealbook/Greenbook forecasts by the Federal Reserve Board of Governors. Differently from the SPF, the Greenbook forecasts are not intended for public consumption but are prepared for internal Federal Reserve purposes as part of the FOMC preparation process, hence they are less likely to be subject to the strategic incentives facing professional forecasters that compete with one another as part of their business. Moreover, the Greenbook forecasts are published with a 5 year lag, which further diminishes any strategic forces.[7] Thus, under the null hypothesis that the SPF forecast biases are driven by strategic incentives, we would expect that these biases are not present in the Greenbook.

We treat the Greenbook as a time series of individual forecasts, and apply the individual rationality tests to it (both BGMS and our regression (13)). While one can argue that multiple economists contribute to the Greenbook forecast, the assumption we make is that they do so together, sharing their information sets, in which case the Greenbook projections are forecasts made under a single information set, and hence the rationality tests apply readily.

Our main result is that the Greenbook's forecasts indeed do not display neither of the biases documented in professional forecasters surveys – neither overall overreaction to new information, nor the differential under- and overreaction to idiosyncratic relative to common signals. This finding is consistent with the strategic diversification theory, while behavioral theories would imply we should see the same biases.

Data on the Greenbook (GB) projections is provided by the Federal Reserve Bank of Philadelphia. We use that data to construct a forecast dataset with the same structure and coverage as the SPF. Namely, while the GB projections are produced before each FOMC meeting, we group the forecasts at the quarterly level by keeping only the last forecasts of the quarter. The forecasts are produced for up to 9 quarters in the future, but we only keep up to 4 quarters ahead, in-line with the SPF forecasts. There are 15 forecasted variables, but we keep only the 11 appearing also in the SPF (see Table 3). We follow the same procedure as with the SPF and transform all series into forecasts of the implied annual growth rate from $t-1$ to $t+3$ (with the exception of unemployment). Appendix A provides a detailed description of variable construction.

Summary Statistics. Table 3 presents the summary statistics for each series. Columns 1-5 reports the statistics for the Greenbook forecast errors and revisions. Forecast errors are statistically indistinguishable from zero for most of the series except for industrial production and real state and local government consumption.

[7] Unfortunately, it is not straightforward to also compare against household or consumer surveys, since common surveys like the Michigan Survey of Consumer Expectations have a very limited panel component (with households rotating out of the survey) or even only contain repeated cross-sections. Our tests need a substantial time series of forecasts of the same individual.

Table 3: Summary Statistics: Greenbook forecasts

	Errors			Revisions	
	Mean	SD	SE	Mean	SD
Variable	(1)	(2)	(3)	(4)	(5)
Nominal GDP	-0.06	1.46	0.16	-0.10	0.87
GDP price index inflation	-0.07	0.58	0.09	0.06	0.47
Real GDP	-0.13	1.55	0.18	-0.15	0.82
Consumer Price Index	0.15	1.08	0.16	0.00	0.69
Industrial production	-0.94	3.58	0.38	-0.46	1.69
Housing Start	-2.14	15.64	1.83	-2.97	9.51
Real residential investment	0.60	7.13	0.87	-0.92	4.85
Real nonresidential investment	0.68	4.93	0.62	-0.36	2.84
Real state and local government consumption	0.87	3.06	0.34	0.22	1.70
Real federal government consumption	-0.19	1.30	0.17	-0.08	0.89
Unemployment rate	-0.09	0.59	0.06	0.01	0.41

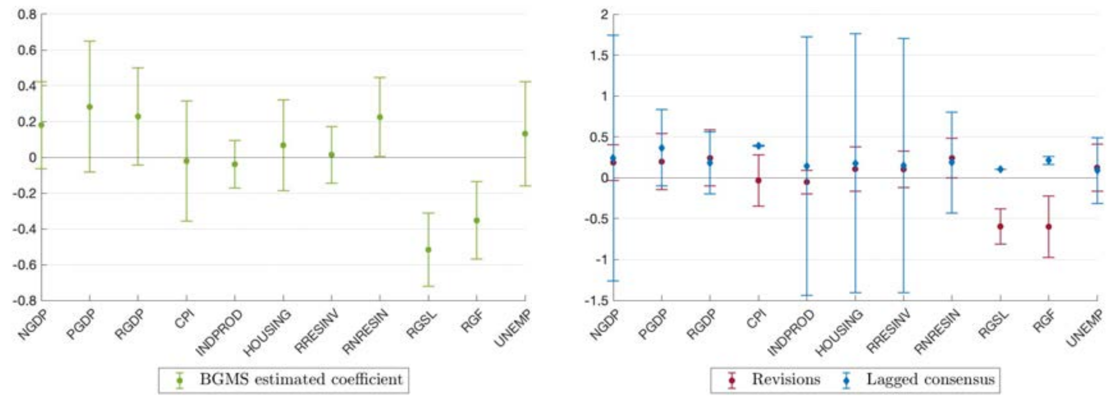
Notes: Columns 1 to 5 show statistics for consensus forecast errors and revisions using forecasts from the Federal Reserve Green Book dataset. Errors are defined as actual realizations of forecasted variables minus forecasts. Revisions are the forecast provided in t minus the forecast provided in $t-1$ about the same future time period $t+h$.

No overreaction overall. Panel (a) of Figure 3 plots the coefficients estimated by running the BGMS regression, equation (6), on the GB forecast data. The results show that with the only exception of forecasts of government consumption, the GB forecasts do not exhibit an overreaction bias to new information as the SPF forecasts do. Table 4 reports full details on the regression estimates for the GB survey at both 3 and 2 quarters horizons.

Table 4: Estimated coefficients on the Greenbook survey

	BGMS			Our regression (13)					
	β_{BGMS}	SE	p-value	β_1	SE	p-value	β_2	SE	p-value
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nominal GDP	0.18	0.15	0.23	0.18	0.13	0.17	-0.03	0.24	0.91
GDP price index inflation	0.28	0.22	0.21	0.20	0.21	0.35	0.39	0.37	0.28
Real GDP	0.23	0.16	0.17	0.24	0.21	0.25	0.22	0.18	0.23
Consumer Price Index	-0.02	0.20	0.92	-0.03	0.19	0.86	1.11	0.39	0.01
Industrial production	-0.04	0.08	0.63	-0.05	0.09	0.56	0.01	0.14	0.96
Housing Start	0.07	0.15	0.66	0.11	0.16	0.52	0.01	0.18	0.96
Real residential investment	0.01	0.10	0.88	0.10	0.13	0.45	0.01	0.15	0.94
Real nonresidential investment	0.22	0.13	0.10	0.24	0.15	0.10	0.17	0.19	0.38
Real state and local government consumption	-0.52	0.12	0.00	-0.60	0.13	0.00	0.38	0.10	0.00
Real federal government consumption	-0.35	0.13	0.01	-0.60	0.23	0.01	0.46	0.21	0.03
Unemployment rate	0.13	0.18	0.46	0.12	0.18	0.48	-0.10	0.09	0.24

Notes: The table reports the coefficients from the BGMS regression (columns 1-3) and our specification (13) (columns 4-9) using Greenbook forecasts at horizon 3 quarters. Standard errors are Newey-West(1994) with optimal bandwidth selection.



(a) BGMS coefficients

(b) Our regression (13)

Figure 3: Estimated coefficients on the Greenbook survey

Notes: Panel (a) reports the coefficient from the BGMS regression using the Greenbook projections. Panel (b) plots the estimates of our regression (13) using forecasts from the Greenbook. The blue diamonds represent the coefficient β_1 while the red circles represent the coefficient β_2. In both panels, bars report the 90% confidence interval for the estimated coefficients and the forecast are at horizon h=3. Standard errors are Newey and West (1994) with optimal bandwidth selection.

No underreaction to public information. Similarly to the previous section, we use the lagged consensus forecast from the SPF as a public signal. It is similarly available to the Fed's economists at the time of their projection, and this makes the regression directly comparable to our earlier results.

Panel (b) of Figure 3 reports the estimates from regression (13) implemented on the GB forecast data. Again, the results show that in large part the GB forecasts exhibit neither overreaction to new idiosyncratic information ($\beta_1 \approx 0$, red bars), nor underreaction to public information ($\beta_2 \approx 0$, blue bars). The only exceptions are, again, government purchases forecasts. Table 4 provides full estimation details for our benchmark horizon $h = 3$, and Table C.5 in the Appendix reports virtually the same results in the case of $h = 2$.

3.3.2 Comparison between different public signals

The key intuition of the strategic diversification hypothesis is that the forecasters do not just want to provide accurate forecasts, but also to differentiate themselves from the average forecast in the survey. A direct implication we have already exploited is that the forecasters would want to underweight common signals, as those would be overrepresented in the average forecast.

More generally, however, when x_t is not i.i.d., the need to predict the average response of all other forecasters (i.e. $\mathbb{E}_t^{(i)}(\overline{E}_t[x_{t+h}])$) generates an infinite regress of higher order beliefs – as we can see, for example, from our quantitative model in Section 4 below. In that case, the lagged consensus is in fact a very *special* common signal – being a direct signal on $\overline{E}_{t-1}[x_{t+h}]$, it is especially highly correlated with the slow moving higher order beliefs that underlie the current period consensus forecast. As such, the lagged consensus is in fact likely to be more highly under-weighted relative to other common signals.

Thus, in this section we will consider if there is indeed such differential underweighting relative to other public signals. A natural alternative public signal is the latest available data on the actual realization of the forecasted variable x_t. In the case of financial variables, this is the realization in the second month of the quarter (when the survey is collected), in case of macroeconomic variable this is the first release of data on its realization from the previous quarter. We can "demean" this second public signal as well, since the SPF also provides "nowcasts", that is we can construct

$$pi_{2,t+h,t}^{(i)} \equiv x_{t-1} - \widetilde{E}_{t-1}^i[x_{t-1}] \tag{14}$$

and obtain a regressor $pi_{2,t+h}^{(i)}$ that has the same structure as before.

We test the hypothesis that this second type of common signal experiences less under-reaction in two different specification. First, we run our baseline regression (13) with this alternative public signal instead

$$fe_{t+h,t}^{(i)} = \alpha + \beta_1 fr_{t+h,t}^{(i)} + \beta_2 pi_{t+h,t}^{(i)} + err_t^{(i)} \tag{15}$$

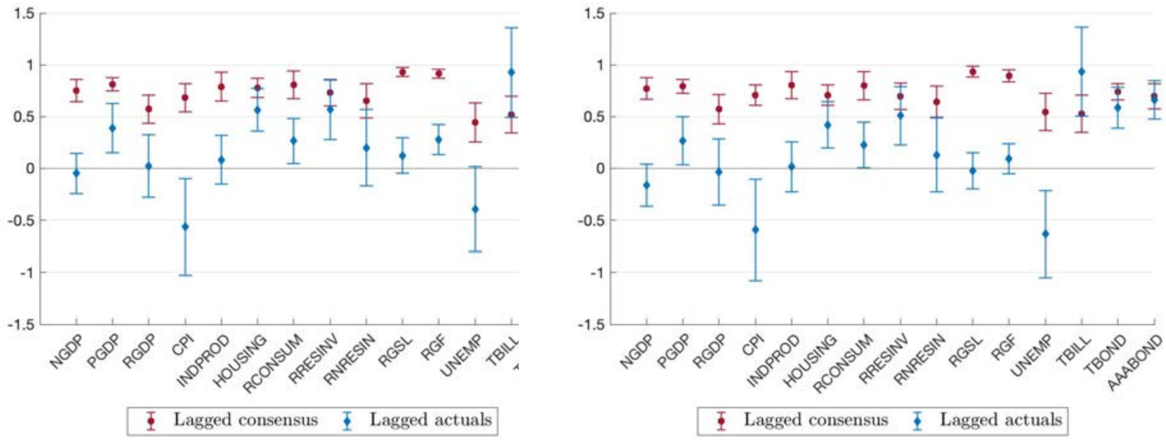
Second, we then include both public signals in the following, augmented regression

$$fe_{t+h,t}^i = \alpha + \beta_1 fr_{t+h,t}^i + \beta_2 pi_{1,t+h,t} + \beta_3 pi_{2,t+h,t} + err_t^i \tag{16}$$

where $pi_{1,t+h,t}^{(i)} = \overline{E}_{t-1}[x_{t+h}] - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]$ is the same variable as before.

Under the strategic diversification framework, we expect that forecasters underweight the lagged consensus more than the latest realization of the forecasted variable, hence we have the two null hypotheses that (i): the β_2 estimate is larger in our original regression (13) than in (15), and (ii): $\beta_2 > \beta_3$ in regression (16).

The empirical estimates of both regressions are reported in Figure 4 and indeed con-



(a) Different regressions

(b) Same regression

Figure 4: Comparison between public signals

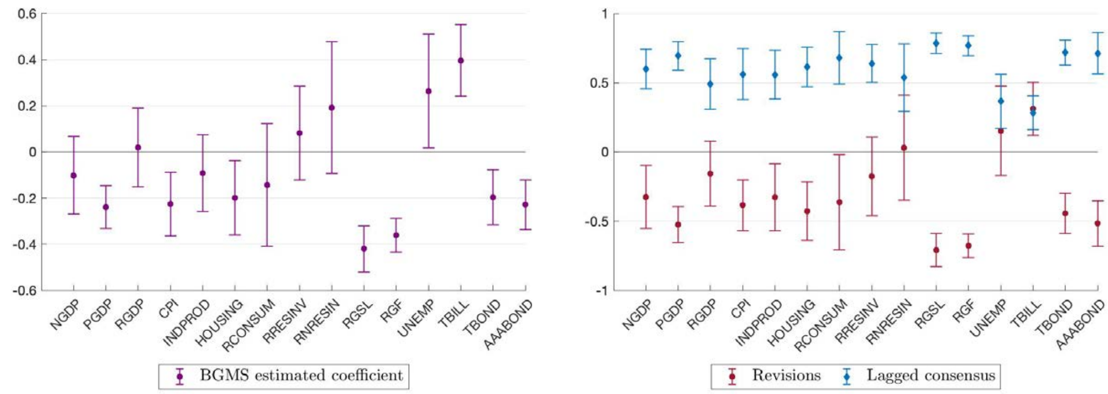
Notes: Panel (a): estimates of β_2 from our original regression (13) (in red), and from (15) (in blue). Panel(b): β_2 (in red) and β_3 (in blue) estimates from regression (16) using the SPF and h=3. Bars reports the 90% confidence interval for the estimated coefficients. Standard errors are robust and clustered at time and forecaster.

firm both implications: underreaction to lagged consensus is larger than underreaction to lagged actuals, which is still weakly larger than zero with the exception of CPI inflation and unemployment. We leave the tables with full details of the estimation at both $h = 3$ and $h = 2$ horizons to Appendix D.

3.4 Discussion

Outliers and Measurement Error. Juodis and Kučinskas (2023) make the powerful argument that the BGMS results could potentially be driven by measurement error in reported forecasts $\widetilde{E}_t^{(i)}[x_{t+h}]$, which show up on both the left and right hand sides of equation (6) and can thus mechanically generate a negative correlation. This is a concern that is more broadly related to the observation of Angeletos et al. (2021) and Broer and Kohlhas (2022) that there are a substantial number of influential outliers in the SPF data, which can by themselves also substantially weaken the BGMS findings.

To the contrary, our results are robust to a variety of aggressive treatments of outliers. In our benchmark analysis up to this point we followed the same procedure to clean outliers as in BGMS in order to be comparable. However, our results also remain virtually unchanged under three alternative strategies suggested in the literature. First, as in Kohlhas and Walther (2021) we trim all observations outside of the first and the 99th per-



(a) BGMS regression

(b) Forecast errors on revisions and public information

Figure 5: Regressions result with stricter data cleaning

Notes:

centile; second, we follow Angeletos et al. (2021) and drop forecasts that are more than 4 interquartile ranges away from the median of each horizon in each quarter; third, we use the median to measure consensus forecasts instead of the mean. To showcase the robustness of our results, in panel (b) of Figure 5 below we show that our benchmark estimates and the key conclusion of $\beta_2 > 0$ do not change even when we apply all three alternative data cleaning strategies *at the same time*, while in panel (b) we show the resulting BGMS estimates, which are indeed noisier and much closer to zero. In Appendix G, we provide details on all empirical results under this stricter data cleaning procedure.

