CFR Working Paper NO. 11-13

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August 2011

[1] For valuable comments we are grateful to the participants of the Financial Management Association European Conference 2011 and the Eastern Finance Association Annual Meeting 2011.

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Abstract

We analyze the quality of macroeconomic survey forecasts. Recent findings indicate that they are anchoring biased. This irrationality would challenge the results of a wide range of empirical studies, e.g., in asset pricing, volatility clustering or market liquidity, which rely on survey data to capture market participants' expectations. We contribute to the existing literature in two ways. First, we show that the cognitive bias is a statistical artifact. Despite highly significant anchoring coefficients a bias adjustment does not improve forecasts' quality. To explain this counterintuitive result we take a closer look at macroeconomic analysts' information processing abilities. We find that analysts benefit from the use of an extensive information set, neglected in the anchoring bias test. Exactly this information advantage drives the misleading anchoring bias test results. Second, we find that the superior information aggregation capabilities enable analysts to easily outperform sophisticated time-series forecasts and therefore survey forecasts should clearly be favored.

Keywords: macroeconomic announcements, efficiency of forecasts, anchoring bias, rationality of analysts

JEL classification: G12, G14, G17, E17, E37

A large and growing body of financial market research relies on survey forecasts to isolate the unanticipated information component in scheduled macroeconomic releases.[1] Recently, Campbell and Sharpe (2009) suggest that there is a substantial "anchoring bias" in analysts' forecasts. This implies that analysts' forecasts would not adequately approximate market participants' expectations since they could be substantially improved. However, we cannot find that macroeconomic analysts' forecasts can be improved – once we apply a look-ahead bias free test and adjustment procedure. In contrast, while anchoring would suggest that analysts' forecasts underperform mechanical time-series models, we find the opposite: macroeconomic analysts substantially outperform mechanical forecasts. This outperformance can be attributed to the fact that analysts use a much richer information set, i.e. they incorporate other information besides the historical time-series the anchoring test focuses on. While analysts' forecasts deviate from time-series forecast, we find that by deviating analysts reduce – not increase – forecasts errors. Moreover, we show that these deviations can be explained largely by other macroeconomic data. More generally, our analysis points out a universal risk inherent in (behavioral) tests focusing on a single time-series property: rational agents' forecasts may deviates from time-series forecasts not only because of cognitive inefficiencies but also because of using a richer information set.

Compared to the extensive research that has been conducted in the area of macroeconomic information processing in financial markets (e.g. Urich and Wachtel (1984), McQueen and Roley (1993), Balduzzi et al. (2001) and Andersen et al.(2003)) comparatively little analysis is available concerning the properties of macroeconomic survey forecasts. This is somewhat surprising, but possibly due to the high quality of survey forecasts. The few thus far available

[1] For example, studies on market efficiency, information processing, liquidity around announcements, or volatility clustering use macroeconomic survey forecasts. Most frequently, Money Market Services (MMS) survey data are used, for example, by Urich and Wachtel (1984), McQueen and Roley (1993), Almeida et al. (1998), Elton (1999), Balduzzi et al. (2001), Flannery and Protopapadakis (2002), Andersen et al. (2003), Green (2004), Bernanke and Kuttner (2005), Hautsch and Hess (2007), Evans and Lyons (2008), and Hautsch et al. (2010), to cite only a few.

forecast rationality studies largely test for general quality properties derived from Muth's Rational Expectations Hypothesis (1961)[2]. As a common outcome, general forecast rationality studies provide no evidence of systematic and persistent inefficiencies.[3] In contrast, Campbell and Sharpe (2009) test for a specific behavioral inefficiency, the anchoring bias, first documented by Tversky and Kahneman (1974) in psychological experiments. Anchoring implies that too much weight is attached to a certain prior available piece of information. In the context of macroeconomic forecasts it would mean that the surveyed analyst puts too much importance on the last months' actual and therefore underweights other important information. Thus the entire information set available at the survey date would not be efficiently incorporated in the forecast generation process. But then, utilizing the entire available information correctly must yield improved forecasts. Only if this is the case, the widely used survey forecasts would have to be viewed as inefficient and poor proxies of market participant's expectations.

However, we cannot reach this conclusion. In contrast, our analysis reveals a counter-intuitive result: Despite a seemingly strong and statistically significant anchoring bias in most macroeconomic survey series, adjusting forecasts for the seemingly apparent bias leads to no systematic forecast improvements. Decomposing the anchoring bias test statistic provides an explanation for this puzzling result: the test itself is biased. Testing solely against univariate time series information the anchoring bias test neglects the possibility that analysts may provide superior forecasts by using a richer information set than just the univariate time series itself. Our empirical results support this explanation, revealing for a broad range of macroeconomic series that efficiency – rather than inefficiency – is producing the large "anchoring bias" coefficients. By arranging a "horse race" between survey and model

[2] See e.g. Pesando (1975), and Mullineaux (1978) Pearce and Roley (1985), Aggarwal et al. (1995), and Schirm (2003).

[3] The most recent study, Schirm (2003), finds only for small number of investigated series some bias. However his results partly contradict the findings of Aggarwal et al. (1995) obtained on a different sample.

forecasts we document that analysts' forecasts aggregate more valuable information than contained in the historical time series and are therefore quite efficient. This forecast comparison is a distinctive contribution to the existing forecast quality literature. While previous studies assumed efficiency, we are the first to hypothesize inefficiency. Rejecting this hypothesis provides evidence in favor of efficient information processing by analysts. Our more general approach allows us to address the more interesting question whether analyst forecasts represent the best available information aggregate instead of testing whether one single piece of information was incorrectly incorporated.

Our analysis proceeds in five steps. First we replicate the anchoring bias test of Campbell and Sharpe (2009). However, we use a much broader set of macroeconomic indicators, allowing for a more comprehensive analysis. More importantly, we use a much longer sample period to facilitate out-of-sample tests. This "dynamic" analysis, i.e. testing on a rolling-window and correspondingly adjusting forecasts out-of-sample, enables us to build on the exact information flow, i.e. to consider only information available to market participants at a given point in time. Hence, our procedure avoids a look-ahead bias. This is of particular importance when we adjust the data for the anchoring bias, because only this real-time proceeding ensures a realistic comparison of unadjusted and adjusted data. In contrast, Campbell and Sharpe's analysis (which we call "static") is based on a single in-sample regression and a corresponding adjustment would incorporate a potentially severe look-ahead bias.

If the highly significant anchoring coefficients would stem from a cognitive bias, then adjusting the original survey forecasts must yield substantial improvements in forecast quality. Surprisingly, despite highly significant anchoring coefficients we can hardly find any significant improvements in forecast quality when adjusting for this seemingly apparent bias. Only when we allow for a look-ahead bias, i.e. for the statical estimation and adjustment, we find some modest improvements. More importantly and even more disturbingly, we can find virtually no improvements of forecast quality for the dynamically estimated anchoring coefficients, which avoid a look-ahead bias. Only for 2 out of 23 series we can find statistically significant improvements, but for another 2 series forecast quality significantly worsens through the adjustment. Overall, we have to conclude that nothing is gained by adjusting forecasts, despite highly significant anchoring test coefficients.

In order to explain this puzzling result we inspect in a third step the mechanics of the anchoring bias test. Most importantly, the anchoring bias test implicitly assumes a univariate time series framework. This creates a substantial problem since it neglects other information which most likely alters rational forecasts. In particular, we show that the overall test statistic can be decomposed into two components: The first component captures inefficient processing of univariate time series information, possibly due to anchoring. The second component, however, captures superior information processing abilities of analysts, supposedly due to using a richer information set. Hence, large and significant anchoring coefficients can not only arise when analysts face a cognitive bias but also when they correctly incorporate additional information in their predictions and therefore outperform time series forecasts. This suggests that neglecting other information may be responsible for the misleading anchoring bias test results. In fact, in line with previous research on the properties of stock market analysts' forecasts,[4] we find that macroeconomic survey forecasts substantially outperform optimized time series forecasts. Overall, this analysis shows that the anchoring bias test is biased itself. Large coefficients could be just due to efficient – rather than inefficient – information processing.

