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# Herding and Anchoring in Macroeconomic Forecasts: The Case of the PMI

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## Abstract

We test if analysts display multiple biases in forecasting the Institute for Supply Management's (ISM) manufacturing Purchasing Manager's Index (PMI). We adopt a test that does not require knowledge of the forecaster's prior information set and is robust to rational clustering, correlated forecast errors and outliers. We find that analysts forecast the PMI poorly and display multiple biases when forecasting. In particular, forecasters anti-herd and anti-anchor. Anti-herding supports a reputation-based notion that forecasters are rewarded not only for forecast accuracy but also for being the best forecast at a single point in time. Anti-anchoring is consistent with forecasters overreacting to private information. The two biases show a strong positive correlation suggesting that the incentives that elicit anti-herding also elicit anti-anchoring behavior. Both biases result in larger absolute errors, although the effect is stronger for anti-herding.

JEL classification: C83, D83, E44, G17, G24

Keywords: (Anti)-Herding; (Anti)-anchoring; PMI; forecast accuracy; panel data; multiple biases

# Herding and Anchoring in Macroeconomic Forecasts: The Case of the PMI

## 1 Introduction

The impact of new information on asset prices is central to our understanding of price discovery and the valuation process. To track information about the economy and the business cycle, analysts and investors use economic indicators such as payrolls data, GDP, and retail sales as a guide. Economic agents form expectations of these indicators and the "news" or "surprise" in such data releases is measured relative to these expectations. In efficient markets, only unanticipated information should impact asset prices. Consequently, a large literature has tracked the impact of the unexpected component of these data releases on asset prices (see Gilbert, Scotti, Strasser and Vega, 2015, and references therein). A critical component of the reaction of economic agents to new information centers on the expectations regarding that piece of data. Professional forecasters provide forecasts of economic data prior to the announcement of the actual data. The median or mean of the survey responses is then viewed as the "consensus" estimate for that piece of data. Asset market responses to such data releases are based on the extent to which the actual data are higher or lower than the consensus expectation. In other words, the news or surprise that asset markets react to is really forecast error.

The literature examining analysts' forecasts of macroeconomic indicators is not as deep as the literature for corporate earnings. In particular, there is a dearth of work dealing with bias in macroeconomic time-series. Schuh (2001) found that individual forecasts of U.S. GDP were either all good (unbiased and efficient) or all bad (biased and inefficient) pointing to differential ability among forecasters. More recent work has focused on behavioral explanations for forecast errors. Lansing and Pyle (2015) point to persistent bias in the track records of professional forecasters with respect to growth, inflation and unemployment. They conclude that the evidence raises doubts about rational expectations. Allowing for departures from rational expectations in economic models would be a way to more accurately capture features of real-world behavior.[1]

In this study, we test whether professionals exhibit behavioral biases in forecasting a key macroeconomic data series. The implications of forecasters using behavioral heuristics is that

[1] Loungani (2002), states "the record of failure to predict recessions is virtually unblemished." This conclusion was based on the finding that only two of the 60 recessions that occurred around the world during the 1990s were predicted by forecasters a year in advance. About 40 of the 60 impending recessions remained undetected seven months before they occurred.

forecasts may be systematically biased and/or inefficient. In particular, we examine forecasts for evidence of herding and anchoring. Herding refers to imitation behavior whereby analysts underweight or abandon their own private information in favor of group or leader opinion (e.g. Truman (1994); DeBondt and Forbes (1999)). Anti-herding or bold forecasting suggests that analysts systematically scatter their forecasts away from the forecasts of other analysts. Such behavior has been found in a variety of survey sources such as Consensus Economics, Livingston, *Wall Street Journal*, and OECD, and forecasts such as housing values, oil prices, interest rates, inflation rates (e.g. Lamont 1995; Clement and Tse 2005; Nakazono 2013; Pierdzioch et al. 2013a). Bernhardt, Campello and Kutsoati (2006), BCK hereafter, concluded that "analysts systematically issue anti-herding [earnings] forecasts that overemphasize their private information".