Similarly, our estimates and conclusions are virtually identical whether we run our regression using forecasts at horizon $h = 3$ quarters as in the main text, or the other alternative for which we have data, $h = 2$ as we have also shown throughout the Appendix.

Public and private information in previous papers In a recent paper, Broer and Kohlhas (2022) argue that survey of forecasts in fact show both under- and overreaction to public signals, not just under-reaction as we find. To show this, they run the regression

$$fe^{(i)}_{t+h,t} = \alpha + \beta_{BK}\overline{E}_{t-1}[x_{t+h}] + err^{(i)}_t \tag{17}$$

where they also consider the lagged consensus as a relevant public signal. However, estimating β_{BK} across different variables they find the results are widely dispersed on both sides of zero, sometimes being positive, while other times negative. This contrasts to our finding that β_2 is consistently positive for *all* forecasted variables, and the reason is that their specification presents two important differences with respect to our regression (13).

On the one hand, Broer and Kohlhas (2022) use a univariate regression where we consider a multivariate one, but perhaps most importantly, they use the lagged consensus alone as the regressor, while we "demean" it and construct the associated "surprise" in that signal at the individual forecaster level by defining: $pi_{t+h,t}^{(i)} = \overline{E}_{t-1}[x_{t+h}] - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]$. Broer and Kohlhas (2022) motivate their regression specification with a *static* conceptual framework, and in that case the agent's prior belief is just a constant, and hence it wont matter in the regression, and thus they never consider it.

However, in a dynamic setting omitting the prior beliefs leads to a misspecified regression, because the omitted $\widetilde{E}_{t-1}^{(i)}[x_{t+h}]$ is correlated with the regressor $\overline{E}_{t-1}[x_{t+h}]$ (e.g. see eq. (12)). This introduces a bias in the β_{BK} coefficient, such that deviations of β_{BK} from zero do not in fact speak directly to either under- or overweighting of public signals. Under our conceptual framework (2) and a general, but stationary process for x_t, we can formally derive the following if and only if condition for β_{BK} to be positive.

Proposition 4 *When forecasts follow a linear structure as in (2) and x_t is stationary*

$$\beta_{BK} > 0 \iff \frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}} \frac{\Sigma^{RE}}{\tilde{\Sigma} + Cov(x_{t+h} - \widetilde{E}_{t-1}^{(i)}[x_{t+h}], \widetilde{E}_{t-1}^{(i)}[x_{t+h}])}$$

If x_t is i.i.d. (which is equivalent to a static conceptual framework), then $Cov(x_{t+h} - \widetilde{E}_{t-1}^{(i)}[x_{t+h}], \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) = 0$ and $\Sigma^{RE} = \tilde{\Sigma}$, and hence $\beta_{BK} > 0$ if and only if $\frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}}$, in which case β_{BK} will indeed be directly informative about whether the lagged consensus is under- or overweighted (relative to the agent's prior, which has the weight of $1-G$). However, away from the restrictive assumption of x_t being i.i.d. (clearly not satisfied in the data for the majority of forecasted series), the direction of the deviation of β_{BK} from zero is not that informative. We can think of examples where signals will be objectively underweighted, but we would still estimate $\beta_{BK} < 0$, since $Cov(x_{t+h} - \widetilde{E}_{t-1}^{(i)}[x_{t+h}], \widetilde{E}_{t-1}^{(i)}[x_{t+h}])$ could be both positive or negative, depending on the time series dynamics of x_t.

But if we demean the lagged consensus, and use $pi_{t,t+h}^{(i)} = g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]$ as the regressor

$$fe_{t+h,t}^{(i)} = \alpha + \beta_{BK_{dm}} pi_{t+h,t}^{(i)} + err_t^{(i)} \tag{18}$$

then we can prove the following, tighter prediction for the new coefficient $\beta_{BK_{dm}}$.

Proposition 5 *When forecasts follow a linear structure as in (2) and x_t is stationary*

$$\beta_{BK_{dm}} > 0 \iff \frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}} \frac{\Sigma^{RE}}{\widetilde{\Sigma}}$$

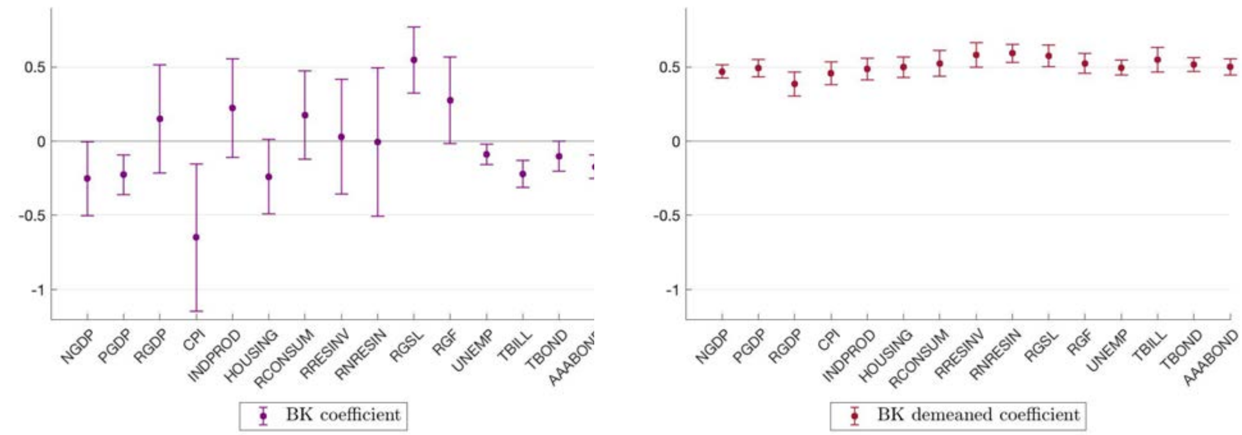
This condition does not suffer from the $Cov(x_{t+h} - \widetilde{E}_{t-1}^{(i)}[x_{t+h}], \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) \neq 0$ problem, and thus yields more robust and informative results when x_t is not i.i.d.

And indeed, when we implement regression (18), we find very different results than Broer and Kohlhas (2022). We plot the estimated $\beta_{BK_{dm}}$ in panel (b), Figure 6, and find those coefficients are consistently and robustly *positive* for all forecasted variables, similar to our estimates of β_2. On the other hand, replicating the original BK regression on the same data we get coefficients that are noisily estimated and dispersed both under and over the zero line, as shown in Panel (a) of Figure 6.[8] Thus, we can indeed conclude that the lagged consensus is a public signal that is *consistently* underweighted. We find no evidence of the signal being sometimes underweighted, and other times overweighted.

Lastly, note that $\beta_{BK_{dm}} > 0$ has the subtle meaning that the lagged consensus is underweighted *relative* to the agents' priors. This finding is also consistent with the strategic diversification hypothesis. On the one hand, as already explained in Section 3.3.2, the lagged consensus is a very special common signal in that it is highly correlated with the slow moving higher order beliefs that underlie the consensus forecast. In a dynamic model, forecasters would very much like to underweight this type of signal more than any other source of commonality, such as their priors. Moreover, if we allow for heterogeneous priors for the long-run mean of the process x_t (i.e. μ_i that differ across i, which is empirically relevant as argued by, for example, Patton and Timmermann (2010)), then *any* common signal g_t should be underweighted compared to the agents' differing priors, and thus imply $\beta_{BK_{dm}} > 0$. While a full quantitative characterization of such model is out of the scope of this paper, as an example in Appendix H we solve numerically an illustrative model that assumes i.i.d. x_t, and show that it can generate all of the evidence including $\beta_{BK_{dm}} > 0$.

Anonymity. It is sometimes argued that strategic considerations do not readily apply to anonymous surveys like the SPF. However, to the contrary, the forecasting literature has noted that when the same forecasters participate in both anonymous and non-anonymous

[8] Appendix C.4 reports all estimation details at both 3 and 2 quarters horizons.



(a) Not demeaned (BK)

(b) Demeaned

Figure 6: Forecast errors on lagged consensus

Notes: this figure plots the panel estimates of regressions (17)and (18), in panel (a) and panel (b) respectively, with individual fixed effect and horizon h=3. Bars reports the 90% confidence interval for the estimated coefficients. Standard errors are robust and clustered at both time and individual forecaster level.

surveys, they simply submit the same forecast to both types of surveys, thus introducing strategic considerations in the anonymous survey as well. For example, Marinovic et al. (2013) notes that "According to industry experts, forecasters often seem to submit to the anonymous surveys the same forecasts they have already prepared for public (i.e. non-anonymous) release. There are two reasons for this. First, it might not be convenient for the forecasters to change their report, unless they have a strict incentive to do so. Second, the forecasters might be concerned that their strategic behavior could be uncovered by the editor of the anonymous survey."

In fact, we find direct evidence to this effect from a supplement to the European Central Bank's own Survey of Professional Forecasters. In that supplement, respondents were explicitly asked whether they "prepare a new forecast specifically for the SPF" (which is anonymous) or just submit the "latest available forecast" (p.8, European Central Bank (2014)). There are two waves of this questionnaire, and in both the respondents overwhelmingly indicated they do not produce a new forecast, but rather use one that is already available. In 2013, more than 80% of the panelists responded with "the last available", while in 2008 more than 90% gave the same answer (European Central Bank, 2014).

Lastly, as shown in Bordalo et al. (2020) and elsewhere, the basic facts of the underreaction of the consensus forecast and the over-reaction of individual-level forecasts, are essentially the same in both the SPF and the Blue Chip survey, which is not anonymous. Thus, overall, forecasters both explicitly state they do not make any different forecasts for anonymous surveys like the SPF, and in practice this seems to be the case. Thus, any strategic interactions the forecasters face due to competing with each other in the marketplace would play out in the SPF as well.

4 Quantitative Analysis

An important implication of the strategic diversification theory is that forecasts reported in the surveys would be only a biased measure of the underlying true beliefs of agents. As a result, moments of the survey of forecasts do not speak directly to the actual level of information frictions and noise in the forecasters' information sets, although the literature regularly turns to surveys to estimate such deep characteristics of interest. For example, surveys are often used to inform the calibration of information frictions and also to construct measures of uncertainty both in the time series and in the cross-section (see also the discussion in Coibion and Gorodnichenko (2015)).

In order to uncover the true underlying beliefs and degree of information frictions, we estimate a quantitative version of the strategic incentives model of Section 3.1, where we generalize the time series process for x_t to a AR(1) process and estimate all key parameters from the data. Agents are rational, and understand that x_t follows the AR(1) process

$$x_t = \rho x_{t-1} + u_t \tag{19}$$

with $u_t \sim N(0, \chi^{-1})$. They observe the two signals in equation (1), and form posterior beliefs about x_{t+h} according to the Kalman filter

$$\mathbb{E}_t^{(i)}[x_{t+h}] = \mathbb{E}_{t-1}^{(i)}[x_{t+h}] + G_1^{RE}(s_t^{(i)} - \mathbb{E}_{t-1}^{(i)}[x_{t+h}]) + G_2^{RE}(g_t - \mathbb{E}_{t-1}^{(i)}[x_{t+h}])$$

where the optimal Kalman gain weights are given by

$$G_1^{RE} = \frac{\tau}{1/\Sigma^{RE} + \nu + \tau} \text{ and } G_2^{RE} = \frac{\nu}{1/\Sigma^{RE} + \nu + \tau} \tag{20}$$

with the optimal posterior forecast error variance

$$\Sigma^{RE} \equiv Var(x_{t+h} - \mathbb{E}_{t-1}^{(i)}[x_{t+h}]) \\ = \frac{-[(\rho^2-1)\chi + (\tau+\nu)] + \sqrt{[(\rho^2-1)\chi + (\tau+\nu)]^2 + 4(\tau+\nu)\chi}}{2} \tag{21}$$

Strategic interactions The agents face the same objective function as in Section 3.1, equation (7), which leads them to report forecasts $\widetilde{E}_t^{(i)}[x_{t+h}]$ given by:

$$\widetilde{E}_t^{(i)}[x_{t+h}] = \frac{1}{1-\lambda}\mathbb{E}_t^{(i)}[x_{t+h}] - \frac{\lambda}{1-\lambda}\mathbb{E}_t^{(i)}(\overline{E}_t[x_{t+h}]) \tag{22}$$

Solving the first order condition above involves finding a fixed point, and we do so by following the approach in Woodford (2001) and Coibion and Gorodnichenko (2012). We average the expression for $\widetilde{E}_t^{(i)}[x_{t+h}]$ in equation (22) across agents and use repeated substitution in that same equation to obtain the following relation:

$$F_t \equiv -\frac{1}{1-\lambda}\sum_{k=0}^{\infty}\left(\frac{\lambda}{1-\lambda}\right)^k \bar{E}_t^{(k)}[x_{t+h}] = \frac{1}{1-\lambda}\bar{E}_t[x_{t+h}] - \frac{\lambda}{1-\lambda}\bar{\mathbb{E}}_t[\bar{E}_t[x_{t+h}]] \tag{23}$$

We then guess and verify that the law of motion for F_t and the other unobserved state variables is an VAR(1) process:[9]

$$Z_t \equiv \begin{bmatrix} x_{t+h} \\ F_t \\ w_t \end{bmatrix} = MZ_{t-1} + m \begin{bmatrix} u_{t+h} \\ e_t \end{bmatrix} \tag{24}$$

Where

$$M = \begin{bmatrix} \rho & 0 & 0 \\ M_{2,1} & M_{2,2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \text{and} \quad m = \begin{bmatrix} 1 & 0 \\ m_{2,1} & m_{2,2} \\ 0 & 1 \end{bmatrix}. \tag{25}$$

[9] It is analytically convenient to introduce a third element of the state vector Z_t, $w_t \equiv e_t$, which is methodologically useful to handle the correlation of common shocks e_t in the signal g_t and F_t

We collect the two signals about x_{t+h} in the vector

$$V_t^i \equiv \begin{bmatrix} g_t \\ s_t^i \end{bmatrix} = HZ_t + \begin{bmatrix} 0 \\ \eta_t^i \end{bmatrix} \tag{26}$$

where

$$H = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \tag{27}$$

Agents use the conjectured law of motion (24) and the observables (26) to build the optimal posterior estimate of the state vector

$$\begin{aligned} \mathbb{E}_t^{(i)}[Z_t] &= M\mathbb{E}_{t-1}^{(i)}[Z_{t-1}] + K(V_t^i - \mathbb{E}_{t-1}^{(i)}[V_t^{(i)}]) \\ &= (I - KH)M\mathbb{E}_{t-1}^{(i)}[Z_{t-1}] + KHMZ_{t-1} + KHm \begin{bmatrix} u_t \\ e_t \end{bmatrix} + K \begin{bmatrix} 0 \\ \eta_t^i \end{bmatrix} \end{aligned} \tag{28}$$

where K is the rational 3x2 Kalman gain matrix. The first line of the vector equation above is the optimal forecast of x_{t+h}, thus naturally $G_1^{RE} = K_{(1,2)}$ and $G_2^{RE} = K_{(1,1)}$, where $K_{(i,j)}$ is the (i, j) entry of the optimal Kalman gain matrix K.

Lastly, average (28) to find the average posterior belief over the state vector.

$$\overline{\mathbb{E}}_t[Z_t] = (I - KH)M\overline{\mathbb{E}}_{t-1}[Z_{t-1}] + KHMZ_{t-1} + KHm \begin{bmatrix} u_t \\ e_t \end{bmatrix} \tag{29}$$

At this point, the definition of F_t in (23) and equations (24) and (29) define a fixed point, which we can use to solve for the unknown coefficients in our conjecture. Leaving the algebraic details to Appendix E, we find that the *reported* forecast of agent i follows a Kalman-like recursion, with gain coefficients that deviate from optimality. Specifically,

$$\widetilde{E}_t^{(i)}[x_{t+h}] = \widetilde{E}_{t-1}^{(i)}[x_{t+h}] + G_1(s_t^i - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) + G_2(g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]), \tag{30}$$

where

$$G_1 = \frac{G_1^{RE} - \lambda K_{(2,2)}}{1 - \lambda} \text{ and } G_2 = \frac{G_2^{RE} - \lambda K_{(2,1)}}{1 - \lambda}$$

Two observations are in order. First, similar to the analytical framework we analyzed in

Section 3.1, when $\lambda > 0$ the reported forecasts deviate from optimality by overweighting the private signal at the expense under-weighting the public signal in the sense of $\frac{G_1}{G_1^{RE}} > \frac{G_2}{G_2^{RE}}$. To see this, note that $G_2^{RE} < K_{(2,1)}$: intuitively, the public signal is more informative about the average forecast than about the actual state, because the average belief depends also on the public signal noise. On the other hand, $G_1^{RE} > K_{(2,2)}$: intuitively, the private signal is less informative about the average forecast than about the actual state, as the average forecast also depends on the public noise.