Outperforming optimal univariate time-series forecasts implies that analysts have to use some additional information while generating their forecast. In fact, in a fourth step, we provide

[4] For example, it has long been argued that financial analysts provide more accurate earnings forecasts than univariate time series models because analysts use a broader information set than just the univariate time series of historical earnings. For earnings forecasts this enlarged information set presumably includes, among other things, macroeconomic information. See, e.g., Brown (1993) and Brown et. al. (1997).

evidence supporting the view that macroeconomic analysts use a much broader information set than just the univariate time series. In particular, we find that a substantial part of the forecast improvement analysts achieve over time series models can be explained by other macroeconomic data. This result suggests that analysts draw on several other macroeconomic indicators. We find that in particular those macroeconomic figures that are identified to be the most "important" ones by Gilbert et. al. (2010), i.e. those with substantial information content and those being released early in the monthly release cycle seem to contribute. Consequently, analysts seem to be rather efficient information processors pooling a large amount of valuable information.

Fifth, we quantify the relative contributions of the "inefficiency" and the "additional information" component to the overall anchoring bias test coefficient. Our results suggest that for the majority of significantly biased forecast series, the "additional information" component accounts for more than half of the overall anchoring bias coefficients' size. This explains the puzzling result that almost all survey forecasts seem to be severely anchoring biased while an adjustment does not lead to improvements.

Overall, our analysis yields an astonishing result. Rather than detecting inefficiencies in U.S. macroeconomic survey forecasts we find strong evidence for superior information processing abilities of analysts. The highly significant anchoring bias test results are not due to a cognitive bias of analysts, but result from their superiority compared to time series models. For every single macroeconomic series analysts easily outperform the out-of-sample forecasts of dynamically optimized time series models. This strongly indicates that survey forecasts aggregate additional information beyond the univariate time series data, in particular, other currently released macroeconomic figures. Obviously, it is extremely difficult if not impossible to adequately model the entire available information set and to come up with a better forecasting model. Therefore, we have to conclude that survey forecasts are still the best available approximation of market participants' expectations. Moreover, our analysis shows that testing for a specific bias such as anchoring by exclusively focusing on univariate time series properties is dangerous since it neglects the ability of analysts to aggregate additional information. Overall, our findings suggest that anchoring does not constitute any problem for earlier information processing studies building on survey forecasts.

With this study we contribute to different strands of literature. Our results directly add to the scarce literature analyzing possible biases in macroeconomic forecasts by showing that analysts' forecasts are the most comprehensive and efficient information aggregates. Consequently they best represent market participants' expectations regarding upcoming macroeconomic releases. Moreover, our findings have important implications for a broad range of studies relying on macroeconomic survey forecasts in order to extract unanticipated information components in scheduled releases (e.g. Andersen et al. (2003), Green (2004), Bernanke and Kuttner (2005), Hautsch and Hess (2007), Evans and Lyons (2008) to name just a few). Furthermore, since the anchoring bias adjusted forecast is basically a weighted combination of the survey forecast and an autoregressive model we contribute to the area of forecast combination in which currently no results concerning monthly macroeconomic survey forecasts are available.

The remainder of the study is organized as follows. In section 1 we briefly delineate the anchoring bias test and introduce our framework for the evaluation of analysts' forecasts. Section 2 describes the data and their properties. Section 3 provides the empirical results and section 4 concludes.

I. Methodology

The basic assumption of the anchoring bias test[5] is that the MMS survey forecast (F_t) is a linear combination of an unbiased forecast for the next month's actual, $E\left[A_t\right]$, and an average of already released values for the $\bar{h}$ previous months:

$$F_t = \lambda \cdot E\left[A_t\right] + \left(1-\lambda\right) \cdot A_{\bar{h}}. \tag{1}$$

The unbiased estimator for next month's actual already incorporates all available information efficiently. The inclusion of additional past information is redundant and therefore λ should be one. A value of λ significantly smaller than one would suggests anchoring, i.e. putting too much weight on previously released values in comparison to an unbiased estimator.

Since the unbiased estimator is unobservable a direct estimation of equation (1) is not feasible. It can be shown that an indirect estimation of λ is possible by means of (2) (see Appendix A for a derivation):

$$S_t = \gamma \cdot \left(F_t - A_{\bar{h}}\right) + \eta_t \,, \quad \text{with } \gamma \equiv \frac{\left(1-\lambda\right)}{\lambda}, \tag{2}$$

where S_t denotes the unanticipated news component defined as actual minus forecast[6]. On the one hand, $\gamma > 0$ would indicate anchoring, i.e. $\lambda < 1$. On the other hand, there is no economically plausible explanation for $\gamma < 0$, i.e. $\lambda > 1$. Nevertheless, significant negative coefficients imply partly predictable surprises. Following, we might be able to improve forecast quality even in cases in which the anchoring bias test leads to results contradicting its purpose.

5 Campbell and Sharpe (2009)

6 Although equation (2) does not include a constant we always include one in the estimation.

Equation (1) suggests that the unbiased estimate $E\left[A_t\right]$ is compounded of the survey based forecast and the anchor:

$$E\left[A_t\right] = \frac{F_t}{\lambda} - \frac{\left(1-\lambda\right)}{\lambda} \cdot A_{\bar{h}} = \left(1+\gamma\right) \cdot F_t - \gamma \cdot A_{\bar{h}}. \tag{3}$$

Equation (3) in connection with γ estimated on the basis of (2), the original forecast data can be adjusted for the anchoring induced bias. These adjusted forecasts serve as central input variables for our forecast quality comparison tests to determine the economical significance of the anchoring bias. We perform two different adjustments. First, to evaluate the in-sample impact of the anchoring bias we estimate (2) over the entire sample period and adjust the forecasts retrospectively. Additionally, to avoid an in-sample look-ahead bias, we perform a dynamic adjustment by means of a rolling estimation of (2). Given the current coefficient we adjust the next forecast in a way market participants would have been able to adjust the data. Since this approach represents an implementable strategy it has to be taken as the real test of the anchoring bias' impact.

To analyze the implicit time series framework underlying the anchoring bias test we assume that A_t follows some ARMA(p,q) process, a fairly general representation. Moreover we suppose that analysts use a corresponding ARMA(p,q) model to generate forecasts. However, we believe that analysts do not restrict themselves to looking at historical time-series information. Instead we suppose that they possess some additional information Z_t useful to predict the innovation e_t in A_t, e.g., from inspecting other macroeconomic announcements or simply from reading the daily press. Based on these considerations we show that γ in (2) can be written as (see Appendix B)

$$\hat{\gamma} = \frac{Cov\left(e_t, x'_{t-1}\right) + Cov\left(y'_{t-1}, x'_{t-1}\right) - Cov\left(Z_t, x'_{t-1}\right) + Cov\left(e_t, Z_t\right) - Var\left(Z_t\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)}. \quad (4)$$

To separate the part of γ driven by the additional information set measured by Z_t we decompose $\hat{\gamma}$ into two parts

$$\hat{\gamma}_1 = \frac{Cov\left(y'_{t-1}, x'_{t-1}\right) + Cov\left(e_t, x'_{t-1}\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)} \quad (5)$$

and

$$\hat{\gamma}_2 = \frac{Cov\left(e_t, Z_t\right) - Var\left(Z_t\right) - Cov\left(Z_t, x'_{t-1}\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)} \quad (6)$$

with

$$\begin{aligned} y'_{t-1} &\equiv \sum_{j=1}^{\infty}\left(\beta_j - \hat{\beta}_j\right) \cdot e_{t-j} \\ x'_{t-1} &\equiv \sum_{j=1}^{\infty}\hat{\beta}_j \cdot e_{t-j} - \frac{1}{h}\sum_{i=1}^{h}\left(e_{t-i} + \sum_{j=1}^{\infty}\beta_j \cdot e_{t-j-i}\right) \end{aligned}$$

$\hat{\gamma}_1 = 0$ if $Cov\left(y'_{t-1}, x'_{t-1}\right) = 0$, i.e., if analysts' estimates $\hat{\beta}_j$ are unbiased ($\hat{\beta}_j = \beta_j \; \forall j$ implying in this case $y'_{t-1} = 0$) and if, at the same time, $Cov\left(e_t, x'_{t-1}\right) = 0$. Since x'_{t-1} contains exclusively time series information up to time t-1 it should not contain predictive power to explain the innovation. If x'_{t-1} would allow to predict the innovation e_t, then "old" time series information would yield a more precise forecast than the survey forecast. In this case analysts' forecast (or the models they use) would be inefficient. Therefore, $\hat{\gamma}_1$ captures inefficiencies in analysts' forecasts.