The anchoring-and-adjustment heuristic influences the way people intuitively assess probabilities. It refers to cases in which forecasts are anchored to some easily observable (usually uninformative) prior and leave out important information in forming and adjusting current forecasts. Campbell and Sharpe (2009) found consensus forecasts of several macroeconomic series anchored on the previous month's release. Nakazono (2013) found that Federal Reserve officials (non-governors) tend to anchor on their own previous forecast. However, Pierdzioch and Rulke (2013b) report anti-anchoring or repelling forecast bias with respect to inflation forecasts relative to a central bank's announced inflation target. In such cases, forecasts systematically deviate from the anchor and suggest over-reaction to new information.

In this paper, we study individual forecasts of a key macroeconomic indicator, the Institute for Supply Management's (ISM) manufacturing Purchasing Manager's Index (PMI). The PMI is a much-watched barometer of economic health because it is the first available indication of business conditions in the preceding month. [2] The subcomponents of the index are related to other useful pieces of information such as industrial production, durable goods orders, factory payrolls, producer price index and merchandise trade and are often used to forecast official data which are released several weeks later (Bachman 2010; Hess and Orbe 2013; Lahiri

[2] Baumohl (2013, p. 184) writes that a PMI reading of 50 is "believed to be consistent with real GDP growth of about 2.5%. Every full point in the index above 50 can add another 0.3 percentage points or so of growth every year."

and Monokroussos 2013).[3] In their study on information content and timeliness, Gilbert et al. (2015) opine that the PMI, not nonfarm payrolls, might be the true “king of announcements.”

There are many issues with testing herding and anchoring in time series data. Hess and Orbe (2013) challenge the anchoring finding in Campbell and Sharpe (2009) arguing that time series tests of cognitive biases may generally be flawed if the prior information available to participants is not properly controlled for. Moreover, unanticipated market shocks could cause all forecasts to appear clustered, and exceed or fall short of announced values. Further, clustered forecasts need not imply that analysts herd (Bernhardt et al. 2006). This is because forecasters may share the same public information and the same established techniques and relationships. When a forecaster’s incentive structure or loss function cannot be observed, the issue must be empirically sorted out.

We adopt an empirical approach to test for anchoring and herding in analysts’ forecasts that does not require knowledge of the forecasting model used by forecasters. The test, based on the work of BCK (2006), is robust to the shape of the forecaster’s loss function and the test statistic is invariant to whether the forecaster targets the mean or median of an asymmetric distribution of the variable under investigation. This test also accounts for rational clustering and is impervious to the choice of anchor. Importantly, the test statistic is robust to correlated forecast errors and to the occurrence of major disruptive events (e.g. the credit crisis) and outliers (Pierdzioch and Rulke 2013b).

To the best of our knowledge, this is the first study to use PMI forecasts as reported by Bloomberg, the most widely used news service in the finance industry, for purposes of studying behavioral biases. We present evidence for the first time on herding related to the ISM series. We also present an approach to studying herding and anchoring in time series data where only single forecasts of a fixed horizon event exist, i.e. there are no observable forecast revisions. In the case of herding, we construct an evolving consensus, as in BCK (2006), to circumvent a look-ahead bias. We explicitly control for the credit crisis, macroeconomic uncertainty and forecaster experience. Finally, we examine the impact of forecast bias on forecast accuracy.

[3] The ISM website cites Joseph E. Stiglitz, former chairman of President Clinton's Council of Economic Advisors, as saying, “The [ISM] Manufacturing [index]…has one of the shortest reporting lags of any macro-economic series and gives an important early look at the economy. It also measures some concepts (such as lead times and delivery lags) that can be found nowhere else. It makes an important contribution to the American statistical system and to economic policy.” Lahiri and Monokroussos (2013) add that, “..because of their nature as survey responses, ISM data are typically subject to small revisions at most. As such, they preserve most of the real-time nature that is crucial in many estimation and forecasting exercises…”

In our panel data study, we find that analysts forecast the PMI poorly. Forecasts appear to be pessimistic and forecast errors are elevated in times of uncertainty. Our tests point to strong evidence of anti-herding and anti-anchoring in the cross section of forecasting firms. Moreover, anti-herding and anti-anchoring appear to go together. Both biases cause larger absolute errors, although the effect is stronger for anti-herding.