Second, the structure of the reported forecasts $\widetilde{E}_t^{(i)}[x_{t+h}]$ falls within the general linear framework (2). Thus, given this now-familiar implication of relative under- and over-weighting of common and idiosyncratic signals, it follows that this more general model also implies $\beta_1 < 0$ and $\beta_2 > 0$ in regression (13), as we have found is true in the data.

4.1 Estimation

We estimate the model and show that it offers a very good quantitative match of the key empirical facts. Once we have convinced ourselves the model offers a good fit of the data, we then use the model to filter out the true expectations of forecasters that underlie the forecasts they report to the SPF.

We estimate the model separately for each forecasted series in the SPF. For each series (e.g. GDP growth), we first estimate an AR(1) process on its realized values and recover the autoregressive coefficient ρ and the fundamental disturbance variance χ^{-1} that best describe each series. Given those parameters, we use simulated method of moments (SMM) to estimate the remaining parameters of the model: the public noise variance $\sigma_e^2 \equiv \nu^{-1}$, the private noise variance $\sigma_\eta^2 \equiv \tau^{-1}$ and the strategic incentive parameter λ.

The data moments we target for the SMM step are the average cross sectional dispersion of forecast errors, the coefficient β_1 from our key regression in equation (13), and estimated information gain coefficient G from regression (5) We choose these three moments as they are differently affected by the three parameters to be estimated and therefore provide good identification.

First, as foreshadowed in Section 3.1, a larger strategic incentive parameter λ increases the elasticity of posted forecasts to new information G, since the new information (i.e. g_t and $\eta_t^{(i)}$) is partly idiosyncratic and thus gets overweighted as a whole (see first result in Proposition 1) . Similarly, G is increasing in the precision of both the public and the

Table 5: Estimated parameters

Variable	ρ (1)	$\frac{\sigma_e}{\sigma_u}$ (2)	$\frac{\sigma_\eta}{\sigma_u}$ (3)	λ (4)
Nominal GDP	0.93	1.48	1.70	0.74
GDP price index inflation	0.93	1.60	2.13	0.88
Real GDP	0.80	1.30	1.36	0.47
Consumer Price Index	0.78	1.38	1.60	0.61
Industrial production	0.85	1.28	1.86	0.68
Housing Start	0.85	1.38	1.81	0.70
Real Consumption	0.87	1.33	1.84	0.67
Real residential investment	0.89	1.56	1.74	0.49
Real nonresidential investment	0.89	2.37	1.28	0.25
Real state and local government consumption	0.89	1.32	2.79	0.90
Real federal government consumption	0.80	1.29	2.90	0.87
Ten-year Treasury rate	0.83	1.81	1.56	0.72
AAA Corporate Rate Bond	0.85	1.76	1.82	0.87

private signals, ν and τ respectively, since G_1^{RE} and G_2^{RE} are increasing in those. On the other hand, as per Proposition 3, β_1 is directly informative about the weight put on the idiosyncratic signal $\eta_t^{(i)}$, G_1, which is increasing in the precision of the private signal τ but decreasing in the precision of the public signal ν, since those have opposite effects on the underlying optimal weight G_1^{RE}. Lastly, the dispersion of forecasts is increasing in λ (since that directly increases the weight put on the idiosyncratic signal, G_1), but decreasing in the precision of public signal ν (since that lowers the underlying optimal weight on the idiosyncratic signal, G_1^{RE}).

Table 5 reports the estimated parameters for each series. Most prominently, we find that the estimated strategic incentives coefficient is large and also similar across the different series, with an average value of roughly 0.7. The only exception being real non-residential investment, in which case we estimate a lower, but still substantially positive $\lambda = 0.25$.

In Table 6 we report how well the model fits both the targeted moments, and a number of untargeted moments. First, we note that the model is able to essentially perfectly match all targeted moments (columns 1-6).

Second, we also evaluate the model against several untargeted moments. For this exercise, we consider the model's fit of the influential regression coefficients of CG and BGMS,

Table 6: Moments in data and model

	Targeted moments						Untargeted moments					
	Mean Dispersion		C		β_1		β_{CG}		β_{BGMS}		β_2	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Nominal GDP	1.49	1.49	0.53	0.53	-0.54	-0.54	0.52	0.41	-0.25	-0.31	0.75	0.21
GDP price index inflation	0.33	0.33	0.49	0.49	-0.68	-0.68	0.29	0.50	-0.35	-0.44	0.81	0.31
Real GDP	0.92	0.92	0.56	0.56	-0.34	-0.34	0.65	0.33	-0.10	-0.15	0.57	0.13
Consumer Price Index	0.31	0.31	0.49	0.49	-0.48	-0.48	0.22	0.38	-0.30	-0.24	0.67	0.16
Industrial production	3.71	3.71	0.50	0.50	-0.59	-0.59	0.21	0.22	-0.30	-0.22	0.79	0.26
Housing Start	110.04	110.04	0.49	0.49	-0.58	-0.58	0.38	0.32	-0.28	-0.28	0.78	0.23
Real Consumption	0.51	0.51	0.49	0.49	-0.56	-0.56	0.31	0.25	-0.26	-0.23	0.80	0.23
Real residential investment	27.03	27.03	0.41	0.41	-0.37	-0.37	1.22	0.40	-0.08	-0.17	0.73	0.11
Real nonresidential investment	7.38	7.38	0.48	0.48	-0.12	-0.12	1.21	0.94	0.08	-0.10	0.65	0.01
Real state and local government consumption	1.41	1.41	0.47	0.47	-0.84	-0.84	0.63	0.17	-0.48	-0.41	0.91	0.45
Real federal government consumption	6.40	6.40	0.43	0.43	-0.83	-0.83	-0.23	0.12	-0.56	-0.35	0.93	0.37
Ten-year Treasury rate	0.17	0.17	0.51	0.51	-0.47	-0.47	-0.01	0.69	-0.22	-0.38	0.76	0.09
AAA Corporate Rate Bond	0.34	0.34	0.54	0.54	-0.61	-0.61	-0.03	0.62	-0.27	-0.48	0.83	0.18

and also the β_2 coefficient in our key regression, all of which we had left untargeted. Indeed, note that the CG coefficient is different from our estimation target G, since the common noise term biases β_{CG} away from being a one-to-one function of G (see discussion in Section 2.2). Similarly, the β_1 coefficient we target is indicative of overreaction specifically of the idiosyncratic signal, but not of the overall overreaction BGMS captures.

We find that the model does an excellent job of fitting the BGMS coefficients for virtually all series. This shows that the model is very much able to generate empirically relevant amounts of over-reaction in individual forecasts, without the need to assume any deviations from rationality. Second the model also generally fits the CG coefficients well, except for the case of the interest rate series. And third, the model also consistently generates positive β_2 coefficients, and if anything underestimates the degree to which public information is underweighted in the data. Thus, our estimation is in fact conservative in terms of its implications of the underweighting of public info.

Lastly, we use the estimated model to recover the implied true beliefs of forecasters. A first important finding of this analysis is that the true individual beliefs of forecasters are significantly less precise than what might be inferred from the reported forecasts. To showcase this we report several moments of interest in Table 7.

First, we compute the actual elasticity to new information of the true underlying beliefs, which we call G^{Honest} to differentiated from the elasticity of the reported forecasts, which we have labeled G all along. This elasticity was the key object of interest of Coibion and Gorodnichenko (2015) study, and speaks to the degree of information noise and frictions in the economy.

In column 1, we report the G that we would estimate if were to assume that the reported forecasts $\widetilde{E}_t^{(i)}[x_{t+h}]$ are the true expectations of the agents and we apply directly regression (5). This was a targeted moment of our estimation, and the model's implication there perfectly matches the data when we apply the same regression to reported SPF forecasts. We call this the "posted" G. In column 2, instead, we report the true underlying elasticity to new information, G^{RE}, that is implied by our estimated model. We call this the "honest" or true G. Comparing the two series of estimates, we find that the true beliefs are significantly "stickier", and put a much smaller weight on new information as compared to the raw reported forecasts. The average G of the true beliefs is about 20-25% lower than that of the raw reported forecasts themselves.

Table 7: Posted and honest moments

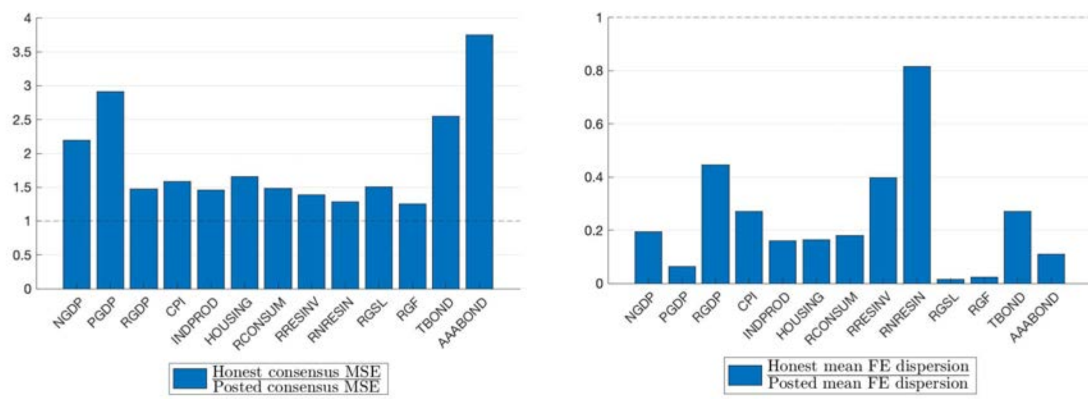
	G			Consensus MSE			Dispersion		
Variable	Posted (1)	Honest (2)	Ratio (3)	Posted (4)	Honest (5)	Ratio (6)	Posted (7)	Honest (8)	Ratio (9)
Nominal GDP	0.53	0.40	0.76	0.49	1.07	2.19	1.49	0.29	0.19
GDP price index inflation	0.49	0.32	0.66	0.05	0.14	2.92	0.33	0.02	0.06
Real GDP	0.56	0.49	0.88	0.78	1.14	1.47	0.92	0.41	0.44
Consumer Price Index	0.49	0.40	0.82	0.23	0.36	1.58	0.31	0.08	0.27
Industrial production	0.50	0.44	0.87	3.51	5.11	1.46	3.71	0.60	0.16
Housing Start	0.49	0.40	0.82	69.95	115.75	1.65	110.04	18.10	0.16
Real Consumption	0.49	0.42	0.86	0.46	0.68	1.49	0.51	0.09	0.18
Real residential investment	0.41	0.36	0.87	29.60	40.95	1.38	27.03	10.76	0.40
Real nonresidential investment	0.48	0.43	0.90	4.12	5.30	1.29	7.38	6.01	0.82
Real state and local government consumption	0.47	0.40	0.86	0.54	0.81	1.51	1.41	0.02	0.02
Real federal government consumption	0.43	0.39	0.90	5.96	7.49	1.26	6.40	0.14	0.02
Ten-year Treasury rate	0.51	0.33	0.64	0.04	0.11	2.55	0.17	0.05	0.27
AAA Corporate Rate Bond	0.54	0.29	0.54	0.04	0.14	3.75	0.34	0.04	0.11

The reason is intuitive. The strategic diversification incentives give reason for agents to overweight their idiosyncratic signals and underweight the public signals in their reported forecasts. However, as discussed before, in their reported forecasts agents optimally overweight the idiosyncratic signals by a higher degree than the degree to which they underweight public signals, and as a result the overall weight put on new information in reported forecasts is higher than for the true underlying beliefs of the agents.

A second, related, but distinct implication is that the consensus forecast $\overline{E}_t[x_{t+h}]$ is in fact a highly accurate predictor of x_{t+h}, even though the individual forecasts underlying that consensus are suboptimal and display predictable errors. As explained in Section 3.1, the reason is that the overweighted idiosyncratic errors wash out when we average across forecasters. The magnitude of the relative difference in precision can be appreciated by looking at the difference between the mean squared error of the average of reported forecasts (i.e. the "consensus") and the corresponding MSE of the average of the agent's underlying true beliefs. We juxtapose those two numbers, as estimated by our model, in columns 4 and 5 of Table 7 and also plot the ratio visually in panel (a) of Figure 7. For some variables (nominal GDP, CPI, Housing Start, Ten-year and AAA bond rate) the true mean squared error is more than *1.5 times larger* than the MSE of the actual reported consensus forecast. Thus, the strategic behavior in reporting actually has the unintended consequences of making the reported consensus forecast a surprisingly good predictor, as it harnesses the dispersed information available to agents better than the average of the true underlying expectations.

And finally, the overweighting of idiosyncratic signals also artificially increases the cross-sectional dispersion of both forecast errors and reported forecasts, which two moments are often used as a model-free proxies for uncertainty and disagreement in the literature (e.g. Kozeniauskas et al. 2018). We report both the dispersion of the reported forecasts and the dispersion of the true underlying beliefs in columns 7 and 8, and also plot them visually in panel (b) Figure 7. We find the striking result that the actual, true dispersion of agents' beliefs is often *less than half* of the dispersion in reported forecasts.

All three of these results suggest that we should be cautious about the use of SPF moments for directly inferring the information noise and frictions that agents actually face. First, reported forecasts overweight new information, so estimates of G at the individual level are overstated. Second, the precision of the consensus forecast is artificially much higher than the precision of the actual underlying beliefs of the forecasts. And lastly, the dispersion in the SPF forecasts is also much higher than the actual dispersion in beliefs. Surveys of forecasts can still be very useful for inferring deep economic parameters of interest, such as signal precision, but the survey data needs to be filtered to uncover the



(a) Mean Squared Errors

(b) Forecast dispersion

Figure 7: Honest and posted forecasts

Notes:

true underlying beliefs by taking into account the strategic incentives facing forecasters.

5 Conclusion

In this paper we revisit empirical tests of the FIRE hypothesis using survey of expectations data. Our key insight is that strategic consideration might bias reported forecasts away from the underlying true beliefs of agents. We show that in order for a model of strategic interactions to be consistent with the seminal empirical findings of Coibion and Gorodnichenko (2015) and Bordalo et al. (2020), it needs to feature strategic diversification incentives in particular. We then show that a characteristic and differentiating prediction of such a model is that common noisy signals should be *underweighted*, even though new information as a whole should be overweighted. We take this prediction to the data and find strong and robust evidence that common signals are indeed underweighted.

Our conclusion that survey of expectations is affected by strategic incentives has far reaching implications about the use of such expectational surveys in the broader economic literature. Most obviously, the surveys are not a direct and unbiased measure of expectations, as such the raw moments cannot be directly targeted to calibrate information frictions or uncertainty parameters in models. Still, the true beliefs and the likely true parameters of the underlying information sets of agents can be estimated once the strategic incentives are taken into account, and we do so and provide such estimates in the paper.

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A Variable definitions

The forecast data come from two different datasets: the Survey of Professional Forecasters, collected by the Federal Reserve Bank of Philadelphia, and the Tealbook/Greenbook of the Federal Reserve Board of Governors.

Survey of Professional Forecasters All surveys are collected around the 3rd week of the middle month in the quarter. In this section, x_t indicate the actual value and $F_t x_{t+h}$ the forecast provided in t about horizon h. All actual values of macroeconomic series (1-12) use the first release level, which are available to forecasters in the following quarter. We transform the macroeconomic level in year-over-year growth, following the literature.

1. NGDP

   - Variable: nominal GDP.
   - Question: The level of nominal GDP in the current quarter and the next 4 quarters.
   - Forecast: Nominal GDP growth from end of quarter $t-1$ to end of quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
   - Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
   - Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

2. RGDP

   - Variable: real GDP.
   - Question: The level of real GDP in the current quarter and the next 4 quarters.
   - Forecast: real GDP growth from end of quarter $t-1$ to end of quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
   - Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
   - Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

3. PGDP

   - Variable: GDP deflator.