Since x'_{t-1} only consists of past innovations of the actual generating process it should at best be weakly correlated with Z_t. Furthermore, if analysts have superior forecasting abilities compared to the optimal time series model the correlation between Z_t and e_t should be positive. Consequently, if $Cov\left(e_t, Z_t\right) > Var\left(Z_t\right) + Cov\left(Z_t, x'_{t-1}\right)$ this suggests that a positive part of the anchoring coefficient γ is driven by the additional information amount used by the surveyed analysts.

Since additional information, Z_t, is not directly observable we have to use a proxy measure. The basic idea is to generate an optimal univariate time-series forecast to extract Z_t as the residual from the MMS survey forecast. First, we estimate an "optimal" ARIMA model for the actual. We select the optimal order of differencing d according to a Phillips-Perron test. Then we estimate the model for all combinations of p = 0, …, 6 and q = 0, 1. We chose the best fitting model according to Bayes' information criterion (BIC) among those models providing residuals that are not serially correlated. Based on this selection procedure, we obtain an "optimal" time series model to describe the actual. The generated residuals of this model serve as proxy measure for the innovation of the actual generating process (ε_t), i.e., the component in A_t which is not predictable from historical univariate time series information.

Now we analyze survey forecasts F_t, applying a distributed lag model corresponding to the optimal ARIMA specification of actual, i.e. we regress the (differenced) forecasts F_t on p lags of A_t and q lags of $\hat{e}_t$. The residuals of this estimation serves as approximations for Z_t, i.e., the component in survey forecasts F_t which cannot be traced back to past observed actuals.

To rule out the possibility that our proxy for the additional information, Z_t, just picks up noise and to answer the question where analysts' outperformance comes from we analyze how Z_t is related to information available at the time when analysts produce their forecasts. For this purpose we estimate the following model:

$$Z_t = \alpha + \beta M_t + \varphi_t, \tag{7}$$

where Z_t denotes the approximated additional information component in survey forecasts and M_t a vector containing the available macroeconomic information set for the 23 considered indicators seven days prior to an announcement. Using a stepwise regression approach allows us to determine whether Z_t is an inappropriate proxy for additional information or whether it is related to other macroeconomic news.

Finally we quantify the contribution of the "additional information" and the "inefficiency" component to the overall anchoring bias coefficient. Based on our theoretical considerations including equation (5) and (6) a partition is feasible and we can conclude whether irrationality or information efficiency drives the anchoring bias test results.

II. Data Description

We use a comprehensive data set comprising 23 well known macroeconomic indicators. Table 1 lists the series along with the abbreviations used in the following sections, their availability during the sample periods and the respective reporting unit. Medians of analysts' forecasts for these macroeconomic data are obtained from MMS and Action Economists[7]. As

[7] Each Friday, MMS polls analysts' forecasts of macroeconomic figures to be released during the following week. Survey responses are received over a three- to four-hour period every Friday morning via fax or phone. The results of the survey are published at around 1:30 PM EST. In September 2003 MMS was acquired by Informa. However, the original MMS survey was conducted until mid of December 2003. For the time after December 2003 we use forecasts provided by Action Economics (AE). Although AE is not MMS' legal

a robustness check we use Bloomberg and Reuters forecasts. Since the results are virtually identical we do not report them. Whenever available, we use ALFRED vintage data to measure actual announced values.[8] Otherwise announced values provided by the survey agencies are used.

Table 2 shows sample means (μ) and standard deviations (σ) for the 23 considered indicators (actuals, forecasts, and surprises). Sample means of the surprises are close to zero for most indicators implying that the forecasts are unbiased if not conditioned on a specific information set. Moreover, except for a few series (in particular, HE) the standard deviations of surprises are substantially smaller than the standard deviations of actual implying positive correlations of the actual and the forecast.[9]

III. Empirical Results

Our empirical analysis proceeds in four steps. First, we perform both in- and out-of-sample anchoring tests for a broad range of macroeconomic series. Given the bias estimates, we analyze in a second step whether analysts' forecasts can be improved by adjustments for anchoring. Then in a third step, we evaluate the analysts' forecasting abilities in comparison to optimally selected univariate time series models. Furthermore, to explain analysts' outperformance we analyze which additional information are processed in their forecasts. Finally, we decompose the estimated anchoring coefficients $\hat{\gamma}$ into an "inefficiency" component $\hat{\gamma}_1$ and an "additional information" component $\hat{\gamma}_2$ and evaluate their relative contributions to determine the factor driving the anchoring bias test results.

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successor in terms of content it is, because most of the former MMS employees responsible for the survey founded AE after the takeover. In the following we always name the median forecast time series MMS forecasts, although it is continued with AE forecasts.

[8] The Federal Reserve Bank of St. Louis provides excess to a broad set of US macroeconomic data in their online database called ArchivaL Federal Reserve Economic Data.

[9] The correlation between A_t and F_t is positive if $V[S_t] < V[A_t] + V[F_t]$.

a. Anchoring tests results

We start with a "static" or in-sample test design and estimate equation (2) on the full sample for three different specifications of $\overline{h}$, where $\overline{h} = 1$ corresponds to anchoring on the last month's actual only and $\overline{h} = 2$ or 3 to anchoring on the mean of the two or three previously announced actual values, respectively. Since the static test involves a serious look-ahead-bias we perform a "dynamic" analysis in addition, estimating the anchoring coefficients on a rolling window with a fixed length of 10 years.

Table 3 reports results for the static as well as for the dynamic test. Regarding the static tests, we report the optimal $\overline{h}$, i.e. which regression specification performed best according to the Bayes' information criterion (BIC), along with the corresponding anchoring bias coefficient $\hat{\gamma}$. These results suggest that in about two thirds of the cases analyst use an average and not a single value as anchor. According to the test results survey forecasts for 18 out of the 23 macroeconomic series are significantly biased. However, for two of these series we obtain significantly negative coefficients which could hardly be explained by anchoring. Moreover, the large variation in the estimated coefficients suggests substantially different degrees of anchoring. For factory orders (FO), for example, this would imply that analysts put about 4% weight on last month's release and about 96% on the expected value, i.e., the unbiased forecast. In contrast, for consumer confidence (CC) it seems that the unbiased estimator and the previously released actual enter the MMS forecast with approximately equal weights.

Results of the dynamic anchoring tests are given in Table 3 as well. For simplicity we only report the most frequently observed optimal $\overline{h}$ along with means and the standard deviations of the $\hat{\gamma}$ s estimated on rolling windows of 10 years length. For most macroeconomic series the mean dynamic $\hat{\gamma}$ are largely comparable to their static $\hat{\gamma}$ counterparts, in particular, for the series which exhibit a significant static $\hat{\gamma}$. Surprisingly, the standard deviations of the dynamic γ estimates are rather large and indicate a substantial variation over the sample. For example, for CC we obtain a mean of 0.922 and a standard deviation of 0.365, stemming from a range of dynamic $\hat{\gamma}$ s (not reported) of -0.306 to 1.434. In fact, many series exhibit a substantial time variation in the $\hat{\gamma}$ coefficients.

Although the dynamic test results appear to be slightly weaker overall they are akin to the static test outcomes. For both static and dynamic we get sizable $\hat{\gamma}$ coefficients for most of the macroeconomic forecast series indicating substantial anchoring. At first sight this suggests partly predictable surprises and portends a poor quality of the frequently used MMS forecasts. Consequently this questions their appropriateness as proxy measures for market participants' expectations.

b. Can anchoring adjustments improve analysts' forecasts?