The rest of this paper is organized as follows: section 2 summarizes some key literature; sections 3 and 4 describe the methodology and data, respectively; section 5 contains the empirical findings regarding herding and anchoring, section 6 contains a discussion of forecast bias and forecast accuracy, and section 7 concludes.

## 2 Literature Review

Herding may arise for a number of reasons. For instance, analysts may lack confidence in their private information and/or there is uncertainty concerning public information (Bikhchandani et al. 1992). Herding may increase with task difficulty (Kim and Pantzalis 2003), when analysts' private signal is pessimistic (Olsen 1996), or when analysts want to signal that their information is correlated with their peers (Truman 1994). Compensation-based herding arises when analysts fear penalties for being incorrect (e.g. Hong et al. 2000). There is also some evidence that herding may be culturally motivated (Ashiya and Doi 2001).

Why might forecasters anti-herd? Laster, Bennett and Geoum (1999) argue that forecasters are rewarded not only for forecast accuracy but, most importantly, for being the *best* forecast at a single point in time. The latter gives rise to forecast heterogeneity and thus anti-herding. Their model depends on the positive recognition of forecasters who, in any given period, prove to be the most accurate (e.g. through ranking systems or awards for best forecasters). This publicity enhances a forecaster's reputation, credibility and name recognition.[4] In a similar vein, Effinger and Polborn (2001) point out that much of the herding literature implicitly assumes that the remuneration of experts does not depend directly on whether their predictions are right. Therefore, the key incentive to forecast correctly is reputation. However, when the expert's value is additionally dependent on how many other experts are competing with him, then the value of hiring an able forecaster drops as the number of competing experts

[4] When we asked an award-winning analyst what the incentive was to turn in a forecast to Bloomberg, he replied, "Pride, publicity, and career advancement via name recognition from the Bloomberg posting."

increases. Consequently, the expert is most valuable when he is the *only* able expert. In this scenario, if the value of being the best is sufficiently large relative to the value of being one of several able experts, then anti-herding becomes attractive.

No universal measure of herding exists. Most attempts at detecting herding do so by estimating the deviation of each forecast from the mean or median of all forecasts reported in the forecasting cycle (see Hong et al. 2000; Clement and Tse 2005). Gallo, Granger, and Jeon (2002) find that GDP forecasts converge as the date on which GDP is announced draws nearer, but that final forecasts are either uniformly too low or too high. Pons-Novell (2003) finds that in the unemployment rate forecasts from the Livingston Survey, forecasters in some sectors anti-herd and forecasters in other sectors herd toward the consensus.

Bewley and Fiebig (2002) analyze the interest rate forecasts of 104 forecasters for eight countries taken from Consensus Economics and find that more than half of the forecasters have significant herding tendencies, and the degree of herding behavior increases with the volatility of interest rates, i.e. with forecast difficulty.[5] Pierdzioch and Rulke (2013a) study interest rate forecasts from the Livingston Survey. They apply the BCK test and find evidence of anti-herding, contrary to Bewley and Fiebig (2002), and that anti-herding results in lower forecast accuracy. They speculate that forecasters might have a non-standard loss function as described by Laster et al. (1999). Similarly, Pierdzioch et al. (2013b) find pervasive anti-herding in *Wall Street Journal* survey data on housing starts and housing price changes. Pierdzioch et al. (2016) find evidence of time-varying bias, i.e. South African forecasters of the inflation rate herd in times of heightened uncertainty and anti-herd in times of stability.