- Question: The level of GDP deflator in the current quarter and the next 4 quarters.
- Forecast: GDP price deflator inflation from end of quarter $t-1$ to end of quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

4. CPI

- Variable: Consumer Price Index.
- Question: CPI growth rate in the current quarter and the next 4 quarters.
- Forecast: CPI inflation from end of quarter $t-1$ to end of quarter $t+3$: $F_t(z_t/4+1) * F_t(z_{t+1}/4+1) * F_t(z_{t+2}/4+1) * F_t(z_{t+3}/4+1)$, where z is the annualized quarterly CPI inflation in quarter t.
- Revision: $F_t(z_t/4+1)*F_t(z_{t+1}/4+1)*F_t(z_{t+2}/4+1)*F_t(z_{t+3}/4+1) - F_{t-1}(z_t/4+1) * F_{t-1}(z_{t+1}/4+1) * F_{t-1}(z_{t+2}/4+1) * F_{t-1}(z_{t+3}/4+1)$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$. Real time data is not available before 1994Q3. For actual periods prior to this date, we use data published in 1994Q3 to measure the actual outcome.

5. RCONSUM

- Variable: Real consumption.
- Question: The level of real consumption in the current quarter and the next 4 quarters.
- Forecast: GDP price deflator inflation from end of quarter $t-1$ to end of quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

6. INDPROD

- Variable: Industrial production index.

- Question: The average level of the industrial production index in the current quarter and the next 4 quarters.
- Forecast: Growth of the industrial production index from quarter $t-1$ to quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

7. RNRESIN

- Variable: Real non-residential investment.
- Question: The level of real non-residential investment in the current quarter and the next 4 quarters.
- Forecast: Growth of real non-residential investment from quarter $t-1$ to quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

8. RRESIN

- Variable: Real residential investment.
- Question: The level of real residential investment in the current quarter and the next 4 quarters.
- Forecast: Growth of real residential investment from quarter $t-1$ to quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

9. RGF

- Variable: Real federal government consumption.
- Question: The level of real federal government consumption in the current quarter and the next 4 quarters.

- Forecast: Growth of real federal government consumption from quarter $t-1$ to quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

10. RGSL

- Variable: Real state and local government consumption.
- Question: The level of real state and local government consumption in the current quarter and the next 4 quarters.
- Forecast: Growth of real state and local government consumption from quarter $t-1$ to quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

11. HOUSING

- Variable: Housing starts.
- Question: The level of housing starts in the current quarter and the next 4 quarters.
- Forecast: Growth of housing starts from quarter $t-1$ to quarter $t+3$: $\frac{F_t x_{t+3}}{x_{t-1}} - 1$
- Revision: $\frac{F_t x_{t+3}}{x_{t-1}} - \frac{F_{t-1} x_{t+3}}{F_{t-1} x_{t-1}}$
- Actual: $\frac{x_{t+3}}{x_{t-1}} - 1$

12. UNEMP

- Variable: Unemployment rate.
- Question: The level of average unemployment rate in the current quarter and the next 4 quarters.
- Forecast: Average quarterly unemployment rate in quarter $t+3$: $F_t x_{t+3}$
- Revision: $F_t x_{t+3} - F_{t-1} x_{t+3}$
- Actual: x_{t+3}

13. TB3M

    - Variable: 3-month Treasury rate.
    - Question: The level of average 3-month Treasury rate in the current quarter and next 4 quarters.
    - Forecast: Average quarterly 3-month Treasury rate in quarter $t+3$: $F_t x_{t+3}$
    - Revision: $F_t x_{t+3} - F_{t-1} x_{t+3}$
    - Actual: x_{t+3}

14. TN10Y

    - Variable: 10-year Treasury rate.
    - Question: The level of average 10-year Treasury rate in the current quarter and next 4 quarters.
    - Forecast: Average quarterly 10-year Treasury rate in quarter $t+3$: $F_t x_{t+3}$
    - Revision: $F_t x_{t+3} - F_{t-1} x_{t+3}$
    - Actual: x_{t+3}

15. AAA

    - Variable: AAA corporate bond rate.
    - Question: The level of average AAA corporate bond rate in the current quarter and next 4 quarters.
    - Forecast: Average quarterly AAA corporate bond rate in quarter $t+3$: $F_t x_{t+3}$
    - Revision: $F_t x_{t+3} - F_{t-1} x_{t+3}$
    - Actual: x_{t+3}

Tealbook/Greenbook projections The Tealbook/Greenbook is produced by the Research staff at the Federal Reserve Board of Governors before each meeting of the Federal Open Market Committee. We aggregate at quarterly frequency by considering only the last projection available in any quarter. The projections from the Tealbook/Greenbook are released to the public with a lag of five years. We consider the variables forecasted also in the SPF, meaning all the macroeconomic variables with the exception of real consumption.

For most variables (NGDP, PGDP, RGDP, CPI, INDPROD, RRESINV, RNRESIN, RGF, RGSL) the projections are provided n quarter-over-quarter growth, while HOUSING is provided in level. We transform m in tear-over-year growth in order to compare them with SPF forecasts. Similarly, we keep projections for UNEMP in level. The actuals are the same as for the SPF data.

B Proofs

Proposition 1 *In the strategic incentives game in (7), the resulting forecasts imply*

$$\beta_{BGMS} = \frac{-\lambda\tau\chi}{([(1-\lambda)\nu+\tau]^2 + (1-\lambda)^2\nu\chi)} < 0 \iff \lambda > 0$$
$$\beta_{CG} = \frac{(1-\lambda)\tau\chi}{([(1-\lambda)\nu+\tau]^2 + [(1-\lambda)^2\nu+\tau]\chi)} \iff \lambda < 1$$

Proof. From equation (10),

$$\widetilde{E}_t^{(i)}[x_{t+h}] = \mu + G_1(s_t^{(i)} - \mu) + G_2(g_t - \mu)$$

and using $G = G_1 + G_2$, we have that

$$\begin{aligned} \widetilde{E}_t^{(i)}[x_{t+h}] &= \mu + G(x_{t+h} - \mu) + G_1\eta_t^{(i)} + G_2 e_t \\ (1-G)(\widetilde{E}_t^{(i)}[x_{t+h}] - \mu) &= G(x_{t+h} - \widetilde{E}_t^{(i)}[x_{t+h}]) + G_1\eta_t^{(i)} + G_2 e_t \\ (\underbrace{x_{t+h} - \widetilde{E}_t^{(i)}[x_{t+h}]}_{fe_t^{(i)}}] &= \frac{1-G}{G}(\underbrace{\widetilde{E}_t^{(i)}[x_{t+h}] - \mu}_{fr_t^{(i)}}) - \frac{G_1}{G}\eta_t^{(i)} - \frac{G_2}{G}e_t \end{aligned} \tag{31}$$

From here, we can compute the large sample limit of β_{BGMS} as:

$$\begin{aligned} \beta_{BGMS} &= \frac{1-G}{G} + \frac{Cov(\widetilde{E}_t^{(i)}[x_{t+h}] - \mu, -\frac{G_1}{G}\eta_t^{(i)} - \frac{G_2}{G}e_t)}{Var(\widetilde{E}_t^{(i)}[x_{t+h}] - \mu)} \\ &= \frac{1-G}{G} + \frac{-\frac{G_1^2}{G}\tau^{-1} - \frac{G_2^2}{G}\nu^{-1}}{G^2\chi^{-1} + G_1^2\tau^{-1} + G_2^2\nu^{-1}} \end{aligned} \tag{32}$$

substitute for the optimal choices of G_1 and G_2:

$$G_1 = \frac{G_1^{RE}}{(1-\lambda) + \lambda G_1^{RE}}$$

$$G_2 = \frac{(1-\lambda)G_2^{RE}}{(1-\lambda) + \lambda G_1^{RE}}$$

and the optimal weights $G_1^{RE} = \frac{\tau}{\tau+\nu+\chi}$ and $G_2^{RE} = \frac{\nu}{\nu+\tau+\chi}$ to obtain

$$\hat{\beta}_{BGMS} = \frac{-\lambda\tau\chi}{([(1-\lambda)\nu+\tau]^2 + [(1-\lambda)^2\nu+\tau]\chi)} < 0 \iff \lambda > 0 \tag{33}$$

For the β_{CG}, integrate equation (31) across i to obtain

$$(\underbrace{x_{t+h} - \overline{E}_t[x_{t+h}]}_{\overline{fe}_t} = \frac{1-G}{G}(\underbrace{\overline{E}_t[x_{t+h}] - \mu}_{\overline{fr}_t}) - \frac{G_2}{G}e_t$$

Then we can compute the large sample limit as

$$\begin{aligned}\beta_{CG} &= \frac{1-G}{G} + \frac{Cov(\overline{E}_t[x_{t+h}] - \mu, -\frac{G_2}{G}e_t)}{Var(\overline{E}_t[x_{t+h}] - \mu)} \\ &= \frac{1-G}{G} + \frac{-\frac{G_2^2}{G}\nu^{-1}}{G^2\chi^{-1} + G_1^2\nu^{-1}}\end{aligned} \tag{34}$$

Substituting through with G_1, G_2, G_1^{RE} and G_2^{RE} and simplifying we get

$$\beta_{CG} = \frac{(1-\lambda)\tau\chi}{([(1-\lambda)\nu+\tau]^2 + [(1-\lambda)^2\nu+\tau]\chi)} \iff \lambda < 1$$

■

Proposition 2 *In the strategic incentives game in (7) with $\lambda \in (0,1)$, the resulting consensus forecast implies*

$$Var(x_{t+h} - \overline{E}_t(x_{t+h})) = \frac{(1-\lambda)^2}{(1-\lambda+\lambda G_2^{RE})^2} Var(x_{t+h} - \overline{\mathbb{E}}_t(x_{t+h})) < Var(x_{t+h} - \overline{\mathbb{E}}_t(x_{t+h}))$$

Proof.

$$\begin{aligned}
Var(x_{t+h} - \overline{\mathbb{E}}_t[x_{t+h}]) &= Var((1 - (\underbrace{G_1^{RE} + G_2^{RE}}_{\equiv G^{RE}}))x_{t+h} + G_2^{RE} e_t) \\
&= (1 - G^{RE})^2 \frac{1}{\chi} + \frac{(G_2^{RE})^2}{\nu} \\
&= \frac{\chi + \nu}{(\nu + \tau + \chi)^2}
\end{aligned}$$

Meanwhile, the MSE of the consensus of the reported forecasts is

$$\begin{aligned}
Var(x_{t+h} - \overline{E}_t[x_{t+h}]) &= Var((1 - G)x_{t+h} + G_2 e_t) \\
&= (1 - G)^2 \frac{1}{\chi} + \frac{(G_2)^2}{\nu} \\
&= \frac{(1 - \lambda)^2}{(1 - \lambda + \lambda G_2^{RE})^2} \frac{\chi + \nu}{(\nu + \tau + \chi)^2} \\
&= \frac{(1 - \lambda)^2}{(1 - \lambda + \lambda G_2^{RE})^2} Var(x_{t+h} - \overline{\mathbb{E}}_t(x_{t+h}))
\end{aligned}$$

And thus

$$Var(x_{t+h} - \overline{E}_t[x_{t+h}]) < Var(x_{t+h} - \overline{\mathbb{E}}_t(x_{t+h}))$$

since

$$\frac{(1 - \lambda)^2}{(1 - \lambda + \lambda G_2^{RE})^2} < 1$$

for $\lambda \in (0, 1)$. ■

Proposition 3 *If agents forecasts follow (2), then for any stationary process* x_t

$$\beta_1 < 0 \iff G_1 > \frac{G_1^{RE}}{G^{RE} + \frac{\Sigma^{RE}}{\widetilde{\Sigma}}(1 - G^{RE})}$$

$$\beta_2 > 0 \iff \frac{G_1}{G_1^{RE}} > \frac{G_2}{G_2^{RE}}$$

where $\widetilde{\Sigma} \equiv var(x_t - \widetilde{E}_{t-1}^{(i)}[x_t])$ *and* $\Sigma^{RE} \equiv var(x_{t+h} - \mathbb{E}_{t-1}^{(i)}[x_{t+h}])$.

Proof. Rewriting (2) we can express forecast errors as

$$fe_{t+h,t}^{(i)} = \frac{1 - G_1}{G_1}(\widetilde{E}_t^{(i)}[x_{t+h}] - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) - \frac{G_2}{G_1}(g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) - \eta_t^{(i)}$$

Let $pi^{(i)}_{t+h,t} = g_t - \widetilde{E}^{(i)}_{t-1}[x_{t+h}]$, then we can write regression (13) as

$$fe^i_{t,t} = X\beta + u^{(i)}_t \tag{35}$$

with $X = [fr^i_{t+h,t} \quad pi^i_{t+h,t}]$, $\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix}$ and $u^{(i)}_t = \eta^{(i)}_t$. The resulting probability limit of the regression coefficient is

$$\beta = \begin{bmatrix} \frac{1-G_1}{G_1} \\ -\frac{G_2}{G_1} \end{bmatrix} + \Sigma^{-1}_{XX}\Sigma_{Xu} \tag{36}$$

where

$$\begin{aligned}
\Sigma_{XX} &= \begin{bmatrix} var(fr^i_{t+h,t}) & cov(fr^i_{t,t}, pi^i_{t+h,t}) \\ cov(fr^i_{t+h,t}, pi^i_{t,t}) & var(pi^i_{t+h,t}) \end{bmatrix} \\
\Sigma^{-1}_{XX} &= \frac{1}{var(fr^i_{t+h,t})var(pi^i_{t+h,t}) - cov(fr^i_{t+h,t}, pi^i_{t+h,t})^2} \begin{bmatrix} var(pi^i_{t+h,t}) & -cov(fr^i_{t+h,t}, pi^i_{t+h,t}) \\ -cov(fr^i_{t+h,t}, pi^i_{t+h,t}) & var(fr^i_{t+h,t}) \end{bmatrix} \\
\Sigma_{Xu} &= \begin{bmatrix} cov(fr^i_{t+h,t}, u^{(i)}_t) \\ cov(pi^i_{t+h,t} u^{(i)}_t) \end{bmatrix}
\end{aligned} \tag{37}$$

Given that

$$\begin{aligned}
var(fr^i_{t+h,t}) &= [G^2\widetilde{\Sigma} + G_1^2\tau^{-1} + G_2^2\nu^{-1}] \\
var(pi^i_{t+h,t}) &= \widetilde{\Sigma} + \nu^{-1} \\
cov(fr^i_{t+h,t}, pi^i_{t,t}) &= [G\widetilde{\Sigma} + G_2\nu^{-1}] \\
cov(fr^i_{t+h,t}, u^i_t) &= -G_1\tau^{-1} \\
cov(pi^i_{t+h,t}, u^i_t) &= 0
\end{aligned} \tag{38}$$

and $\widetilde{\Sigma} = var(x_{t+h} - \widetilde{E}_{t-1}^{(i)}[x_{t+h}])$, it follows that

$$\begin{aligned}
\beta_1 &= \frac{1-G_1}{G_1} + \frac{var(pi_{t+h,t}^i)cov(fr_{t+h,t}^i, u_t^i)}{var(fr_{t+h,t}^i)var(pi_{t+h,t}^i) - cov(fr_{t+h,t}^i, pi_{t+h,t}^i)^2} \\
&= \frac{1-G_1}{G_1} - \frac{(\widetilde{\Sigma}+\nu^{-1})G_1\frac{1}{\tau}}{(\widetilde{\Sigma}+\nu^{-1})(G^2\hat{\Sigma} + G_1^2\tau^{-1} + G_2^2\nu^{-1}) - (G\widetilde{\Sigma} + G_2\nu^{-1})^2} \\
&= \frac{1}{G_1}\left(G_1^{RE}\frac{\nu+\tau+1/\Sigma^{RE}}{\nu+\tau+1/\widetilde{\Sigma}} - G_1\right) \\
&< 0 \iff G_1^{RE}\frac{\nu+\tau+1/\Sigma^{RE}}{\nu+\tau+1/\widetilde{\Sigma}} < G_1
\end{aligned} \tag{39}$$

Using the definitions $G_1^{RE} = \frac{\tau}{\tau+\nu+1/\Sigma^{RE}}$ and $G_2^{RE} = \frac{\nu}{\tau+\nu+1/\Sigma^{RE}}$, where again $\Sigma^{RE} = var(x_{t+h} - \mathbb{E}_t^{(i)}[x_{t+h}]$ is the rational posterior variance, it follows that

$$\beta_1 < 0 \iff G_1 > \frac{G_1^{RE}}{G^{RE} + \frac{\Sigma^{RE}}{\widetilde{\Sigma}}(1-G^{RE})}$$