Given the highly significant and sizable anchoring coefficients we would expect that analysts' forecast can be substantially improved by adjusting them according to equation (3). Results are given in Table 4. First, we compute in-sample adjustments applying the estimated static γ coefficients. Then, to evaluate the real economical impact, we apply dynamic γ coefficients. To adjust the forecast for period *t* we use the dynamic γ coefficients estimated on information up to time *t-1*. In contrast to the static adjustments, this avoids a look-ahead bias. For both static and dynamic adjustments we report the change in root mean squared forecast errors (Δ RMSFE) resulting from these adjustments. Negative values indicate that the RMSFE of the adjusted MMS forecast is smaller than the unadjusted one, i.e. that the anchoring bias adjustment improves forecasts. To test whether these improvements are significant, we run Diebold and Mariano (1995) tests on differences in mean squared errors

(MSE). [10] Since macroeconomic analysts, in contrast to stock market analysts, have no incentives to issue systematic overoptimistic or pessimistic forecasts the assumption of a quadratic loss function implied by the MSE is uncritical.

By construction, the static (or in-sample) adjustments cannot yield a larger RMSFE of the adjusted series. Nevertheless, the improvements are rather small. We observe a reduction of 8.38% at best. Moreover, the Diebold Mariano tests find that only about 60% of the significantly biased forecast series can be improved. This is somewhat surprising since the static anchoring tests make use of forward looking information. Naturally, one would expect significant forecast changes whenever we get a significant anchoring test coefficient, at least for the static case.

The results of dynamic adjustments are much worse. When we adjust forecasts dynamically, i.e. without using forward looking information, almost no improvements can be obtained. There are only two exceptions, CC and DGO for which we obtain significantly improved forecasts according to the Diebold-Mariano test on differences in MSE. These correspond to a reduction in RMSFEs of nearly 8% for CC and less than 6% for DGO. On the other hand, we observe also two cases with significantly worsening forecast errors, i.e. NF and TRD. For all other series, changes in forecast errors are insignificant though large in some cases. For example, we observe the largest though insignificant forecast error change for RS, worsening the series' RMSFE by around 15%. Since the dynamical adjustment best represents market participants' approach to correct for the cognitive bias our results provide strong evidence against the economical significance of the anchoring bias.

Moreover, note that the size of the anchoring coefficient is at best loosely related to the improvements. For instance the durable goods orders bias coefficient is 0.398 and results in

[10] The test we apply includes the small sample adjustment of Harvey, Leybourne and Newbold (1997).

an RMFSE improvement of about 4.6%. In contrast the personal consumption expenditures anchoring bias coefficient is only 0.189 and leads to a considerable larger RMFSE reduction of about 7%. This odd pattern provides evidence that the anchoring bias test results might be misleading, i.e., a sizable $\hat{\gamma}$ does not necessarily lead to large forecast improvements.

c. Incremental forecast improvement over time series models

Our theoretical analysis provides a possible – though disturbing – explanation for the disconnection of forecast improvements and $\hat{\gamma}$ -coefficients. Equation (6) suggests that we may find a significant anchoring bias simply because analysts provide sophisticated forecasts by incorporating additional information beyond the univariate time-series information. This is definitely not unreasonable. For example, just by reading the current newspapers, analysts can process other contemporaneous business news. Technically speaking, γ -coefficients may just reflect that analysts can forecast part of the innovation in the data generating process, i.e. part of the change from the last month's actual unpredictable with univariate time-series information, by drawing on a richer information set. This would imply that survey forecasts are quite efficient – not inefficient as indicated by the anchoring bias test results.

To analyze this issue, we compare analysts' median forecasts F_t for a given month t with an "optimal" univariate time series forecast F_t^{TS}. To obtain an optimal forecast series without a look-ahead bias, we estimate various time series models using a rolling window. More precisely, for each point in time $t-1$ we estimate a broad range of different ARIMA(p,d,q) specifications (i.e. all combinations of p = 1, …,6, d = 0,1, and q = 0,1) using the last 10 years of data. Out of these we select the best fitting model according to the BIC. The estimated coefficients of this best fitting model are then used to produce a one-period-ahead time-series forecast F_t^{TS} for period t. Then we shift the estimation window by one observation and repeat the procedure to obtain a forecast for the next period. Concatenating these one-step-ahead forecasts, we obtain a time series of optimal forecasts.

Summary statistics for this optimal forecasts series are given in Table 5. The first column reports the parameters p, d, q for the most frequently best fitting ARIMA model. For example, for CC a specification with p=1, d=0 and q=0, i.e. a simple AR(1) model, turns out to provide the best fit in most cases. An even simpler model emerges for ISM: the most frequently optimal specification is p=0, d=1 and q=0, i.e. a model in first differences including solely a constant term. Thus for ISM the most frequently optimal model is a random walk with drift. Similarly for the majority of the other series the optimal model is rather simple. In most cases we find an AR(1), MA(1), or ARMA(1,1) processes (after first differencing) to be optimal. Only a few series call for second or third order processes.

Note that our time series of one-step-ahead forecasts F_t^{TS} estimated on a rolling window exploits the historical time series information available at any point in time most efficiently, but at the same time, avoids a look-ahead bias. In this sense it provides a benchmark for analysts' forecasts. Anchoring is equivalent to overestimating the influence of past observations, e.g. using a larger than optimal first-order autoregressive parameter when applying an AR(1) model. Hence, if analysts produce forecasts that are more or less strongly anchoring biased we would expect that an efficiently estimated time series model (avoiding this bias) outperforms analysts' forecasts. However, this only holds if the underperformance induced by the anchoring bias outweighs the overperformance resulting from the use of a broader information set.

This is definitely not the case. Columns 2 and 3 of Table 5 provide a comparison of forecast errors (RMSFE) of our out-of-sample time series forecasts and analysts' predictions. Column 5 reports the relative difference. For every single macroeconomic series the RMSFE of analysts' forecasts is smaller, for most series by more than 20% implying economically significant better forecasts. To evaluate the statistical significance of these forecast improvements, we use again a Diebold-Mariano test with small sample adjustment. For 20 out of the 23 series we find significant differences in MSE. For the vast majority of macroeconomic series analysts' forecasts significantly outperform the time series forecasts. For the remaining three series, i.e. core PPI, HS, and CS, analysts' forecasts have a smaller error as well, though the differences are statistically insignificant.

Overall, for none of the macroeconomic series our sophisticated time-series models outperform analysts' forecasts. Hence, in line with previous research on stock analysts' forecast performance (see e.g. Brown et al. (1987)), our estimation results clearly show that analysts provide superior forecasts in comparison to optimally selected univariate time series models.

Outperforming a model which optimally exploits univariate time series information can only stem from using a richer information set. To extract the forecast component which is unrelated to historical announcements (i.e., Z_t) we use the procedure described in section 1. Based on a distributed lag model, we decompose F_t into a component explained by historical time series information and a residual $\hat{Z}_t$. Now, this residual could just represent noise picked up by analysts when producing their forecasts. In this case $\hat{Z}_t$ would not help to predict A_t, or more precisely, would be uncorrelated with our estimate of the innovation in A_t, i.e., $\hat{e}_t$.

Correlations of $\hat{Z}_t$ and $\hat{e}_t$ are reported in Table 6. Most importantly, we find solely positive and highly significant correlations of $\hat{Z}_t$ and $\hat{e}_t$. This strongly suggests that $\hat{Z}_t$ represents not just noise being picked up somehow by analysts. In contrast, the additional information component in analysts' forecasts is able to predict some part of the innovation in announcements. Since our approximated innovation $\hat{e}_t$ constitutes the unpredictable part in an announcement after employing optimally univariate time-series information, the high correlation of $\hat{Z}_t$ and $\hat{e}_t$ also suggests that analysts' superior forecasting abilities stem from the incorporation of valuable additional information. Again, this finding is in line with studies analyzing stock analysts' forecast performance. For instance Fried and Givoly (1982) document that stock analysts' outperformance over time-series models is based on autonomous, i.e. additional information.