Tversky and Kahneman (1974) report that anchoring appears to be pervasive in financial decision-making and to be undiminished by task familiarity or financial incentives. Amir and Ganzach (1998) point out that anchored forecasts underweight the forecaster's private information and are biased toward the anchor (i.e. overweighting past information). Campbell and Sharpe (2009) find that consensus forecasts of monthly economic releases display anchoring and are systematically biased toward the value of the previous month's release. In their test, the null hypothesis of no bias is tested against an alternative of anchoring. Other tests of anchoring use alternative anchors: the analyst's previous forecast (Nakazono 2013), or the current or lagged

[5] They use the term herding to denote the tendency to produce a range of forecasts which is narrower than that which would likely be observed if the forecasts were produced on a strictly independent basis because a forecaster takes the previous consensus mean into account.

median forecast (Nakazono (2013); Cen et al. (2013)). Campbell and Sharpe (2009) and Hess and Orbe (2013) use the previous month's level of the PMI as the anchor in analyzing forecasts of the ISM. However, Hess and Orbe argue that analysts use more information than is assumed by the Campbell and Sharpe test. They construct an *ad hoc* information set comprising other macroeconomic data that analysts may have access to and find that this additional information accounts for more than half of the overall anchoring bias coefficient. They however, do not provide an improved test of anchoring.

Nakazano (2013) conducted a joint test of herding and anchoring using a test similar to Campbell and Sharpe and found that Fed governors herd to the previous consensus and deviate from their own previous forecasts. They report that non-governors tend to anti-herd and anchor on their previous forecast. Pierdzioch and Rulke (2013b) adapt the BCK approach to test whether a central bank's declared inflation target serves to anchor or repel inflation forecasts collected by Consensus Economics. From data for 22 countries, they conclude that forecasters appear to scatter their inflation forecasts away from the inflation target, suggesting that the target repels rather than anchors inflation expectations at least in the short run. They offer no explanation for this phenomenon.

Why might forecasters anti-anchor? While there does not appear to be much theory to address this question, we suggest that anti-anchoring may be viewed as the opposite of anchoring, i.e. forecasters overweight their private information and systematically deviate from an anchor. This behavior might be especially dominant if forecasters believe other forecasters tend to anchor on a particular anchor, e.g. the previous month's value of a macroeconomic variable. We speculate that, consistent with Laster et al (1999), forecasters will tend to deviate from observable anchors if they are motivated to be the best forecaster among a large group of forecasters. Such incentives will also lead forecasters to make bold forecasts and consequently to anti-herd.

In sum, the evidence appears to be mixed regarding (anti-)herding and (anti-)anchoring tendencies among macroeconomic forecasters. We empirically explore this issue further.

## 3 Methodology

To uncover herding and anchoring behavior, we rely on the BCK test. To illustrate how the test works, it is useful to consider a forecaster who forms an efficient private forecast that uses all available information to form a posterior distribution over the PMI. We notate this unobservable optimal forecast as $F_t^*$. The forecast is unbiased if the forecast is equal to the posterior estimate of the median or mean of the PMI. However, the forecaster may issue forecasts ($F_t$) that are biased. The probability that an unbiased private forecast overshoots or undershoots the announced PMI ($A_t$) is 0.5, and this probability should be unrelated to the consensus forecast, $\overline{F}_t$. Accordingly,

$$\text{Prob}\,(F_t > A_t \mid F_t > \overline{F}_t\,,\, A_t \neq F_t) = 0.5 \;\text{ and Prob}\,(F_t < A_t \mid F_t < \overline{F}_t\,,\, A_t \neq F_t) = 0.5 \qquad (1)$$

Herding arises if a published forecast is biased towards the consensus forecast. If the biased published forecast exceeds the consensus forecast then we have $\overline{F}_t < F_t < F_t^*$, i.e. the forecast will be located between the consensus and his best estimate. As a result, the probability that the biased published forecast overshoots the PMI will be less than 0.5. Similarly, if the biased published forecast is less than the consensus forecast then we have $\overline{F}_t > F_t > F_t^*$, and the probability that the biased published forecast undershoots the PMI also will be less than 0.5. Notating $z^+$ as the event that the forecast overshoots the consensus ($F_t > \overline{F}_t$), and $z^-$ as the event that the forecast undershoots the consensus ($F_t < \overline{F}_t$), herding implies that

$$\text{Prob}\,(F_t > A_t \mid z^+, A_t \neq F_t) < 0.5 \text{ and Prob}\,(F_t < A_t \mid z^-, A_t \neq F_t) < 0.5 \qquad (2)$$