Next, working with the second regression coefficient we have

$$\begin{aligned}
\beta_2 &= -\frac{G_2}{G_1} + \frac{-cov(fr_{t+h,t}^i, pi_{t+h,t}^i)cov(fr_{t+h,t}^i, u_t^i)}{var(fr_{t+h,t}^i)var(pi_{t+h,t}^i) - cov(fr_{t+h,t}^i, pi_{t+h,t}^i)^2} \\
&= -\frac{G_2}{G_1} + \frac{(G\widetilde{\Sigma}+G_2\nu^{-1})G_1\frac{1}{\tau}}{(\widetilde{\Sigma}+\nu^{-1})(G^2\hat{\Sigma} + G_1^2\tau^{-1} + G_2^2\nu^{-1}) - (G\widetilde{\Sigma} + G_2\nu^{-1})^2} \\
&= \frac{1}{G_1}\frac{\nu+\tau+1/\Sigma^{RE}}{\nu+\tau+1/\widetilde{\Sigma}}\left(G_1G_2^{RE} - G_2G_1^{RE}\right) \\
&> 0 \iff \frac{G_1}{G_1^{RE}} > \frac{G_2}{G_2^{RE}}
\end{aligned} \tag{40}$$

■

Proposition 4 *When forecasts follow a linear structure as in (2) and x_t is stationary*

$$\beta_{BK} > 0 \iff \frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}}\frac{\Sigma^{RE}}{\widetilde{\Sigma} + Cov(x_{t+h} - \widetilde{E}_{t-1}^{(i)}[x_{t+h}], \widetilde{E}_{t-1}^{(i)}[x_{t+h}])}$$

Proof. Using

$$fe_{t+h,t}^{(i)} = \frac{1-G_1}{G_1}(\widetilde{E}_t^{(i)}[x_{t+h}] - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) - \frac{G_2}{G_1}(g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) - \eta_t^{(i)}$$

it follows that the probability limit of the β_{BK} coefficient is

$$
\begin{aligned}
\beta_{BK} &= \frac{Cov(fe^{(i)}_{t+h,t}, g_t)}{Var(g_t)} \\
&= \frac{-\frac{G_2}{G_1}Cov(g_t - \widetilde{E}^{(i)}_{t-1}[x_{t+h}], g_t) + \frac{1-G_1}{G_1}Cov(G(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) + G_1\eta^{(i)}_t + G_2 e_t, g_t)}{Var(x_t) + \nu^{-1}} \\
&= \frac{\frac{G_2}{G_1}\left(Cov(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}], x_{t+h})[(1-G_1)\frac{G}{G_2} - 1] - G_1\nu^{-1}\right)}{Var(x_t) + \nu^{-1}} \\
&= \frac{\frac{G_2}{G_1}\left((Cov(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}], \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) + \widetilde{\Sigma})[(1-G_1)\frac{G}{G_2} - 1] - G_1\nu^{-1}\right)}{Var(x_t) + \nu^{-1}} \\
&> 0 \iff (Cov(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}], \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) + \widetilde{\Sigma})[(1-G_1)\frac{G}{G_2} - 1] - G_1\nu^{-1} > 0 \\
&\iff (Cov(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}], \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) + \widetilde{\Sigma})(1-G) > G_2\nu^{-1} \\
&\iff \frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}}\frac{\Sigma^{RE}}{\widetilde{\Sigma} + Cov(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}], \widetilde{E}^{(i)}_{t-1}[x_{t+h}])}
\end{aligned}
$$

■

Proposition 5 *When forecasts follow a linear structure as in (2) and x_t is stationary*

$$
\beta_{BK_{dm}} > 0 \iff \frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}}\frac{\Sigma^{RE}}{\widetilde{\Sigma}}
$$

Proof. Using

$$
fe^{(i)}_{t+h,t} = \frac{1-G_1}{G_1}(\widetilde{E}^{(i)}_t[x_{t+h}] - \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) - \frac{G_2}{G_1}(g_t - \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) - \eta^{(i)}_t
$$

it follows that the probability limit of the $\beta_{BK_{dm}}$ coefficient is

$$
\begin{aligned}
\beta_{BK_{dm}} &= \frac{Cov(fe^{(i)}_{t+h,t}, g_t)}{Var(g_t - \widetilde{E}^{(i)}_{t-1}[x_{t+h}])} \\
&= \frac{-\frac{G_2}{G_1}(\widetilde{\Sigma} + \nu^{-1}) + \frac{1-G_1}{G_1}Cov(G(x_{t+h} - \widetilde{E}^{(i)}_{t-1}[x_{t+h}]) + G_1\eta^{(i)}_t + G_2 e_t, g_t - \widetilde{E}^{(i)}_{t-1}[x_{t+h}])}{\widetilde{\Sigma} + \nu^{-1}} \\
&= \frac{-\frac{G_2}{G_1}(\widetilde{\Sigma} + \nu^{-1}) + \frac{1-G_1}{G_1}(G\widetilde{\Sigma} + G_2\nu^{-1})}{\widetilde{\Sigma} + \nu^{-1}}
\end{aligned}
$$

$$= \frac{(1-G)\widetilde{\Sigma} - G_2\nu^{-1}}{\widetilde{\Sigma} + \nu^{-1}}$$

$$> 0 \iff (1-G)\widetilde{\Sigma} > G_2\nu^{-1}$$

$$\iff \frac{1-G}{1-G^{RE}} > \frac{G_2}{G_2^{RE}} \frac{\Sigma^{RE}}{\widetilde{\Sigma}}$$

■

C Additional tables

C.1 Full details on Coibion and Gorodnichenko (2015) regressions

Table C.1: Standard CG regression estimates

	3 quarters horizon				2 quarters horizon			
	β_{CG}	SE	p-value	Median	β_{CG}	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	0.53	0.02	0.00	0.49	0.61	0.01	0.00	0.62
GDP price index inflation	0.49	0.03	0.00	0.52	0.63	0.02	0.00	0.68
Real GDP	0.56	0.03	0.00	0.52	0.63	0.02	0.00	0.62
Consumer Price Index	0.49	0.02	0.00	0.53	0.70	0.02	0.00	0.71
Industrial production	0.50	0.03	0.00	0.52	0.59	0.02	0.00	0.63
Housing Start	0.49	0.03	0.00	0.55	0.53	0.02	0.00	0.56
Real Consumption	0.49	0.03	0.00	0.48	0.63	0.03	0.00	0.62
Real residential investment	0.41	0.03	0.00	0.44	0.56	0.02	0.00	0.64
Real nonresidential investment	0.48	0.02	0.00	0.49	0.61	0.03	0.00	0.61
Real state and local government consumption	0.43	0.04	0.00	0.40	0.60	0.05	0.00	0.56
Real federal government consumption	0.47	0.04	0.00	0.48	0.62	0.03	0.00	0.62
Unemployment rate	0.49	0.02	0.00	0.54	0.56	0.02	0.00	0.62
Three-month Treasury rate	0.55	0.02	0.00	0.59	0.63	0.03	0.00	0.67
Ten-year Treasury rate	0.51	0.02	0.00	0.54	0.60	0.02	0.00	0.63
AAA Corporate Rate Bond	0.54	0.02	0.00	0.56	0.61	0.02	0.00	0.62

Notes: The table shows the result from regression (3) Columns (1)-(3) report coefficients, standard errors and p-values from the panel data regression with individual fixed effects. Column (4) reports the median coefficient from individual regressions using demeaned variables. Columns (5)-(8) reports the same statistics for the 2 quarters horizon. Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level.

C.2 Full details on Bordalo et al. (2020) regressions

C.3 Underreaction to public information at shorter horizon

C.4 Demeaned and non-demeaned Broer and Kohlhas (2022) regressions

Table C.2: Difference between estimated gains G and G_{CG}, horizon 3 quarters

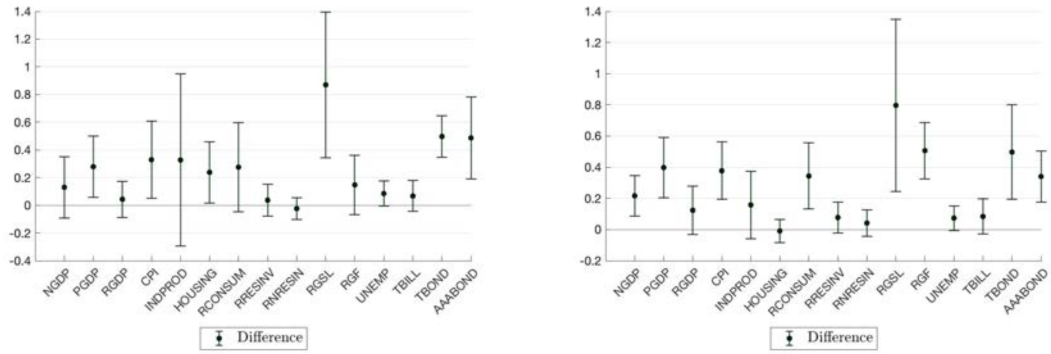
Variable	G_{CG} (1)	SE (2)	G (3)	SE (4)	Difference (5)	SE (6)	p-value (7)
Nominal GDP	0.66	0.13	0.53	0.02	0.13	0.13	0.17
GDP price index inflation	0.77	0.13	0.49	0.03	0.28	0.13	0.02
Real GDP	0.60	0.07	0.56	0.03	0.04	0.08	0.29
Consumer Price Index	0.82	0.17	0.49	0.02	0.33	0.17	0.03
Industrial production	0.83	0.38	0.50	0.03	0.33	0.38	0.19
Housing Start	0.72	0.13	0.49	0.03	0.24	0.13	0.04
Real Consumption	0.76	0.19	0.49	0.03	0.28	0.20	0.08
Real residential investment	0.45	0.07	0.41	0.03	0.04	0.07	0.30
Real nonresidential investment	0.45	0.04	0.48	0.02	-0.02	0.05	0.69
Real state and local government consumption	1.30	0.32	0.43	0.04	0.87	0.32	0.00
Real federal government consumption	0.61	0.12	0.47	0.04	0.15	0.13	0.13
Unemployment rate	0.57	0.05	0.49	0.02	0.08	0.05	0.06
Three-month Treasury rate	0.62	0.07	0.55	0.02	0.07	0.07	0.16
Ten-year Treasury rate	1.01	0.09	0.51	0.02	0.50	0.09	0.00
AAA Corporate Rate Bond	1.03	0.18	0.54	0.02	0.49	0.18	0.00

Notes: Columns (1)-(2) reports the implied gain from CG regressions of table 3. Columns (3)-(4) replicate the gain estimate from regression (5) Columns (5)-(8) reports the difference between column (1) and (3), its standard error and the probability of rejecting the null of column (5) lower or equal to zero.

Table C.3: Difference between estimated gains G and G_{CG}, horizon 2 quarters

Variable	G_{CG} (1)	SE (2)	G (3)	SE (4)	Difference (5)	SE (6)	p-value (7)
Nominal GDP	0.83	0.08	0.61	0.01	0.22	0.08	0.00
GDP price index inflation	1.03	0.12	0.63	0.02	0.40	0.12	0.00
Real GDP	0.75	0.09	0.63	0.02	0.12	0.09	0.10
Consumer Price Index	1.08	0.11	0.70	0.02	0.38	0.11	0.00
Industrial production	0.75	0.13	0.59	0.02	0.16	0.13	0.11
Housing Start	0.52	0.04	0.53	0.02	-0.01	0.04	0.58
Real Consumption	0.97	0.12	0.63	0.03	0.34	0.13	0.00
Real residential investment	0.64	0.06	0.56	0.02	0.08	0.06	0.10
Real nonresidential investment	0.66	0.04	0.61	0.03	0.04	0.05	0.21
Real state and local government consumption	1.40	0.33	0.60	0.05	0.80	0.34	0.01
Real federal government consumption	1.12	0.11	0.62	0.03	0.51	0.11	0.00
Unemployment rate	0.63	0.05	0.56	0.02	0.07	0.05	0.06
Three-month Treasury rate	0.71	0.06	0.63	0.03	0.08	0.07	0.11
Ten-year Treasury rate	1.10	0.18	0.60	0.02	0.50	0.18	0.00
AAA Corporate Rate Bond	0.95	0.10	0.61	0.02	0.34	0.10	0.00

Notes: Columns (1)-(2) reports the implied gain from CG regressions of table 3. Columns (3)-(4) replicate the gain estimate from regression (5). Columns (5)-(8) reports the difference between column (1) and (3), its standard error and the probability of rejecting the null of column (5) lower or equal to zero.



(a) Horizon 3 quarters

(b) Horizon 2 quarters

Figure C.1: Estimated gains: our measure vs CG

Notes: the Figure plot the difference between the gain G implied by the original CG regression (3) and our estimated coefficients in regression (5). Standard errors are robust to heteroskedasticity and Newey-West with the automatic bandwidth selection procedure of Newey and West (1994). Bars reports the 90% confidence interval for the estimated coefficients. Panel (a) reports the result for the 3 quarters horizon, panel (b) for the 2 quarters.

Table C.4: BGMS: Individual errors on revisions

	3 quarters horizon				2 quarters horizon			
	β_{BGMS}	SE	p-value	Median	β_{BGMS}	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.25	0.08	0.00	-0.19	-0.11	0.06	0.10	-0.08
GDP price index inflation	-0.35	0.04	0.00	-0.35	-0.25	0.04	0.00	-0.26
Real GDP	-0.10	0.08	0.24	0.07	-0.07	0.10	0.45	0.02
Consumer Price Index	-0.30	0.09	0.00	-0.29	-0.24	0.07	0.00	-0.24
Industrial production	-0.30	0.14	0.04	-0.31	-0.01	0.10	0.94	0.03
Housing Start	-0.28	0.09	0.00	-0.28	0.12	0.05	0.03	0.07
Real Consumption	-0.26	0.12	0.04	-0.24	-0.16	0.08	0.07	-0.16
Real residential investment	-0.08	0.10	0.44	-0.07	0.07	0.08	0.41	0.02
Real nonresidential investment	0.08	0.13	0.56	0.15	0.10	0.07	0.18	0.10
Real state and local government consumption	-0.56	0.05	0.00	-0.52	-0.30	0.05	0.00	-0.26
Real federal government consumption	-0.48	0.04	0.00	-0.40	-0.28	0.04	0.00	-0.27
Unemployment rate	0.24	0.16	0.13	0.19	0.20	0.11	0.09	0.20
Three-month Treasury rate	0.24	0.10	0.03	0.29	0.14	0.08	0.09	0.21
Ten-year Treasury rate	-0.22	0.07	0.01	-0.24	-0.24	0.09	0.01	-0.27
AAA Corporate Rate Bond	-0.27	0.07	0.00	-0.32	-0.22	0.06	0.00	-0.29

Notes: The table reports the coefficients from the BGMS regression (individual forecast errors on individual revisions). Columns (1) to (3) shows the panel data with fixed effect coefficient with standard errors and corresponding p-values. Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level. Columns (7) shows the median coefficient of the BGMS regression at the individual level.

Table C.5: Estimated coefficients on Greenbook survey: horizon 2 quarters

	BGMS			Our regression (13)					
	β_{BGMS}	SE	p-value	β_1	SE	p-value	β_2	SE	p-value
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nominal GDP	0.09	0.10	0.36	0.10	0.10	0.32	0.07	0.11	0.50
GDP price index inflation	0.31	0.18	0.09	0.25	0.16	0.11	0.24	0.20	0.22
Real GDP	0.17	0.16	0.28	0.18	0.18	0.30	0.23	0.09	0.01
Consumer Price Index	0.16	0.08	0.03	0.18	0.09	0.04	0.59	0.26	0.02
Industrial production	0.12	0.12	0.33	0.12	0.14	0.38	0.18	0.10	0.08
Housing Start	0.02	0.10	0.83	0.03	0.10	0.79	-0.12	0.11	0.26
Real residential investment	0.02	0.09	0.80	0.09	0.12	0.48	0.01	0.10	0.96
Real nonresidential investment	0.18	0.12	0.15	0.24	0.15	0.12	0.11	0.11	0.31
Real state and local government consumption	-0.19	0.10	0.06	-0.26	0.08	0.00	0.43	0.09	0.00
Real federal government consumption	-0.41	0.11	0.00	-0.65	0.21	0.00	0.49	0.20	0.01
Unemployment rate	-0.03	0.14	0.83	-0.03	0.14	0.82	-0.02	0.12	0.84

Notes: The table reports the coefficients from the BGMS regression (columns 1-3) and our regression (13) (columns 4-9) using forecasts from the Federal Reserve Green Book at horizon 2 quarters. Standard errors are robust to heteroskedasticity and Newey-West with the automatic bandwidth selection procedure of Newey and West (1994).