One potential source of valuable additional information are other macroeconomic news. Due to interrelations between macroeconomic indicators it is quite plausible that analysts utilize these releases in their forecast generation process. Therefore, other macroeconomic news should be able to, at least partly, explain the additional information approximated by $\hat{Z}_t$. Especially indicators released early in the cycle and those with large information content about the state of the economy should be useful (Gilbert et. al. 2010). As described in Section I we regress $\hat{Z}_t$ on all macroeconomic information available seven days prior to the announcements using a stepwise regression approach to identify the most influential indicators. Table 7 shows the regression results for selected indicators. Table 8 provides an overview for all indicators showing how many other indicators contribute to the explanation of $\hat{Z}_t$ in column (1). Column (2) reports the associated R^2 and the last column shows how often the indicator is useful to explain Z_t of other macroeconomic series. Consumer Confidence for instance helps to explain Z_t of 10 other macroeconomic series, i.e. is contained in the best model for 10 indicators. The results provide strong evidence that additional macroeconomic information can partly explain analysts' outperformance compared to optimized univariate time-series models. Depending on the indicator, between 7.0% (CPI) and almost 81% (PCE) of the variation in $\hat{Z}_t$ can be explained by other macroeconomic information. On average, R-squares amount to 36%. Furthermore, column (3) reveals that the most influential indicators are those which are released relatively early and which are commonly viewed to be good indicators of current or future economic activity. Consequently, we find ISM, CC, RS, NFP and UN to be the most important components of the additional macroeconomic information set. ISM for instance contributes in 14 out of 23 cases to the explanation of $\hat{Z}_t$.

Moreover, our results indicate that analyst process even more information beyond a broad set of macroeconomic news, probably including data which are not easily accessible via regular databases This suggests that their contribution as information intermediaries is valuable. Nevertheless, we cannot rule out that analysts' forecasts may still contain some behavioral bias. At least, our results suggest that the advantage of using a richer information set by far exceeds possible disadvantages associated with behavioral biases.

d. Decomposition of anchoring test results

Coming back to the question why the anchoring test produces so significant results, the high correlations of $\hat{Z}_t$ and $\hat{e}_t$ may provide an answer. According to equations (4) to (6) we can decompose the anchoring coefficient $\hat{\gamma}$ into an "inefficiency" component $\hat{\gamma}_1$ and an "additional information" component $\hat{\gamma}_2$. Table 9 provides statistics on $\hat{\gamma}_1$ and $\hat{\gamma}_2$. For comparison, static as well as dynamic γ-estimates are displayed in columns 1 and 2, respectively. Column 3 shows the approximated $\hat{\gamma}$ calculated on the basis of equation (4). In addition, columns 4 and 5 show the two components of $\hat{\gamma}$, i.e., the "inefficiency" component $\hat{\gamma}_1$ and the "additional information" component $\hat{\gamma}_2$.

The results clearly show that the additional information component $\hat{\gamma}_2$ is largely responsible for a substantial part of the overall $\hat{\gamma}$. Considering the macroeconomic series with a significantly positive anchoring bias coefficient, we find that in 11 out of 16 cases $\hat{\gamma}_2$ accounts for more than 50% of $\hat{\gamma}$. In two additional cases $\hat{\gamma}_2$ accounts for more than 25%.

The theoretical decomposition analysis has already shown that the anchoring test can produce biased results due to the "additional information" component it contains.[11] The empirical results now show that this "additional information" component is quite large for most macroeconomic series. This clearly indicates that the test itself includes a bias which is substantial.

These findings also provide an explanation for the puzzling forecast improvement results. If the anchoring bias test does not solely measure a cognitive bias, it is not surprising that controlling for such a bias cannot significantly change the quality of survey forecasts.

IV. Conclusion

The anchoring bias test recently suggested by Campbell and Sharpe (2009) indicates that the survey forecasts for a broad range of US macroeconomic releases are severely biased. This irrationality implies that survey forecasts could be substantially improved when we control for the bias. Surprisingly, applying a dynamic test and adjustment procedure we find hardly any forecast improvements. Our theoretical analysis explains this puzzling empirical result: Focusing on the univariate time-series properties of announcements the anchoring test neglects the possibility that analysts draw on a more comprehensive information set. Given the univariate setting of the anchoring test, our "horse race" of survey forecasts against univariate time series model forecasts clearly shows that analysts have superior information

[11] An adjustment based solely on $\widehat{\gamma_1}$ leads to comparable results and is therefore not reported.

processing abilities. Most likely, their outperformance is due to using a richer information set embracing more than just the univariate macroeconomic series. Obviously, analysts have access to a lot more information, for example, other related macroeconomic data or recent policy statements. We find that analysts use other macroeconomic information to generate their forecasts. Especially indicators released early in the month and those with much content about current and future economic activity are part of their information set.

Our empirical decomposition of the estimated anchoring bias coefficients shows that analysts' outperformance has a strong impact on the anchoring test. For the majority of significant anchoring tests, the "additional information" component explains more than half the size of the overall anchoring coefficient. This leads us to conclude that the anchoring test is highly misleading. In the majority of cases efficiency – not inefficiency –leads to the statistical significant results.

Given the strong bias in the test and the weak forecast improvements associated with anchoring adjustments, the economical significance of anchoring in macroeconomic surveys is more than questionable. Overall, our results suggest that there is no reason to question the results of earlier studies using the MMS macroeconomic forecasts.

An intriguing question for further research is therefore whether and to what extent macroeconomic analysts could outperform more sophisticated time series models. Naturally, a statistical model will never be able to capture the entire available information set. However, model based forecasts should be free of any cognitive bias. Yet, in order to obtain better forecasting models it is necessary to develop a better understanding of the factors driving the outperformance of analysts. While we cannot rule out with certainty that analysts' forecasts may contain some bias, our results clearly show that analysts' forecasts substantially outperform time series forecasts. Finally we have to conclude that survey forecasts provide the best available approximation of market participant's expectations.

Appendix A

As stated the direct estimation of

$$F_t = \lambda \cdot E\left[A_t\right] + \left(1-\lambda\right) \cdot A_{\bar{h}}, \tag{8}$$

is not possible. However the estimation becomes feasible by means of the well known definition of the unanticipated news component of a macroeconomic release:

$$S_t = A_t - F_t, \tag{9}$$

where S_t denotes the unanticipated news component called surprise, A_t the actual announced value of the macroeconomic indicator and F_t the survey based forecast. Taking the expectation of equation (9) and rearranging it leads to:

$$E\left[A_t\right] = F_t + E\left[S_t\right] \tag{10}$$

Substituting $E\left[A_t\right]$ in (8) with (10) gives the model for the further investigation:

$$E\left[S_t\right] = \frac{\left(1-\lambda\right)}{\lambda} \cdot \left(F_t - A_{\bar{h}}\right). \tag{11}$$

For reasons of clarity we define the slope coefficient in our model as:

$$\gamma \equiv \frac{\left(1-\lambda\right)}{\lambda} \quad . \tag{12}$$

Therefore the regression model for the test of the anchoring bias is given by[12]:

$$S_t = \gamma \cdot \left(F_t - A_{\bar{h}}\right) + \eta_t . \tag{13}$$

[12] Although equation (13) does not include a constant we always include one in the estimation.