Anti-herding implies that forecasters try to differentiate their forecasts from the forecasts of others. In such cases, the published forecast will be further away from the consensus forecast than the private forecast. Accordingly, $\overline{F}_t < F_t^* < F_t$ and $F_t < F_t^* < \overline{F}_t$ , and the probabilities of overshooting or undershooting the PMI will be greater than 0.5. Anti-herding implies that:

$$\text{Prob}\,(A_t < F_t \mid z^+, A_t \neq F_t) > 0.5 \text{ and Prob}\,(A_t > F_t \mid z^-, A_t \neq F_t) > 0.5 \qquad (3)$$

The non-parametric herding statistic, $S_H$, proposed by BCK is the average of the sample estimates of the overshooting and undershooting conditional probabilities. The test statistic is constructed as follows:

$$S_H(z^+, z^-) = \frac{1}{2}\left[\frac{\sum \delta_\tau^+}{\sum \gamma_\tau^+} + \frac{\sum \delta_\tau^-}{\sum \gamma_\tau^-}\right] \qquad (4)$$

where $\gamma^+$ and $\gamma^-$ are conditioning indicator functions such that $\gamma^+ = 1$ if $z^+$ occurred, zero otherwise. Likewise, $\gamma^- =1$ if $z^-$ occurred, zero otherwise. Similarly, $\delta^+$ and $\delta^-$ are overshooting binary indicator functions such that $\delta^+ = 1$ if $z^+$ occurred and $F_t > A_t$, while $\delta^- = 1$ if $z^-$ occurred and $F_t < A_t$.

Under the null, $S_H = 0.5$. When $S_H < 0.5$, the test suggests herding, and when $S_H > 0.5$, the test suggests anti-herding. The herding statistic has an asymptotic normal distribution under the null hypothesis that forecasters form unbiased forecasts with mean of 0.5 and variance of $\frac{1}{16}\left[\frac{1}{\sum \gamma_\tau^+} + \frac{1}{\sum \gamma_\tau^-}\right]$.

In the case of anchoring, Pierdzioch and Rulke (2013b) apply the BCK test to show that anchoring arises if a published forecast is biased towards the anchor. In this adaptation of the BCK test, the consensus forecast is replaced with the hypothesized anchor, $\overline{H}_t$. The overshooting and undershooting probabilities and the S-statistic ($S_A$) are computed similarly to (2), (3) and (4) above. Similar to the herding case, under the null, $S_A = 0.5$. When $S_A < 0.5$, the test suggests anchoring, and when $S_A > 0.5$, the test suggests repelling or anti-anchoring.

## 4 Data

The ISM manufacturing survey goes out to more than 300 corporate purchasing managers and supply executives representing 20 different industries (Baumohl, 2013). Respondents are asked to assess whether activity is better/same/worse relative to the previous month in the following ten areas: New Orders, Production, Employment, Supplier Deliveries, Inventories, Customers' Inventories, Prices, Backlog of Orders, New Export Orders and Imports.[6,7] We focus on the purchasing manager's index (PMI) which is an equally-weighted composite diffusion index based on the first five subcomponents, and is released on the first business day of each month.

[6] The backlog index compares current month unfilled orders with the prior month. The inventory index compares current month units on hand, not the dollar value, with the prior month.

[7] Specifically, five types of choices are offered as follows: For new orders, production and exports, the choices are better/same/worse; for employment, inventories, prices and imports, the choices are higher/same/lower; for supplier deliveries, the choices are slower/same/faster; for customer inventories, the choices are too high/about right/too low; and for order backlogs, the choices are greater/same/less.