Table C.6: Broer and Kohlhas (2022) original (not demeaned)

	3 quarters horizon			2 quarters horizon		
	β_{BK}	SE	p-value	β_{BK}	SE	p-value
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Nominal GDP	-0.25	0.15	0.11	-0.10	0.08	0.21
GDP price index inflation	-0.23	0.08	0.01	-0.09	0.08	0.24
Real GDP	0.15	0.22	0.50	0.10	0.13	0.48
Consumer Price Index	-0.65	0.30	0.04	-0.48	0.22	0.04
Industrial production	0.22	0.20	0.28	0.16	0.13	0.25
Housing Start	-0.24	0.15	0.12	-0.09	0.13	0.51
Real Consumption	0.18	0.18	0.34	0.10	0.12	0.38
Real residential investment	0.03	0.24	0.90	0.12	0.17	0.47
Real nonresidential investment	-0.01	0.31	0.99	0.05	0.16	0.76
Real state and local government consumption	0.55	0.14	0.00	0.24	0.10	0.02
Real federal government consumption	0.28	0.18	0.13	0.20	0.13	0.13
Unemployment rate	-0.09	0.04	0.04	-0.05	0.03	0.11
Three-month Treasury rate	-0.22	0.06	0.00	-0.15	0.04	0.00
Ten-year Treasury rate	-0.10	0.06	0.11	-0.09	0.05	0.05
AAA Corporate Rate Bond	-0.17	0.05	0.00	-0.15	0.04	0.00

Notes: The table reports the coefficients from the BK regression (individual forecast errors on public signal not demeaned). Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level.

Table C.7: Broer and Kohlhas (2022) our modified version (demeaned)

	3 quarters horizon			2 quarters horizon		
	β_{BK}	SE	p-value	β_{BK}	SE	p-value
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Nominal GDP	0.47	0.03	0.00	0.40	0.02	0.00
GDP price index inflation	0.49	0.04	0.00	0.37	0.03	0.00
Real GDP	0.39	0.05	0.00	0.37	0.03	0.00
Consumer Price Index	0.46	0.05	0.00	0.27	0.05	0.00
Industrial production	0.49	0.04	0.00	0.40	0.03	0.00
Housing Start	0.50	0.04	0.00	0.46	0.03	0.00
Real Consumption	0.53	0.05	0.00	0.41	0.04	0.00
Real residential investment	0.58	0.05	0.00	0.42	0.04	0.00
Real nonresidential investment	0.59	0.04	0.00	0.40	0.04	0.00
Real state and local government consumption	0.58	0.04	0.00	0.40	0.05	0.00
Real federal government consumption	0.53	0.04	0.00	0.37	0.03	0.00
Unemployment rate	0.50	0.03	0.00	0.44	0.03	0.00
Three-month Treasury rate	0.55	0.05	0.00	0.49	0.05	0.00
Ten-year Treasury rate	0.52	0.03	0.00	0.44	0.03	0.00
AAA Corporate Rate Bond	0.50	0.03	0.00	0.40	0.04	0.00

Notes: The table reports the coefficients from our version of the BK regression (individual forecast errors on public signal demeaned). Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level.

D Comparison between public signals

Table D.1: Idiosyncratic and public information: alternative measure of public information

Panel A: 3 quarters horizon

	Revision				Public signal			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.25	0.08	0.00	-0.18	-0.05	0.12	0.69	-0.13
GDP price index inflation	-0.40	0.04	0.00	-0.40	0.39	0.15	0.01	0.30
Real GDP	-0.10	0.08	0.22	0.06	0.02	0.18	0.90	-0.09
Consumer Price Index	-0.19	0.08	0.03	-0.14	-0.56	0.28	0.06	-0.52
Industrial production	-0.30	0.14	0.03	-0.35	0.08	0.14	0.57	0.11
Housing Start	-0.09	0.09	0.36	-0.13	0.57	0.13	0.00	0.37
Real Consumption	-0.30	0.12	0.01	-0.25	0.27	0.13	0.06	0.15
Real residential investment	-0.09	0.10	0.39	-0.07	0.57	0.18	0.00	0.48
Real nonresidential investment	0.06	0.14	0.65	0.18	0.20	0.22	0.38	0.14
Real state and local government consumption	-0.53	0.05	0.00	-0.53	0.12	0.10	0.24	0.17
Real federal government consumption	-0.47	0.04	0.00	-0.39	0.28	0.09	0.00	0.19
Unemployment rate	0.26	0.16	0.10	0.18	-0.39	0.25	0.12	-0.44
Three-month Treasury rate	-0.26	0.10	0.02	-0.31	0.93	0.26	0.00	1.30
Ten-year Treasury rate	-0.63	0.05	0.00	-0.64	0.61	0.11	0.00	0.62
AAA Corporate Rate Bond	-0.69	0.04	0.00	-0.78	0.80	0.10	0.00	0.75

Panel B: 2 quarters horizon

	Revision				Public signal			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.14	0.09	0.11	-0.10	0.12	0.12	0.34	0.04
GDP price index inflation	-0.41	0.04	0.00	-0.38	0.46	0.12	0.00	0.34
Real GDP	-0.13	0.10	0.21	0.07	0.22	0.17	0.22	-0.04
Consumer Price Index	-0.07	0.14	0.59	-0.12	-0.50	0.34	0.16	-0.54
Industrial production	-0.19	0.17	0.26	-0.15	0.35	0.22	0.12	0.32
Housing Start	0.03	0.06	0.67	-0.04	0.29	0.11	0.01	0.27
Real Consumption	-0.25	0.11	0.02	-0.21	0.21	0.13	0.11	0.14
Real residential investment	-0.09	0.09	0.32	-0.12	0.41	0.14	0.00	0.41
Real nonresidential investment	0.13	0.12	0.28	0.17	-0.02	0.20	0.94	-0.11
Real state and local government consumption	-0.40	0.04	0.00	-0.36	0.20	0.10	0.05	0.25
Real federal government consumption	-0.42	0.05	0.00	-0.33	0.29	0.10	0.00	0.08
Unemployment rate	0.22	0.12	0.06	0.20	-0.30	0.18	0.10	-0.28
Three-month Treasury rate	-0.33	0.14	0.02	-0.43	0.78	0.30	0.01	1.04
Ten-year Treasury rate	-0.80	0.06	0.00	-0.92	0.75	0.12	0.00	0.76
AAA Corporate Rate Bond	-0.77	0.05	0.00	-0.83	0.92	0.07	0.00	0.88

Notes: this table reports the coefficients of regression (15) (individual forecast errors on individual revisions and public information), using the latest actual realization of the forecasted variable (i.e. x_t) as the public signal proxy. Columns 1 to 3 show coefficient β_1 (forecast revision) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 4 shows the median coefficient of the same regression at the individual level. Columns 5 to 7 show coefficient β_2 (public information) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 8 shows the median coefficient of the same regression at the individual level. Panel A uses forecast at 3 quarters horizon and panel B uses forecast at 2 quarters horizon.

Table D.2: Comparison between public signals: 3 quarters horizon

	Revision				Public signal: consensus				Public signal: realization			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median	β_3	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Nominal GDP	-0.54	0.12	0.00	-0.46	0.77	0.06	0.00	0.79	-0.16	0.12	0.19	-0.15
GDP price index inflation	-0.71	0.04	0.00	-0.66	0.79	0.04	0.00	0.85	0.27	0.14	0.07	0.22
Real GDP	-0.33	0.12	0.01	-0.18	0.57	0.09	0.00	0.62	-0.03	0.19	0.86	-0.12
Consumer Price Index	-0.36	0.12	0.01	-0.30	0.71	0.06	0.00	0.77	-0.59	0.30	0.06	-0.56
Industrial production	-0.61	0.14	0.00	-0.70	0.80	0.08	0.00	0.82	0.02	0.15	0.92	0.14
Housing Start	-0.41	0.13	0.00	-0.41	0.71	0.06	0.00	0.68	0.42	0.13	0.00	0.31
Real Consumption	-0.59	0.15	0.00	-0.58	0.80	0.08	0.00	0.84	0.23	0.13	0.10	0.14
Real residential investment	-0.36	0.14	0.01	-0.32	0.70	0.08	0.00	0.68	0.51	0.17	0.01	0.34
Real nonresidential investment	-0.12	0.18	0.50	-0.12	0.64	0.09	0.00	0.50	0.13	0.22	0.56	0.06
Real state and local government consumption	-0.84	0.05	0.00	-0.79	0.93	0.03	0.00	0.85	-0.03	0.11	0.81	-0.02
Real federal government consumption	-0.83	0.03	0.00	-0.75	0.89	0.04	0.00	0.83	0.09	0.09	0.30	0.05
Unemployment rate	0.11	0.20	0.58	0.00	0.54	0.11	0.00	0.50	-0.63	0.26	0.02	-0.55
Three-month Treasury rate	-0.44	0.11	0.00	-0.55	0.53	0.11	0.00	0.49	0.93	0.26	0.00	1.26
Ten-year Treasury rate	-0.86	0.07	0.00	-0.83	0.74	0.05	0.00	0.80	0.59	0.12	0.00	0.60
AAA Corporate Rate Bond	-0.90	0.06	0.00	-0.96	0.70	0.07	0.00	0.77	0.66	0.11	0.00	0.58

Notes: this table reports the coefficients of regression (16) (individual forecast errors on individual revisions and both proxies for public information). Columns 1 to 3 show coefficient β_1 (forecast revision) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 4 shows the median coefficient of the same regression at the individual level. Columns 5 to 7 show coefficient β_2 (lagged consensus) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 8 shows the median coefficient of the same regression at the individual level. Panel A uses forecast at 3 quarters horizon and panel B uses forecast at 2 quarters horizon. Columns 9 to 11 show coefficient β_3 (latest actual realization of x_t) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 12 shows the median coefficient of the same regression at the individual level.

Table D.3: Comparison between public signals: 2 quarters horizon

	Revision				Public signal: consensus				Public signal: realization			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median	β_3	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Nominal GDP	-0.35	0.11	0.00	-0.31	0.63	0.05	0.00	0.61	0.00	0.13	0.98	0.05
GDP price index inflation	-0.66	0.04	0.00	-0.62	0.68	0.05	0.00	0.65	0.35	0.12	0.01	0.26
Real GDP	-0.29	0.13	0.03	-0.05	0.53	0.09	0.00	0.47	0.15	0.18	0.43	-0.09
Consumer Price Index	-0.18	0.16	0.27	-0.23	0.59	0.08	0.00	0.64	-0.62	0.36	0.10	-0.57
Industrial production	-0.39	0.18	0.03	-0.43	0.55	0.08	0.00	0.50	0.41	0.22	0.07	0.34
Housing Start	-0.21	0.08	0.02	-0.20	0.52	0.06	0.00	0.53	0.25	0.12	0.03	0.20
Real Consumption	-0.49	0.13	0.00	-0.42	0.66	0.06	0.00	0.69	0.25	0.13	0.06	0.16
Real residential investment	-0.28	0.12	0.02	-0.26	0.49	0.07	0.00	0.46	0.40	0.14	0.01	0.37
Real nonresidential investment	0.02	0.13	0.91	0.06	0.45	0.06	0.00	0.44	-0.05	0.19	0.80	-0.11
Real state and local government consumption	-0.70	0.06	0.00	-0.60	0.77	0.05	0.00	0.69	0.15	0.09	0.10	0.16
Real federal government consumption	-0.79	0.04	0.00	-0.64	0.78	0.04	0.00	0.71	0.23	0.10	0.02	0.08
Unemployment rate	0.10	0.15	0.51	0.11	0.48	0.09	0.00	0.48	-0.52	0.18	0.01	-0.44
Three-month Treasury rate	-0.44	0.12	0.00	-0.53	0.46	0.13	0.00	0.35	0.76	0.29	0.01	1.05
Ten-year Treasury rate	-0.97	0.07	0.00	-1.04	0.67	0.07	0.00	0.76	0.70	0.13	0.00	0.69
AAA Corporate Rate Bond	-0.88	0.05	0.00	-0.95	0.49	0.07	0.00	0.57	0.80	0.09	0.00	0.73

Notes: this table reports the coefficients of regression (16) (individual forecast errors on individual revisions and both proxies for public information). Columns 1 to 3 show coefficient β_1 (forecast revision) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 4 shows the median coefficient of the same regression at the individual level. Columns 5 to 7 show coefficient β_2 (lagged consensus) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 8 shows the median coefficient of the same regression at the individual level. Panel A uses forecast at 3 quarters horizon and panel B uses forecast at 2 quarters horizon. Columns 9 to 11 show coefficient β_3 (latest actual realization of x_t) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 12 shows the median coefficient of the same regression at the individual level.

E Details on solving the dynamic model

From the definition on F_t in 23 it follows that

$$
\begin{aligned}
F_t &= \begin{bmatrix} \frac{1}{1-\lambda} & -\frac{\lambda}{1-\lambda} & 0 \end{bmatrix} \bar{\mathbb{E}}_t[Z_t] \equiv \xi \bar{\mathbb{E}}_t[Z_t] \\
&= \xi(I - KH)M\bar{\mathbb{E}}_{t-1}[Z_{t-1}] + \xi KHMZ_{t-1} + \xi KHm \begin{bmatrix} u_{t+h} \\ e_t \end{bmatrix}
\end{aligned} \tag{41}
$$

$$
\begin{aligned}
F_t =& (-\frac{\lambda}{1-\lambda}\rho + \frac{1}{1-\lambda}M_{2,1})\bar{\mathbb{E}}_{t-1}[x_{t-1}] + \frac{1}{1-\lambda}M_{2,2}\bar{\mathbb{E}}_{t-1}[F_{t-1}] - G\rho\bar{\mathbb{E}}_{t-1}[x_{t-1}] \\
&+ G\rho x_{t-1} + G_2 e_t + G u_{t+h} \\
=& [-\rho\frac{\lambda}{1-\lambda} + \frac{1}{1-\lambda}M_{2,1} + \frac{\lambda}{1-\lambda}M_{2,2} - G\rho]\bar{\mathbb{E}}_{t-1}[x_{t-1}] + \\
&+ M_{2,2}F_{t-1} + G\rho x_{t-1} + G u_{t+h} + G_2 e_t
\end{aligned} \tag{42}
$$

where we used 23 to substitute

$$
\frac{1}{1-\lambda}\bar{\mathbb{E}}_t[F_{t-1}] = F_{t-1} + \frac{\lambda}{1-\lambda}\bar{\mathbb{E}}_{t-1}[x_{t-1}]
$$

and we defined

$$
G_1 \equiv \frac{G_1^{RE} - \lambda K_{(2,2)}}{1-\lambda} \text{ and } G_2 \equiv \frac{G_2^{RE} - \lambda K_{(2,1)}}{1-\lambda}
$$

Equation 42 must equal the second line of the perceived law of motion 24. The solution to the fixed point is given by $M_{2,1} = G\rho$, $m_{2,1} = G$, $m_{2,2} = G_2$ and $M_{2,2} = \rho - M_{2,1}$.

Given the law of motion of unobserved state 24 and the observable 26, the posterior variance of the forecast solves the following Ricatti equation

$$
\begin{aligned}
&\Sigma \equiv \mathbb{E}[(Z_t - Z^i_{t,t-1})(Z_t - Z^i_{t,t-1})'] \\
&\Sigma = M(\Sigma - \Sigma H' \left(H\Sigma H' + \begin{bmatrix} 0 & 0 \\ 0 & \tau^{-1} \end{bmatrix} \right)^{-1} H\Sigma)M' + m \begin{bmatrix} \chi^{-1} & 0 \\ 0 & \nu^{-1} \end{bmatrix} m'
\end{aligned} \tag{43}
$$

and the Kalman filter is

$$
K = \Sigma H' \left(H\Sigma H' + \begin{bmatrix} 0 & 0 \\ 0 & \tau^{-1} \end{bmatrix} \right)^{-1} \tag{44}
$$

Finally, the individual posted forecast is

$$\widetilde{E}_t^{(i)}[x_{t+h}] = \widetilde{E}_{t-1}^{(i)}[x_{t+h}] + G_1(s_t^i - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]) + G_2(g_t - \widetilde{E}_{t-1}^{(i)}[x_{t+h}]), \tag{45}$$

which is equation 30 in the main text.