Appendix B

Assume that A_t follows an ARMA(p,q) process without constant term, i.e.,

$$A_t = b_1 \cdot A_{t-1} + b_2 \cdot A_{t-2} + ... + b_p \cdot A_{t-p} + e_t + c_1 \cdot e_{t-1} + c_2 \cdot e_{t-2} + ... + c_q \cdot e_{t-q}$$

with i.i.d. $e_t \sim N\left(0, \sigma^2\right)$. Provided the process is stationary, it can be rewritten as

$$A_t = \psi(L)e_t \quad \text{with } \psi(L) = \frac{1 + c_1 \cdot L + c_2 \cdot L^2 + ... + c_q \cdot L^q}{1 - b_1 \cdot L - b_2 \cdot L^2 - ... - b_p \cdot L^q}$$

i.e. as an infinite MA process. For example, for an ARMA(1,1) we get[13]

$$A_t = e_t + \sum_{j=1}^{\infty} \beta_j \cdot e_{t-j} \qquad \text{with } \beta_j = b_1^{\,j-1} \cdot c_1 + b_1^{\,j}$$

Moreover suppose that analysts use a corresponding ARMA(p,q) model to generate forecasts. However, suppose that analysts can obtain some additional information Z_t useful to predict the innovation e_t in A_t, e.g., from the inspection of other macroeconomic announcements released earlier. Assume that $corr(e_t, Z_t) \neq 0$ and $corr(e_{t-j}, Z_t) = 0 \; \forall \; j \geq 1$. Then their forecasts may be written as

$$F_t = \sum_{j=1}^{\infty} \hat{\beta}_j \cdot e_{t-j} + Z_t$$

---

[13]
$$\begin{aligned}
A_t &= e_t + c_1 \cdot e_{t-1} + b_1 \cdot A_{t-1} \\
&= e_t + \left(c_1 + b_1\right) \cdot e_{t-1} + b_1 \cdot c_1 \cdot e_{t-2} + b_1^{\,2} \cdot A_{t-2} \\
&= e_t + \left(c_1 + b_1\right) \cdot e_{t-1} + \left(b_1 \cdot c_1 + b_1^{\,2}\right) \cdot e_{t-2} + b_1^{\,2} \cdot c_1 \cdot e_{t-3} + b_1^{\,3} \cdot A_{t-3} \\
&= e_t + \left(c_1 + b_1\right) \cdot e_{t-1} + \left(b_1 \cdot c_1 + b_1^{\,2}\right) \cdot e_{t-2} + \left(b_1^{\,2} \cdot c_1 + b_1^{\,3}\right) \cdot e_{t-3} + ... \\
&= e_t + \sum_{j=1}^{\infty} \left(b_1^{\,j-1} \cdot c_1 + b_1^{\,j}\right) \cdot e_{t-j} \\
&= e_t + \sum_{j=1}^{\infty} \beta_j \cdot e_{t-j} \qquad \text{with } \beta_j = b_1^{\,j-1} \cdot c_1 + b_1^{\,j}
\end{aligned}$$

Substituting the above MA(∞) representations of the ARMA(1,1) processes of A_t and F_t into the anchoring regression yields

$$A_t - F_t = \gamma \cdot \left(F_t - \frac{1}{h}\sum_{i=1}^{h} A_{t-i} \right) + \eta_t$$

$$\left(e_t + \sum_{j=1}^{\infty} \beta_j \cdot e_{t-j} \right) - \left(\sum_{j=1}^{\infty} \hat{\beta}_j \cdot e_{t-j} + Z_t \right)$$
$$= \gamma \cdot \left(\left(\sum_{j=1}^{\infty} \hat{\beta}_j \cdot e_{t-j} + Z_t \right) - \frac{1}{h}\sum_{i=1}^{h} \left(e_{t-i} + \sum_{j=1}^{\infty} \beta_j \cdot e_{t-j-i} \right) \right) + \eta_t$$

$$e_t + \left(\sum_{j=1}^{\infty} \left(\beta_j - \hat{\beta}_j \right) \cdot e_{t-j} \right) - Z_t$$
$$= \gamma \cdot \left(\left(\sum_{j=1}^{\infty} \hat{\beta}_j \cdot e_{t-j} + Z_t \right) - \frac{1}{h}\sum_{i=1}^{h} \left(e_{t-i} + \sum_{j=1}^{\infty} \beta_j \cdot e_{t-j-i} \right) \right) + \eta_t$$

Now, we can rewrite the anchoring bias regression as

$$\underbrace{e_t + y'_{t-1} - Z_t}_{y_t} = \hat{\gamma} \cdot \underbrace{\left(x'_{t-1} + Z_t \right)}_{x_t} + \eta_t$$

$$\text{with } y'_{t-1} \equiv \sum_{j=1}^{\infty} \left(\beta_j - \hat{\beta}_j \right) \cdot e_{t-j}$$

$$\text{and } x'_{t-1} \equiv \sum_{j=1}^{\infty} \hat{\beta}_j \cdot e_{t-j} - \frac{1}{h}\sum_{i=1}^{h} \left(e_{t-i} + \sum_{j=1}^{\infty} \beta_j \cdot e_{t-j-i} \right).$$

Note that y'_{t-1} and x'_{t-1} collect past time series information, or more precisely, terms depending on past innovations ε_t and (true and estimated) time series parameters ($\hat{\beta}_j$ and β_j). In contrast, ε_t captures the innovations (or residuals) of the announcement process, i.e. the component of an announcement which is unpredictable on the basis of past time series information. Z_t is similar to a residual since it cannot be explained by past announcements.

Hence Z_t reflects deviations of analysts' forecasts from purely time series based forecasts, or the influence of "other information" (besides past announcements) on analyst' forecasts.

The coefficient $\hat{\gamma}$ of the anchoring regression is given by

$$\hat{\gamma} = \frac{Cov\left(x_t , y_t\right)}{Var\left(x_t\right)}$$

$$= \frac{Cov\left(e_t + y'_{t-1} - Z_t, x'_{t-1} + Z_t\right)}{Var\left(x'_{t-1} + Z_t\right)}$$

$$= \frac{Cov\left(e_t, x'_{t-1}\right) + Cov\left(y'_{t-1}, x'_{t-1}\right) - Cov\left(Z_t, x'_{t-1}\right) + Cov\left(e_t, Z_t\right) - Var\left(Z_t\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)}$$

where the last line exploits the fact that $Cov\left(Z_t, y'_{t-1}\right) = 0$ by construction.

We can split up this expression for the coefficient $\hat{\gamma}$ into two parts by collecting all terms in the numerator depending on x'_{t-1} and those depending on Z_t :

$$\hat{\gamma}_1 = \frac{Cov\left(y'_{t-1}, x'_{t-1}\right) + Cov\left(e_t, x'_{t-1}\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)}$$

$$\hat{\gamma}_2 = \frac{Cov\left(e_t, Z_t\right) - Var\left(Z_t\right) - Cov\left(Z_t, x'_{t-1}\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)}$$

The first component $\hat{\gamma}_1$ captures the influence of (possibly biased) parameters $\hat{\beta}_j$, while the second component $\hat{\gamma}_2$ captures the influence of Z_t .

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Table 1: Indicator Overview

Indicator	Abbreviation	Sample Period Start	Sample Period End	Unit
Business Inventories	BI	02/1988	10/2009	% change
Consumer Confidence	CC	07/1991	12/2009	Level
Consumer Price Index	CPI	01/1980	11/2009	% change
Consumer Price Index ex Food& Energy	CPI ex	07/1989	11/2009	% change
Construction Spending	CS	02/1988	10/2009	% change
Durable Goods Orders	DGO	01/1980	11/2009	% change
Nonfarm Payrolls	NFP	01/1985	11/2009	Change (Thousands)
Civilian Unemployment Rate	UN	01/1980	11/2009	Level
Hourly Earnings	HE	10/1989	11/2009	% change
Factory Orders	FO	02/1988	10/2009	% change
Housing Starts	HS	01/1980	11/2009	Level (Millions of Units)
Industrial Production	IP	01/1980	11/2009	% change
Capacity Utilization	CU	03/1988	11/2009	Level
NAPM - renamed ISM Starting Aug. 2003	ISM	01/1990	11/2009	Level
Index of Leading Indicators	LI	01/1980	11/2009	% change
New Home Sales	NHS	02/1988	11/2009	Level (Thousands of Units)
Personal Income	PI	01/1980	11/2009	% change
Personal Consumption Expenditures	PCE	06/1985	11/2009	% change
Producer Price Index	PPI	01/1980	11/2009	% change
Producer Price Index ex Food& Energy	PPI ex	07/1989	11/2009	% change
Retail Sales	RS	01/1980	11/2009	% change
Retail Sales ex autos	RS ex	07/1989	11/2009	% change
Goods and Service Trade Balance	TRD	01/1980	10/2009	Level ($ Billions)