Our sample is comprised of analysts' forecasts of monthly ISM announcements from 1998:6 to 2014:4, a total of 191 event days, as reported by Bloomberg.[8] The number of monthly individual analyst estimates for all announcements ranges from 3 to 88, with an average of 62. Figure 1 shows the distribution of firm-forecasts across the sample. There were a total of 11,842 individual forecast observations generated by 224 different firms. Figure 2 show the distribution of firms by number of forecasts. There were 123 firms with more than 20 forecasts; of these, 19 firms provided more than 150 forecasts in the sample. Later, we use this information to classify firms into more-/less-experienced forecaster quartiles.

Bloomberg sends monthly questionnaires to a list of analysts and economists asking for their forecasts of various macroeconomic indicators. Bloomberg publishes the forecasts as they come in (Pierdzioch, Reid and Gupta, 2016). Forecasts are marked with a date, with several forecasts marked with the same date. A limitation of the dataset is that while we have data on all forecasts that Bloomberg published for a particular event date, we cannot precisely track a forecaster's information set. This limitation is important because the herding test requires knowledge of a consensus forecast. Pierdzioch et al. (2016) correctly point out that while early forecasters are likely to have limited information on the forecasts of other forecasters, late forecasters can take into account a potentially large number of forecasts when submitting a forecast. A direct consequence is that we have to make an assumption as to what forecasters know about the forecasts of others when making their forecasts. An additional limitation of the Bloomberg dataset is that we are unable to unambiguously separate forecasters by type, e.g. buy-side versus sell-side, or by industry.

Figure 3 plots the PMI over the sample period along with the standard deviation of forecasts for each event. Table 1 contains descriptive statistics. Raw forecast errors are defined as the announced PMI minus the forecast PMI. Consensus forecasts are defined as the median of all forecasts for each event. We find that the mean monthly consensus forecast error (FE) is no different from zero. Thus, consensus forecasts appear to be unconditionally unbiased. However, the mean individual forecast error is significantly positive (i.e. 0.21) suggesting that, on average, forecasters were pessimistic and underestimated the announced value of the PMI. Predictably, individual errors are also more volatile than the consensus errors judging by the standard

[8] While consensus forecasts are available going back to 1992, individual analyst forecasts are only available from June 1998.

deviations of the errors. Interestingly, mean individual and consensus forecast errors are significantly higher than the errors from a naïve AR(1) forecast, i.e. forecasts equal to last period's PMI. Absolute forecast errors (AFE) and absolute percent forecast errors (APFE), i.e. absolute errors scaled by the announced value, are also larger and more volatile for individuals compared to the consensus. However, absolute forecast errors are smaller than naïve absolute forecast errors, suggesting that analysts might well be adding value.

Is forecasting more difficult in times of elevated uncertainty? We explore this issue by characterizing general macroeconomic uncertainty along three dimensions: 1) recessions as dated by the NBER; 2) the credit crisis dated from 2007:1 to 2009:6; and 3) the Economic Policy Uncertainty Index (EPUI) as presented by Baker, Bloom and Davis (2013). In the case of the EPUI, we classify months when the EPUI increased from the previous month as times of elevated uncertainty.

In Table 2, we report means and standard deviations for absolute percent forecast errors. Such scaling is necessary to make errors comparable by accommodating increases and decreases in the PMI at different times in the business cycle. We find that absolute percent errors were larger and more volatile during periods of heightened uncertainty for both consensus and individual forecast errors. The errors appear to be largest during recessions. Interestingly, naïve forecast errors are much larger than analyst errors in such times of uncertainty suggesting that even though errors are exaggerated in such times, analysts add value to the forecasting process.

Tests of herding and anchoring require knowledge of what it is forecasters herd toward or anchor on. In the case of anchoring, we choose the previous month's announced value of the PMI as the anchor, following Campbell and Sharpe (2009) and Hess and Orbe (2013). In the case of herding, we follow BCK and use the evolving current consensus, defined as the median of forecasts issued prior to the forecast in question. While forecasts are added every day to the portal beginning up to 4 weeks prior to the announcement, the vast majority of forecasts are posted on the Friday preceding the announcement, i.e. 3 to 7 days prior to the announcement.