F Structural estimation at: 2 quarters horizon

Table F.1: Estimated parameters

Variable	ρ (1)	$\frac{\sigma_e}{\sigma_u}$ (2)	$\frac{\sigma_\eta}{\sigma_u}$ (3)	λ (4)
Nominal GDP	0.93	1.51	1.31	0.61
GDP price index inflation	0.90	1.10	1.08	0.32
Real GDP	0.80	1.20	1.19	0.38
Consumer Price Index	0.97	1.14	1.22	0.56
Industrial production	0.85	1.41	1.16	0.29
Housing Start	0.85	2.12	1.20	0.31
Real Consumption	0.73	1.05	1.32	0.39
Real residential investment	0.89	1.44	1.20	0.23
Real nonresidential investment	0.88	3.16	1.04	0.14
Real state and local government consumption	0.74	1.07	1.67	0.73
Real federal government consumption	0.77	1.11	1.61	0.69
Unemployment rate	0.97	3.15	1.03	-0.28
Three-month Treasury rate	0.94	3.16	1.03	0.06
Ten-year Treasury rate	0.83	1.48	1.39	0.69
AAA Corporate Rate Bond	0.85	2.13	1.53	0.83

Table F.2: Moments in data and model

	Targeted moments						Untargeted moments					
	Mean Dispersion		C		β_1		β_{CG}		β_{BGMS}		β_2	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Nominal GDP	0.94	0.94	0.61	0.61	-0.35	-0.35	0.20	0.43	-0.11	-0.22	0.62	0.11
GDP price index inflation	0.34	0.34	0.70	0.70	-0.20	-0.20	0.48	0.20	-0.02	-0.06	0.44	0.10
Real GDP	0.69	0.69	0.63	0.63	-0.25	-0.25	0.33	0.28	-0.07	-0.10	0.54	0.11
Consumer Price Index	0.27	0.27	0.70	0.70	-0.38	-0.38	-0.05	0.21	-0.24	-0.14	0.51	0.20
Industrial production	2.49	2.49	0.59	0.59	-0.16	-0.16	0.33	0.41	-0.01	-0.09	0.49	0.05
Housing Start	75.76	75.76	0.53	0.53	-0.15	-0.15	0.91	0.75	0.12	-0.13	0.54	0.01
Real Consumption	0.34	0.34	0.63	0.63	-0.31	-0.31	0.12	0.16	-0.11	-0.07	0.61	0.16
Real residential investment	16.69	16.69	0.56	0.56	-0.13	-0.13	0.56	0.42	0.07	-0.07	0.49	0.04
Real nonresidential investment	5.02	5.02	0.61	0.59	-0.02	-0.05	0.53	0.67	0.10	-0.05	0.41	0.00
Real state and local government consumption	0.92	0.92	0.61	0.61	-0.65	-0.65	0.05	0.15	-0.24	-0.23	0.77	0.35
Real federal government consumption	4.40	4.40	0.60	0.60	-0.60	-0.60	-0.21	0.18	-0.27	-0.21	0.77	0.31
Unemployment rate	0.09	0.06	0.56	0.55	0.09	0.08	0.59	0.78	0.20	0.08	0.39	0.00
Three-month Treasury rate	0.21	0.12	0.63	0.60	0.02	-0.02	0.40	0.66	0.14	-0.02	0.48	0.00
Ten-year Treasury rate	0.12	0.12	0.60	0.60	-0.46	-0.46	-0.09	0.45	-0.24	-0.31	0.71	0.14
AAA Corporate Rate Bond	0.25	0.25	0.61	0.61	-0.49	-0.49	0.05	0.58	-0.22	-0.44	0.70	0.07

Table F.3: Posted and honest moments

	Gain			Consensus MSE			Dispersion		
	Posted	Honest	Ratio	Posted	Honest	Ratio	Posted	Honest	Ratio
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nominal GDP	0.61	0.49	0.80	0.27	0.60	2.22	0.94	0.41	0.44
GDP price index inflation	0.70	0.66	0.94	0.27	0.37	1.36	0.34	0.22	0.65
Real GDP	0.63	0.57	0.91	0.56	0.80	1.41	0.69	0.39	0.57
Consumer Price Index	0.70	0.62	0.89	0.13	0.23	1.86	0.27	0.10	0.39
Industrial production	0.59	0.54	0.92	1.71	2.29	1.34	2.49	1.79	0.72
Housing Start	0.53	0.47	0.87	35.99	50.84	1.41	75.76	57.87	0.76
Real Consumption	0.63	0.59	0.95	0.57	0.71	1.24	0.34	0.16	0.48
Real residential investment	0.56	0.53	0.94	13.81	17.09	1.24	16.69	12.95	0.78
Real nonresidential investment	0.59	0.57	0.95	2.08	2.43	1.17	5.02	4.65	0.93
Real state and local government consumption	0.61	0.55	0.89	0.73	1.10	1.51	0.92	0.11	0.12
Real federal government consumption	0.60	0.53	0.88	3.60	5.48	1.52	4.40	0.69	0.16
Unemployment rate	0.55	0.60	1.08	0.04	0.03	0.78	0.06	0.07	1.12
Three-month Treasury rate	0.60	0.59	0.98	0.05	0.05	1.07	0.12	0.11	0.97
Ten-year Treasury rate	0.60	0.44	0.73	0.03	0.08	2.48	0.12	0.04	0.29
AAA Corporate Rate Bond	0.61	0.31	0.51	0.02	0.10	4.58	0.25	0.06	0.24

G Alternative data cleaning

In the main text, we follow Bordalo et al. (2020) data trimming procedure, which consists in removing forecasts that are more than 5 interquartile ranges away from the median of each horizon in each quarters. In this section, we replicate our empirical results using a trimming procedure with stricter criteria than the one utilized in the text. First, we follow Kohlhas and Walther (2021) in dropping observations with forecast error is in the unconditional top or bottom 1 percentile. Second, we follow Angeletos et al. (2021) in removing forecasts that are more than 4 interquartile ranges away from the median of each horizon in each quarters. Third, we use median instead of mean forecasts to compute the consensus forecasts. We apply all of these three filters at the same time.

Table G.1: Summary Statistics

	Consensus					Individual		
	Errors			Revisions		Forecast dispersion	Nonrev share	Pr(< 80% revise same direction)
	Mean	SD	SE	Mean	SD			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.29	1.61	0.19	-0.14	0.60	1.00	0.02	0.80
GDP price index inflation	-0.28	0.56	0.08	-0.08	0.22	0.47	0.07	0.83
Real GDP	-0.26	1.57	0.18	-0.15	0.53	0.78	0.02	0.74
Consumer Price Index	-0.08	0.99	0.15	-0.09	0.40	0.50	0.07	0.66
Industrial production	-0.94	3.72	0.44	-0.51	1.02	1.60	0.01	0.71
Housing Start	-3.04	16.81	2.08	-2.31	5.41	8.29	0.00	0.68
Real Consumption	0.32	1.06	0.15	-0.05	0.36	0.60	0.04	0.77
Real residential investment	-0.47	7.78	1.12	-0.64	1.97	4.50	0.04	0.85
Real nonresidential investment	0.20	5.35	0.75	-0.22	1.45	2.42	0.03	0.75
Real state and local government consumption	0.03	2.80	0.36	0.11	0.88	2.00	0.08	0.92
Real federal government consumption	0.00	1.03	0.14	-0.04	0.30	0.91	0.11	0.91
Unemployment rate	0.02	0.65	0.08	0.04	0.29	0.31	0.19	0.66
Three-month Treasury rate	-0.49	1.03	0.14	-0.18	0.44	0.45	0.15	0.58
Ten-year Treasury rate	-0.47	0.70	0.11	-0.12	0.33	0.39	0.11	0.54
AAA Corporate Rate Bond	-0.45	0.75	0.10	-0.11	0.33	0.51	0.09	0.68

Notes: Columns 1 to 5 show statistics for consensus forecast errors and revisions. Errors are defined as actuals minus forecasts, where actuals are the realized outcome corresponding to the variable forecasted. Revisions are forecast provided in t minus forecasts provided in $t-1$ about the same horizon. Columns 6 to 8 show statistics for individual forecasts, with Newey West (1994) standard errors. Forecast dispersion is the average standard deviation of individual forecasts at each quarter. The share of nonrevisions is the average quarterly share of instances in which forecast revision is less than 0.01 percentage points. The final column shows the fraction of quarters where less than 80 percent of the forecasters revise in the same direction.

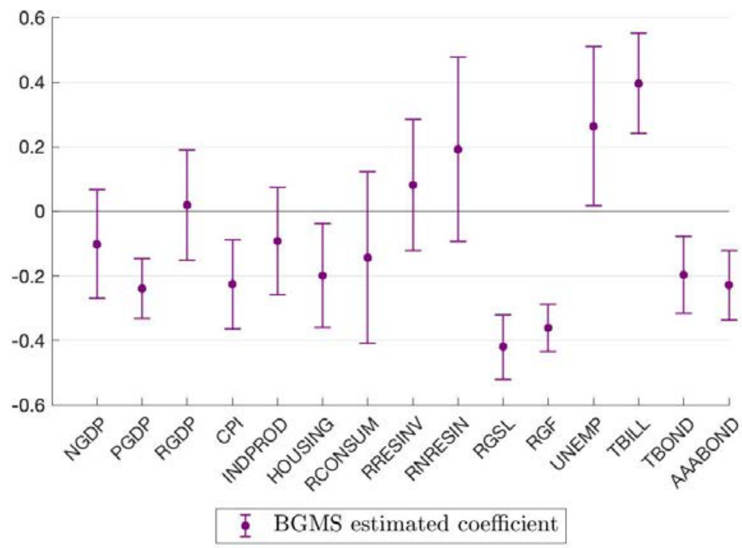


Figure G.1: Forecast errors on forecast revisions and public information

Notes: this figure plots the coefficient from panel data regression 6 with individual fixed effect and horizon h=3. Bars reports the 90% confidence interval for the estimated coefficients. Standard errors are robust and clustered at both time and individual forecaster level.

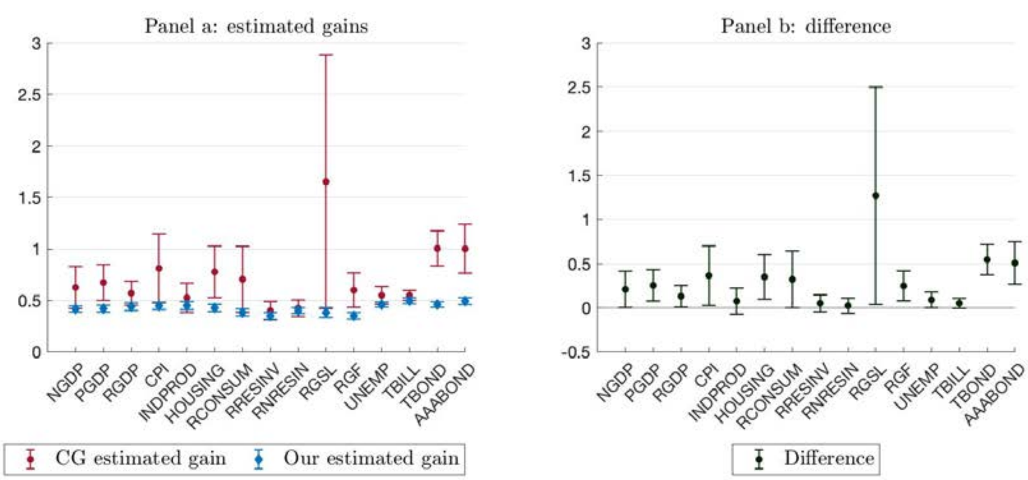


Figure G.2: Estimated gains: our measure vs CG

Notes: Panel (a): the red circles represent the implied gain from estimated coefficients in regression (3) at horizon h=3. Standard errors are robust to heteroskedasticity and Newey-West with the automatic bandwidth selection procedure of Newey and West (1994). The blue diamonds represent the gain estimated from (5) with individual fixed effect at horizon h=3. Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level. Bars reports the 90% confidence interval for the estimated coefficients. Panel (b): difference between the gains reported in panel (a).

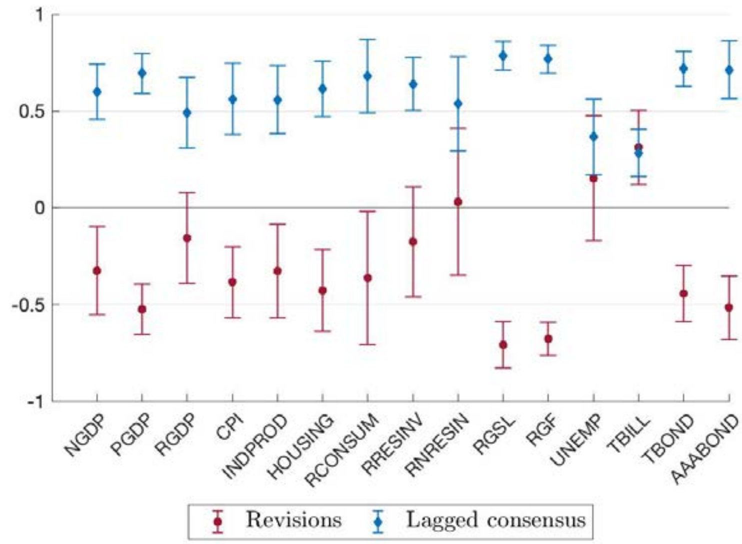


Figure G.3: Forecast errors on forecast revisions and public information

Notes: this figure plots the coefficient from panel data regression (13) with individual fixed effect and horizon h=3. The red circles represent the coefficient β_1 while the blue diamonds represent the coefficient β_2. Bars reports the 90% confidence interval for the estimated coefficients. Standard errors are robust and clustered at both time and individual forecaster level.

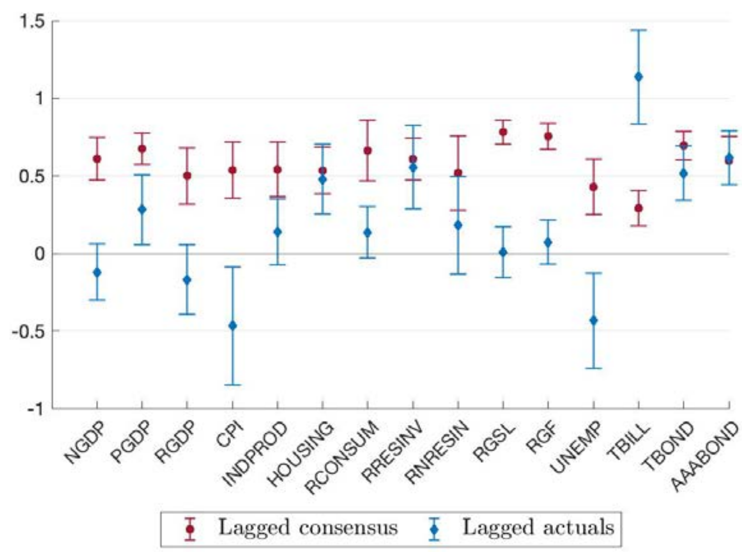


Figure G.4: Comparison between public signals

Notes: this figure plots the coefficient from a panel regression with fixed effects of (16) using forecasts from the Survey of Professional Forecasters and horizon h=3. The red circles represent the coefficient β_2 while the blue diamonds represent the coefficient β_3. Bars reports the 90% confidence interval for the estimated coefficients. Standard errors are robust and clustered at both time and forecaster level.