Table 2: Summary Statistics

Indicator	N	Actual μ	Actual σ	Forecast μ	Forecast σ	Surprise μ	Surprise σ
CC	222	95.595	27.533	95.476	26.779	0.119	5.212
ISM	239	51.579	5.622	51.630	5.418	-0.051	2.022
NF	299	106.080	200.982	115.080	157.507	-8.783	109.935
UN	359	6.150	1.514	6.188	1.518	-0.019	0.164
HE	240	0.273	0.205	0.261	0.064	0.011	0.195
PPI	359	0.219	0.653	0.258	0.382	-0.039	0.399
PPI ex	245	0.135	0.282	0.161	0.091	-0.026	0.265
RS	359	0.305	1.136	0.324	0.749	-0.032	0.734
RS ex	245	0.286	0.592	0.319	0.295	-0.033	0.445
CPI	358	0.291	0.319	0.299	0.258	-0.010	0.151
CPI ex	244	0.225	0.133	0.223	0.062	0.001	0.116
IP	359	0.118	0.687	0.129	0.495	-0.010	0.331
CU	261	80.203	3.586	80.190	3.579	0.006	0.370
HS	359	1.473	0.349	1.461	0.338	0.012	0.098
DGO	357	0.211	3.592	0.191	1.367	0.083	2.979
NHS	261	799.123	244.938	792.236	234.279	6.887	61.263
PI	358	0.456	0.443	0.407	0.304	0.051	0.304
PCE	292	0.413	0.499	0.377	0.385	0.033	0.227
LI	359	0.150	0.764	0.141	0.602	0.009	0.321
CS	260	0.218	1.072	0.113	0.568	0.105	1.003
FO	261	0.254	2.194	0.225	1.935	0.030	0.767
BI	261	0.221	0.458	0.189	0.342	0.032	0.239
TRD	358	-21.695	19.241	-21.524	19.291	-0.170	2.272

This table reports the means (μ) and standard deviations (σ) of the actual announced value (Actual), the MMS forecast (Forecast) and the resulting surprise calculated as the difference of Actual and Forecast.

Table 3: Anchoring Bias Test Results

	Static estimates		Dynamic estimates		
Indicator	$\bar{h}$	$\hat{\gamma}$	$\bar{h}$ most frequent	$\hat{\gamma}$ mean	$\hat{\gamma}$ std.dev.
CC	1	0.940***	1	0.922	0.365
ISM	1	0.297**	2	0.225	0.284
NF	2	0.070	3	0.137	0.271
UN	2	0.054	1	-0.187	0.284
HE	2	0.516***	2	0.439	0.264
PPI	3	0.315***	3	0.303	0.146
PPI ex	1	0.205**	2	0.176	0.262
RS	1	0.166***	1	0.183	0.114
RS ex	1	0.275***	1	0.382	0.217
CPI	3	0.150***	3	0.130	0.127
CPI ex	1	-0.214**	1	-0.149	0.175
IP	3	0.256***	2	0.204	0.173
CU	1	0.319***	1	0.268	0.122
HS	1	0.281**	1	0.339	0.153
DGO	3	0.398***	2	0.350	0.103
NHS	3	-0.104	1	0.557	0.228
PI	2	0.094	3	0.153	0.115
PCE	2	0.189***	2	0.250	0.098
LI	3	0.174***	3	0.150	0.107
CS	3	-0.222***	1	-0.247	0.087
FO	3	0.040**	1	0.036	0.033
BI	3	0.197***	2	0.260	0.108
TRD	3	-0.014	1	0.267	0.210

This table reports results of anchoring bias estimates according to

$$S_t = \gamma \cdot \left(F_t - A_{\bar{h}} \right) + \varepsilon_t,$$

where S_t denotes surprises, i.e. actual values(A_t) minus MMS forecast (F_t), and $A_{\bar{h}}$ is the $\bar{h}$ month anchor (i.e. the mean of the $\bar{h}$ previously released actuals). The first two columns report the optimal $\bar{h}$ and estimated $\hat{\gamma}$ for a test performed on the full sample. Columns (3) to (5) report the results for rolling window regressions with a fixed length of 10 years. Inference is based on White Standard Errors. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 4: Impact of Anchoring Adjustments on Forecast Quality

Indicator	Static $\hat{\gamma}$	Static adjustment: Δ RMSFE	Static adjustment: Diebold Mariano	Dynamic adjustment: Δ RMSFE	Dynamic adjustment: Diebold Mariano
CC	0.940***	-8.38%	3.0611***	-7.94%	2.3913**
ISM	0.297**	-1.14%	1.1600	3.36%	-1.4817
NF	0.070	-0.15%	0.3318	3.47%	-2.0611**
UN	0.054	-0.36%	1.0481	1.06%	-1.1930
HE	0.516***	-6.09%	1.9677*	-2.11%	0.3788
PPI	0.315***	-6.81%	2.2901**	-4.63%	1.5963
PPI ex	0.205**	-2.44%	1.0270	-1.98%	0.7873
RS	0.166***	-5.73%	2.2316**	15.41%	-0.9479
RS ex	0.275***	-6.39%	2.2695**	-7.87%	1.5492
CPI	0.150***	-2.58%	1.7648*	-2.21%	1.0900
CPI ex	-0.214**	-2.42%	1.5437	-0.12%	0.0846
IP	0.256***	-6.01%	1.7234*	-4.82%	1.0857
CU	0.319***	-3.65%	1.7317*	-3.24%	1.3350
HS	0.281**	-1.02%	0.9885	1.22%	-1.0694
DGO	0.398***	-4.56%	3.2828***	-5.71%	2.5341**
NHS	-0.104	-0.33%	0.9153	1.36%	-0.8149
PI	0.094	-0.53%	0.9634	0.56%	-0.7182
PCE	0.189***	-6.95%	1.8066*	-1.09%	0.2461
LI	0.174***	-6.75%	1.0762	-1.56%	0.8598
CS	-0.222***	-1.90%	2.0148**	-2.21%	1.3186
FO	0.040**	-0.70%	0.9962	0.12%	-0.0589
BI	0.197***	-1.40%	1.2159	-1.87%	1.2158
TRD	-0.014	-0.00%	0.1045	3.91%	-1.9588*

This table reports adjustments survey forecasts according to the estimated anchoring bias

$$F_t^{adj} = \left(1+\hat{\gamma}\right)\cdot F_t - \hat{\gamma}\cdot A_{\bar{h}},$$

where F_t denotes MMS forecast (F_t) and $A_{\bar{h}}$ is the $\bar{h}$ months anchor (i.e. the mean of the $\bar{h}$ previously released actuals). For convenience, column (1) redisplays static estimates of $\hat{\gamma}$. Columns (2)-(5) report the results of a Diebold-Mariano test with small sample adjustment for the equality of mean squared errors (MSE). H_0: MSE of F_t^{adj} = MSE of F_t. Inference of $\hat{\gamma}$ is based on White standard errors. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 5: Best Performing Time series Model

Indicator	Most frequent ARIMA(p,d,q) specification	RMSFE ARIMA	RMSFE MMS	Δ RMSFE	Diebold Mariano Test
CC	1,0,0	6.48	5.20	-19.7%	-5.46***
ISM	0,1,0	2.38	2.06	-13.5%	-3.71***
NF	1,0,1	136.71	109.97	-19.6%	-4.17***
UN	2,0,1	0.21	0.17	-15.3%	-2.84***
HE	3,1,1	0.15	0.13	-10.8%	-1.87*
PPI	1,1,1	0.72	0.43	-39.6%	-2.88***
PPI ex	0,1,1	2.10	0.29	-86.2%	-1.04
RS	2,1,1	1.15	0.73	-36.8%	-3.14***
RS ex	0,1,1	0.96	0.53	-45.0%	-2.25**
CPI	1,1,1	0.26	0.13	-49.3%	-3.33***
CPI ex	0,1,1	0.31	0.10	-68.3%	-1.89*
IP	0,1,1	0.63	0.33	-47.2%	-4.77***
CU	1,0,0	0.56	0.40	-28.4%	-4.18***
HS	2,0,0	1.71	0.08	-95.2%	-1.54
DGO	2,1,1	3.12	2.81	-9.8%	-2.50**
NHS	1,0,1	74.11	67.98	-8.3%	-1.87*
PI	0,1,1	0.46	0.31	-32.7%	-3.30***
PCE	2,1,1	0.43	0.20	-52.7%	-2.78***
LI	0,1,1	0.46	0.19	-59.3%	-4.57***
CS	0,1,1	1.22	0.91	-25.4%	-1.52
FO	2,1,1	2.29	0.74	-67.5%	-2.97***
BI	0,1,1	0.37	0.25	-32.7%	-3.75***
TRD	1,0,1	2.93	2.46	-16.2%	-3.01***