We construct the current median for all forecasts prior to the announcement day. For instance, for those who report 7 days prior to an announcement, the median of all previously reported forecasts is considered to be the consensus. For those who reported 5 days prior to the announcement, the median of all reported forecasts up through day -6 is considered to be the consensus, and so on. Note that we include day 0, i.e. the announcement day, because on some occasions Bloomberg uploads forecasts that come in earlier that morning prior to the release of the indicator.

The anchoring-and-adjustment bias refers to forecasts that are anchored to some easily observable prior thereby leaving out important information in forming current forecasts. In particular, when analysts generate numerical estimates of uncertain quantities, adjustments away from some initial value or anchor are often insufficient. In other words, anchoring suggests under-reaction to new information. Anti-anchoring, by contrast, would suggest over-reaction to new information. Initially, we run the BCK test using the previous month's announced PMI as the anchor. We also experiment with alternative anchors including the prior period median forecast and prior individual/own forecast.

## 5 Empirical results

### 5.1 Do analysts herd?

Table 3 contains results of the BCK test of herding. As previously mentioned, we construct the current evolving consensus to prevent a look-ahead bias and ensure that information would be observable by forecasters. In the panel data set, we find pervasive evidence of anti-herding for days -7 through day 0. Analysts appear to position their forecasts away from the consensus. Cross-sectionally, we find that for the 158 firms with 10 or more forecasts, roughly 40% exhibit anti-herding and 60% exhibit no bias according to the BCK test.

To examine the time-series properties of the bias, we calculate S-statistics by year. In Table 4, we report results beginning with 1999 to ensure we have enough forecasts to conduct the test. We find no evidence of time variation in anti-herding: of the 16 years examined, 15 (93%) are characterized by anti-herding, and only 1 is characterized as no bias.

### 5.2 Herding robustness tests

We conduct several tests of the robustness of the (anti-)herding finding. These results are contained in Table 5. We examine herding in sub-samples based on the previously mentioned periods of uncertainty. We also examined the possibility that herding might be related to forecaster experience by segregating forecasters into experience quartiles. Here, we used the number of firm forecasts as a proxy for experience.[9] We also estimated the S-statistic after dividing the sample into pessimistic and optimistic forecasts. Here, pessimistic (optimistic) forecasts were classified based on whether the analyst's forecast was lower (higher) than his previous forecast. Finally, we examined herding in periods of high/low PMI volatility, a proxy for forecast (task) difficulty. Such periods of high/low volatility were based on Pierdzioch et al (2016): In a low-volatility regime, the absolute change in the PMI from the previous month is smaller than or equal to its unconditional full sample mean; in a high-volatility regime, the absolute change in the PMI from the previous month is larger than its unconditional full sample mean. In each case, we found pervasive evidence of anti-herding. Boldness appears to be a systematic characteristic of forecasts of the PMI.[10]

### 5.3 Do analysts anchor?

The BCK test is easily adapted to a test for anchoring. In the panel data set, we find pervasive evidence of anti-anchoring for the full sample with an S-statistic of 0.5617. When we run the BCK test by analyst-firm, using the previous month's announced PMI as the anchor, we find that in the cross section of firms with ten or more forecasts, roughly 18% exhibit an anti-anchoring (or repelling) bias. Interestingly, and in contrast to a broader result presented in Campbell and Sharpe (2009), there is no evidence of anchoring at the firm level.

To get a sense of the time series properties of the S-statistic, we generate S-statistics by year using all forecasts in a particular year. In Table 6, we find that about 68.5% of the time either anchoring (12.5%) or anti-anchoring (56%) bias is evident. For the overall sample, the test clearly indicates anti-anchoring. The time variation in the (collective) bias is interesting and is not related to periods of uncertainty. A deeper exploration of this time variation is the subject of a future study.