Table G.2: Individual errors on revisions

	3 quarters horizon				2 quarters horizon			
	β_{BGMS}	SE	p-value	Median	β_{BGMS}	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.10	0.10	0.33	-0.11	-0.02	0.08	0.86	0.00
GDP price index inflation	-0.24	0.06	0.00	-0.26	-0.18	0.05	0.00	-0.20
Real GDP	0.02	0.10	0.85	0.08	0.05	0.10	0.65	0.04
Consumer Price Index	-0.23	0.08	0.01	-0.18	-0.15	0.08	0.08	-0.16
Industrial production	-0.09	0.10	0.37	-0.11	0.13	0.11	0.24	0.09
Housing Start	-0.20	0.10	0.05	-0.29	0.23	0.08	0.00	0.16
Real Consumption	-0.14	0.16	0.39	-0.20	-0.07	0.10	0.45	-0.12
Real residential investment	0.08	0.12	0.51	0.02	0.16	0.09	0.10	0.03
Real nonresidential investment	0.19	0.17	0.28	0.20	0.22	0.10	0.04	0.21
Real state and local government consumption	-0.42	0.06	0.00	-0.45	-0.18	0.06	0.01	-0.18
Real federal government consumption	-0.36	0.04	0.00	-0.34	-0.22	0.05	0.00	-0.24
Unemployment rate	0.26	0.15	0.09	0.18	0.24	0.12	0.06	0.21
Three-month Treasury rate	0.40	0.09	0.00	0.39	0.30	0.07	0.00	0.31
Ten-year Treasury rate	-0.20	0.07	0.01	-0.23	-0.20	0.10	0.05	-0.22
AAA Corporate Rate Bond	-0.23	0.07	0.00	-0.30	-0.18	0.07	0.01	-0.24

Notes: The table reports the coefficients from the BGMS regression (individual forecast errors on individual revisions). Columns (1) to (3) shows the panel data with fixed effect coefficient with standard errors and corresponding p-values. Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level. Columns (7) shows the median coefficient of the BGMS regression at the individual level.

Table G.3: Stickiness estimation

	3 quarters horizon				2 quarters horizon			
	β	SE	p-value	Median	β	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	0.42	0.02	0.00	0.47	0.53	0.01	0.00	0.58
GDP price index inflation	0.42	0.02	0.00	0.42	0.59	0.02	0.00	0.62
Real GDP	0.44	0.02	0.00	0.49	0.51	0.02	0.00	0.59
Consumer Price Index	0.45	0.02	0.00	0.52	0.65	0.02	0.00	0.69
Industrial production	0.45	0.02	0.00	0.50	0.54	0.02	0.00	0.60
Housing Start	0.43	0.02	0.00	0.49	0.45	0.02	0.00	0.49
Real Consumption	0.38	0.02	0.00	0.42	0.56	0.03	0.00	0.58
Real residential investment	0.35	0.02	0.00	0.39	0.52	0.02	0.00	0.58
Real nonresidential investment	0.40	0.02	0.00	0.46	0.53	0.02	0.00	0.57
Real state and local government consumption	0.38	0.03	0.00	0.35	0.53	0.02	0.00	0.52
Real federal government consumption	0.35	0.02	0.00	0.40	0.53	0.01	0.00	0.58
Unemployment rate	0.46	0.01	0.00	0.51	0.52	0.02	0.00	0.58
Three-month Treasury rate	0.50	0.02	0.00	0.55	0.58	0.02	0.00	0.63
Ten-year Treasury rate	0.46	0.02	0.00	0.50	0.55	0.02	0.00	0.58
AAA Corporate Rate Bond	0.49	0.02	0.00	0.55	0.56	0.02	0.00	0.61

Notes: The table shows the result from regression (5). Columns (1)-(3) report coefficients, standard errors and p-values from the panel data regression with time and individual fixed effect. Column (4) reports the median coefficient from individual regressions. Columns (5)-(8) reports the same statistics for the 2 quarters horizon. Standard errors are robust to heteroskedasticity and clustered at both forecaster and time level.

Table G.4: Difference between estimated gains

Variable	G_{CG} (1)	SE (2)	G (3)	SE (4)	Difference (5)	SE (6)	p-value (7)
Nominal GDP	0.63	0.12	0.42	0.02	0.21	0.13	0.05
GDP price index inflation	0.67	0.11	0.42	0.02	0.25	0.11	0.01
Real GDP	0.57	0.07	0.44	0.02	0.13	0.07	0.04
Consumer Price Index	0.81	0.20	0.45	0.02	0.36	0.21	0.04
Industrial production	0.53	0.09	0.45	0.02	0.08	0.09	0.20
Housing Start	0.78	0.15	0.43	0.02	0.35	0.15	0.01
Real Consumption	0.71	0.19	0.38	0.02	0.32	0.20	0.05
Real residential investment	0.40	0.05	0.35	0.02	0.05	0.06	0.19
Real nonresidential investment	0.42	0.05	0.40	0.02	0.02	0.05	0.32
Real state and local government consumption	1.65	0.75	0.38	0.03	1.27	0.75	0.04
Real federal government consumption	0.60	0.10	0.35	0.02	0.25	0.10	0.01
Unemployment rate	0.55	0.05	0.46	0.01	0.09	0.05	0.05
Three-month Treasury rate	0.55	0.03	0.50	0.02	0.05	0.03	0.06
Ten-year Treasury rate	1.01	0.10	0.46	0.02	0.55	0.10	0.00
AAA Corporate Rate Bond	1.00	0.14	0.49	0.02	0.51	0.15	0.00

Notes: Columns (1)-(2) reports the implied gain from CG regressions. Columns (3)-(4) replicate the gain estimated from regression (5). Columns (5)-(8) reports the difference between column (1) and (3), its standard error and the probability of rejecting the null of column (5) lower or equal to zero.

Table G.5: Private and public information

Panel A: 3 quarters horizon

	Revision				Public signal			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.32	0.14	0.02	-0.35	0.60	0.09	0.00	0.63
GDP price index inflation	-0.52	0.08	0.00	-0.53	0.69	0.06	0.00	0.75
Real GDP	-0.16	0.14	0.28	-0.14	0.49	0.11	0.00	0.57
Consumer Price Index	-0.38	0.11	0.00	-0.40	0.56	0.11	0.00	0.59
Industrial production	-0.33	0.15	0.03	-0.37	0.56	0.11	0.00	0.63
Housing Start	-0.43	0.13	0.00	-0.49	0.61	0.09	0.00	0.69
Real Consumption	-0.36	0.21	0.09	-0.47	0.68	0.12	0.00	0.74
Real residential investment	-0.18	0.17	0.32	-0.31	0.64	0.08	0.00	0.66
Real nonresidential investment	0.03	0.23	0.90	-0.06	0.54	0.15	0.00	0.49
Real state and local government consumption	-0.71	0.07	0.00	-0.74	0.79	0.04	0.00	0.77
Real federal government consumption	-0.68	0.05	0.00	-0.63	0.77	0.04	0.00	0.76
Unemployment rate	0.15	0.20	0.44	0.01	0.37	0.12	0.00	0.40
Three-month Treasury rate	0.31	0.12	0.01	0.29	0.28	0.07	0.00	0.34
Ten-year Treasury rate	-0.44	0.09	0.00	-0.43	0.72	0.05	0.00	0.83
AAA Corporate Rate Bond	-0.52	0.10	0.00	-0.64	0.71	0.09	0.00	0.81

Panel B: 2 quarters horizon

	Revision				Public signal			
	β_1	SE	p-value	Median	β_2	SE	p-value	Median
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nominal GDP	-0.18	0.11	0.11	-0.20	0.47	0.08	0.00	0.50
GDP price index inflation	-0.42	0.08	0.00	-0.45	0.59	0.06	0.00	0.55
Real GDP	-0.08	0.13	0.55	-0.11	0.43	0.09	0.00	0.43
Consumer Price Index	-0.24	0.11	0.05	-0.30	0.38	0.12	0.00	0.34
Industrial production	0.03	0.15	0.85	0.02	0.30	0.11	0.01	0.39
Housing Start	0.08	0.11	0.47	0.01	0.37	0.08	0.00	0.42
Real Consumption	-0.24	0.13	0.07	-0.28	0.52	0.09	0.00	0.57
Real residential investment	-0.01	0.12	0.95	-0.10	0.43	0.07	0.00	0.44
Real nonresidential investment	0.14	0.13	0.31	0.15	0.32	0.09	0.00	0.34
Real state and local government consumption	-0.44	0.08	0.00	-0.48	0.67	0.05	0.00	0.63
Real federal government consumption	-0.56	0.07	0.00	-0.56	0.68	0.05	0.00	0.68
Unemployment rate	0.15	0.16	0.36	0.05	0.32	0.10	0.00	0.33
Three-month Treasury rate	0.23	0.08	0.00	0.21	0.27	0.05	0.00	0.29
Ten-year Treasury rate	-0.38	0.11	0.00	-0.41	0.60	0.07	0.00	0.57
AAA Corporate Rate Bond	-0.38	0.10	0.00	-0.46	0.56	0.11	0.00	0.66

Notes: this table reports the coefficients of regression (13) (individual forecast errors on individual revisions and public information). Columns 1 to 3 show coefficient β_1 (forecast revision) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 4 shows the median coefficient of the same regression at the individual level. Columns 5 to 7 show coefficient β_2 (public information) from the panel regression with individual fixed effect, with standard errors and corresponding p-values. Standard errors are robust and clustered by forecaster and time. Column 8 shows the median coefficient of the same regression at the individual level. Panel A uses forecast at 3 quarters horizon and panel B uses forecast at 2 quarters horizon.

H Strategic diversification with heterogeneous priors

In this section we present an extension to the baseline model of Section 3.1 allowing for heterogeneous long-run mean priors μ_i.

Suppose forecasters have the same objective function and receive the same signals as in section 3.1, but with heterogeneous priors. For tractability we will assume i.i.d x_t process, and for simplicity of exposition we will drop all time subscripts t, since when x_t is iid the model is effectively static. Thus, the forecaster's optimal response is again

$$\hat{x}^i = \frac{1}{1-\lambda}\mathbb{E}^i[x] - \frac{\lambda}{1-\lambda}\mathbb{E}^i[\bar{\hat{x}}] \tag{46}$$

where we label the reported forecast that agent i submits to the survey as $\hat{x}^i$ and $\bar{\hat{x}} = \int \hat{x}^i di$ is the consensus forecast. Similarly to the main text, agents received a private and a public signal, both unbiased and centered around the true x with some noise.

$$\begin{aligned} s^i &= x + \eta^i \\ g &= x + e \end{aligned} \tag{47}$$

with $\eta^i \sim N(0, \tau^{-1})$ and $e \sim N(0, \nu^{-1})$.

Differently from the main text, forecasters have a dispersed priors about the mean of x. We model this by assuming that agents know the unconditional distribution of the fundamental $x \sim N(\mu_x, \chi^{-1})$, but they do not know the mean value μ_x. Their prior is that $\mu_x \sim N(0, \omega^{-1})$ and each forecasters has a private signal about it, $\mu^i = \mu_x + v^i$, with $v^i \sim N(0, \xi^{-1})$.[10]

Posterior on fundamental Their true posterior beliefs about the fundamental are

$$\begin{aligned} \mathbb{E}[\mu_x|\mu^i] &= \frac{\xi}{\xi+\omega}\mu^i \\ Var[\mu_x|\mu^i] &= (\xi+\omega)^{-1} \end{aligned} \tag{48}$$

[10] One can think of a setting where agents use an iid sample of t realizations of x to learn about its mean (Baley and Veldkamp, 2023). The accuracy of their private belief ξ will be proportional to the size of their observed sample, which we assume to be the same for every agent.

which implies

$$\begin{aligned}\mathbb{E}[x|\mu^i] &= \frac{\xi}{\xi+\omega}\mu^i \\ Var[x|\mu^i] &= (\xi+\omega)^{-1} + \chi^{-1}\end{aligned} \tag{49}$$

as a result

$$\mathbb{E}[x|s^i, g^i, \mathbb{E}[x|\mu^i]] = (1-\gamma_1-\gamma_2)\mathbb{E}[x|\mu^i] + \gamma_1 s^i + \gamma_2 g \tag{50}$$

where $\gamma_1 = \frac{\tau}{\tau+\nu+Var[x|\mu^i]^{-1}}$ and $\gamma_2 = \frac{\nu}{\tau+\nu+Var[x|\mu^i]^{-1}}$. If priors are not dispersed, that is $\xi \to \infty$ and we are back to the same posterior belief as in our baseline case we analyze in the main text.

Posterior on mean Similarly, their posterior beliefs about the mean are

$$\begin{aligned}\mathbb{E}[\mu_x|s^i, g] &= \frac{\tau}{\tau+\nu}s^i + \frac{\nu}{\tau+\nu}g \\ Var[\mu_x|s^i, g] &= (\tau+\nu)^{-1} + \chi^{-1}\end{aligned} \tag{51}$$

which implies

$$\mathbb{E}[\mu_x|s^i, g^i, \mathbb{E}[x|\mu^i]] = (1-f)\mathbb{E}[x|\mu^i] + f(hg + (1-h)s^i) \tag{52}$$

where $f = \frac{Var[\mu_x|s^i,g]^{-1}}{\xi+\omega+Var[\mu_x|s^i,g]^{-1}}$ and $h = \frac{\nu}{\nu+\tau}$. If priors are not dispersed, $\xi \to \infty$, therefore $\mathbb{E}[\mu_x|s^i, g^i, \mathbb{E}[x|\mu^i]] = \mu_x$, meaning we are in the common prior baseline case.

Posted forecast We guess the following linear solution for the posted forecast

$$\hat{x}^i = \delta_1 s^i + \delta_2 g + \delta_3 \mu^i \tag{53}$$

The solution of the fixed point between 53 and 46 is given by the following system

$$\begin{aligned}\delta_3 &= \frac{(1-\lambda)(1-\gamma_1-\gamma_2)}{(1-\lambda)+\lambda\gamma_2}\left[\frac{\xi+\omega}{\xi} + \frac{\lambda(1-f)}{1-\lambda} - \frac{\lambda^2 f(1-h)(1-\lambda)(1-\gamma_1-\gamma_2)}{(1-\lambda)+\lambda\gamma_2}\right]^{-1} \\ \delta_2 &= (1-\lambda\delta_2)\gamma_1 - \lambda\delta_3 fh \\ \delta_1 &= \frac{\gamma_2 - \lambda\delta_3 f(1-h)}{(1-\lambda)+\lambda\gamma_2}\end{aligned} \tag{54}$$

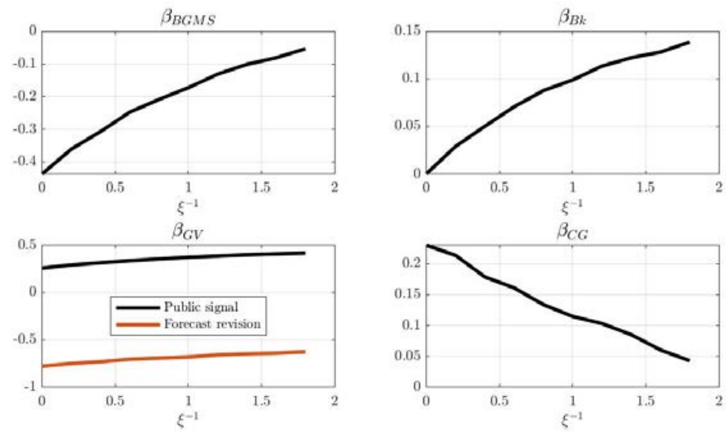


Figure H.1: Simulated coefficients

Notes: This figure reports the coefficients of regressions 3, 6, 13 and 18 in simulated data for different value of individual prior accuracy ξ. The rest of the parameters are set as follow: $\tau = 0.05$, $\nu = 0.5$, $\chi = 1$, $\omega = 0.25$ and $\lambda = 0.8$.

First, one can see that in the case of no strategic incentives $\lambda = 0$, the posted forecast would coincide with the honest belief 50. Second, this is a generalization of the common prior case described in the main text. To see this, consider the case where prior is common, $\xi \to \infty$ which implies $f \to 0$. Then the solution for 53 coincides with the one in main text 10.

Simulated coefficient Since the model with heterogeneous prior is not as tractable as the one in the main text, we use numerical simulation. Figure H.1 reports the coefficients estimated from running regressions 3, 6, 13 and 18 in simulated data for different value of individual prior accuracy ξ^{-1}. If $\xi^{-1} = 0$, the results coincide with the proposition in the main text and $\hat{\beta}$ in regression 18 equal zero. However, when priors are dispersed, $\xi^{-1} > 0$, we find $\hat{\beta} > 0$ while the sign in all the other coefficients is unaffected. This is consistent with our finding in Figure 6.