In column (1) this table reports the most frequent ARIMA specification from the rolling estimation procedure. Column (2) and (3) report the root mean squared forecast errors (RMSFE) of the time series forecasts and the original MMS data. Column (4) shows the percentage difference of the RMSFE, where negative values indicate the superiority of the MMS data. In column (5) contains the results of a modified Diebold- Mariano test for MSE equality (H_0:$MSE^{\text{time series forecast}} = MSE^{MMS}$). *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 6: Residual Correlations

Indicator	$Var(\widehat{\varepsilon_t})$	$Var(\widehat{Z_t})$	Correlation$(\widehat{Z_t}, \widehat{\varepsilon_t})$
CC	41.73	5.06	0.68^{***}
ISM	5.31	0.92	0.50^{***}
NF	19000.00	5182.06	0.60^{***}
UN	0.04	0.01	0.52^{***}
HE	0.04	0.00	0.32^{***}
PPI	0.40	0.12	0.82^{***}
PPI ex	0.08	0.01	0.36^{***}
RS	1.16	0.55	0.77^{***}
RS ex	0.35	0.09	0.69^{***}
CPI	0.07	0.04	0.81^{***}
CPI ex	0.01	0.00	0.24^{***}
IP	0.39	0.17	0.86^{***}
CU	0.28	0.08	0.74^{***}
HS	0.01	0.00	0.57^{***}
DGO	10.79	1.40	0.50^{***}
NHS	4396.60	447.31	0.41^{***}
PI	0.18	0.08	0.71^{***}
PCE	0.22	0.14	0.89^{***}
LI	0.50	0.29	0.90^{***}
CS	1.10	0.32	0.37^{***}
FO	4.16	3.15	0.93^{***}
BI	0.12	0.04	0.77^{***}
TRD	6.69	1.30	0.53^{***}

This table reports the variances of the innovation in announcements $\hat{\varepsilon}_t$ and the approximated additional information component in survey forecasts $\hat{Z}_t$ which we retrieved from optimally fitted distributed lag models as described in section 1. In addition the correlation of $\hat{\varepsilon}_t$ and $\hat{Z}_t$ is provided. ***, **, and * denotes significance of these correlations at the 1%, 5%, and 10% level respectively.

Table 7: Additional Information Content for Selected Indicators

Indicator	CC	DGO	IP	NFP	PPI ex	RS ex
HS			-0.004**	0.762***		0.001*
PPI		0.064***	0.013**	2.668***		0.013***
UN		0.001**	0.001***			0.000***
PCE	0.749***	0.213***	-0.098**	26.725***	0.042***	
CU			0.373***			
HE	-0.309*	0.186*	-0.108***			
NHS						-0.122**
RS		0.108**		7.890*		
TRD						
LI			0.306***		0.023*	0.197**
BI		0.786*		82.475***	0.195***	
CC		0.647***				
ISM			-0.051***		0.017***	
CS	1.124*					
CPI ex						-0.035**
IP			-0.000*	0.059***		
PI					0.017**	
PPI ex				31.745**		
CPI						
FO		0.109**	0.040**	10.280**	0.010**	
NFP		-0.162***				0.073***
DGO						-0.067**
RS ex					-0.001***	

This table report the regression results of the additional information on available macroeconomic information seven days prior to the next announcement:

$$Z_t = \alpha + \beta M_t + \varphi_t,$$

where Z_t denotes the approximated additional information component in survey forecasts and M_t a vector containing the available macroeconomic information set for the 23 considered indicators seven days prior to an announcement. A stepwise regression approach was used to obtain the models. *, **, *** indicates significance at the 10%, 5% and 1% level, respectively.

Table 8: Additional Information Content R-squared and Indicator Frequency

Indicator	# of variables in M_t	R^2	Frequency of indicator in M_t
CC	3	0.121	10
ISM	10	0.213	14
NF	8	0.312	11
UN	6	0.132	14
HE	6	0.391	5
PPI	3	0.084	9
PPI ex	7	0.395	6
RS	6	0.241	8
RS ex	8	0.439	3
CPI	2	0.070	6
CPI ex	6	0.239	4
IP	10	0.399	7
CU	10	0.302	11
HS	9	0.390	4
DGO	9	0.525	5
NHS	7	0.319	12
PI	8	0.429	3
PCE	7	0.808	6
LI	7	0.190	3
CS	6	0.572	7
FO	8	0.768	6
BI	11	0.381	6
TRD	9	0.513	6
Min		0.070	
Max		0.808	
Mean		0.358	
Median		0.381	

This table reports the number of explanatory variables in the vector of available macroeconomic information M_t in the regression $Z_t = \alpha + \beta M_t + \varphi_t,$, the associated R-squared and the frequency of each indicator in M_t, i.e. in how many cases the respective indicator contributes to the explanation of Z_t.

Table 9: Gamma Decomposition

	Test results		Model based approximation		
	Static estimates	Dynamic estimates	total	inefficiency component	add. information component
Indicator	$\hat{\gamma}$	mean $\hat{\gamma}$	$\hat{\gamma}$	$\hat{\gamma}_1$	$\hat{\gamma}_2$
CC	0.940***	0.922	0.940	-0.000	0.940
ISM	0.297**	0.225	0.297	0.118	0.179
NF	0.070	0.137	0.070	-0.028	0.098
UN	0.054	-0.187	0.049	0.031	0.018
HE	0.516***	0.439	0.516	0.486	0.030
PPI	0.315***	0.303	0.311	-0.003	0.314
PPI ex	0.205**	0.176	0.205	0.201	0.005
RS	0.166***	0.183	0.166	0.136	0.030
RS ex	0.275***	0.382	0.275	0.033	0.242
CPI	0.150***	0.130	0.149	0.060	0.090
CPI ex	-0.214**	-0.149	-0.214	-0.158	-0.056
IP	0.256***	0.204	0.254	-0.244	0.498
CU	0.319***	0.268	0.320	0.035	0.285
HS	0.281**	0.339	0.280	0.072	0.208
DGO	0.398***	0.350	0.399	0.225	0.174
NHS	-0.104	0.557	-0.102	-0.211	0.108
PI	0.094	0.153	0.095	0.053	0.041
PCE	0.189***	0.250	0.189	0.127	0.062
LI	0.174***	0.150	0.178	0.026	0.152
CS	-0.222***	-0.247	-0.217	-0.139	-0.078
FI	0.040**	0.036	0.040	-0.002	0.042
BI	0.197***	0.260	0.197	-0.036	0.233
TRD	-0.014	0.267	-0.016	-0.122	0.106

This table reports results of anchoring bias estimations:

$$S_t = \gamma \cdot \left(F_t - A_{\bar{h}} \right) + \varepsilon_t ,$$

where S_t denotes surprises, i.e. actual values (A_t) minus MMS forecast (F_t), and $A_{\bar{h}}$ is the $\bar{h}$ months anchor (i.e. the mean of the $\bar{h}$ previously released actuals). Column (1) contains the coefficients from the static test setting; column (2) reports the mean coefficients from the rolling estimation. Column (3) to (5) show the corresponding approximations of $\hat{\gamma}$ and its decomposition into an "inefficiency" ($\hat{\gamma}_1$) and an "additional information" ($\hat{\gamma}_2$) component:

$$\hat{\gamma}_1 = \frac{Cov\left(y'_{t-1}, x'_{t-1}\right) + Cov\left(e_t, x'_{t-1}\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)}$$

$$\hat{\gamma}_2 = \frac{Cov\left(e_t, Z_t\right) - Var\left(Z_t\right) - Cov\left(Z_t, x'_{t-1}\right)}{Var\left(x'_{t-1}\right) + Var\left(Z_t\right) + 2 \cdot Cov\left(Z_t, x'_{t-1}\right)}$$

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