### 5.4 Anchoring robustness tests

[9] We also examined the impact of forecast number on forecast bias. We collected all the first forecasts of firms, then all the second forecasts and so on. We truncated the sample where we had minimally 10 analysts/firms, i.e. at 168 forecasts. We found pervasive anti-herding.

[10] Pierdzioch et al (2016) examined herding to the previous period's consensus on grounds that expectation formation shows features of adaptive learning (Ehlers and Steinbach, 2007). Although we disagree with this approach to testing for herding, we reexamined the overall sample results for herding to the previous period's median forecast and found pervasive anti-herding.

As further checks on the robustness of our findings, we run the BCK test on sub-samples based on the previously mentioned periods of uncertainty, and using alternative anchors such as the prior period median forecasts and prior individual/own forecasts. These results are contained in Table 7. We find that the anti-anchoring bias dominates and is unaffected by macroeconomic uncertainty or choice of anchor.

## 6 Behavioral biases and forecast accuracy

Our empirical tests show that forecasters exhibit both anti-herding and anti-anchoring characteristics. To examine the relationship between the two biases, we calculate the correlation between forecaster-specific S-statistics, i.e. $S_H$ and $S_A$. The two biases show a strong positive correlation of +0.60, which can also be seen in Figure 4. In other words, anti-herding and anti-anchoring behavior go together. This is consistent with Laster et al (1999) and the notion that forecaster incentive structures reward only the best forecast, which elicits anti-herding behavior. In turn, such behavior might reasonably result in forecasters overreacting to their own private information compared to random anchors, consistent with anti-anchoring behavior.

Finally, we examine the relationship between individual forecast bias and individual forecast accuracy. To do so, we estimate a model similar to that in Pierdzioch and Rulke (2013a), whereby we regress the average forecaster-specific absolute forecast errors and the absolute percent forecast errors on forecaster-specific S-statistics for herding and anchoring.

$$ForecastError_i = \alpha + \beta S_i + \varepsilon_i \quad (5)$$

Table 8 contains the results of these regressions. We find a positive relationship between the S-statistic and forecast error. While the relationship is strongly significant in the case of (anti-)herding, the relationship is not statistically significant in the case of (anti-)anchoring. The herding result indicates that cross-sectional anti-herding results in larger absolute errors, consistent with Pierdzioch and Rulke (2013a).

## 7 Conclusion

In this study, we test whether professionals exhibit behavioral biases in forecasting a key macroeconomic data series. The implications of forecasters using behavioral heuristics is that forecasts may be systematically biased and/or inefficient. In particular, we examine forecasts for evidence of herding and anchoring. We study Bloomberg-reported consensus and individual forecasts of the ISM's manufacturing PMI from 1998:6 to 2014:4.

We find evidence of anti-herding and anti-anchoring in individual forecasts of the PMI. Our results are at odds with Campbell and Sharpe (2009) who found evidence of anchoring. Our findings, however, are consistent with Pierdzioch et al. (2013a, 2013b) and others who found anti-herding and anti-anchoring in other macroeconomic series.

Our anti-herding findings support the notion that forecasters are rewarded not only for forecast accuracy but for being the best forecast at a single point in time as in Laster et al (1999). This is especially true when forecasts are subject to media attention. This publicity enhances a forecaster's reputation, credibility and name recognition and increases the incentive to deviate from the crowd. Our anti-anchoring findings suggest that analysts use a wide variety of information in their forecasts consistent with Hess and Orbe (2013). We find a close correlation between anti-herding and anti-anchoring suggesting that the two behaviors appear to go together.

We find mixed evidence regarding the correlation between individual measures of bias and forecast accuracy: while anti-anchoring does not appear to be related to forecast accuracy, anti-herding causes a deterioration in forecast accuracy.

Developing a more comprehensive theory to explain anti-anchoring could be a fruitful avenue for future research. Future research could also add value by adapting the BCK test to accommodate joint tests of two or more biases. More transparent forecaster/firm characteristics such as gender, experience and size, and better information on the timing of forecasts would allow for cleaner tests of herding.

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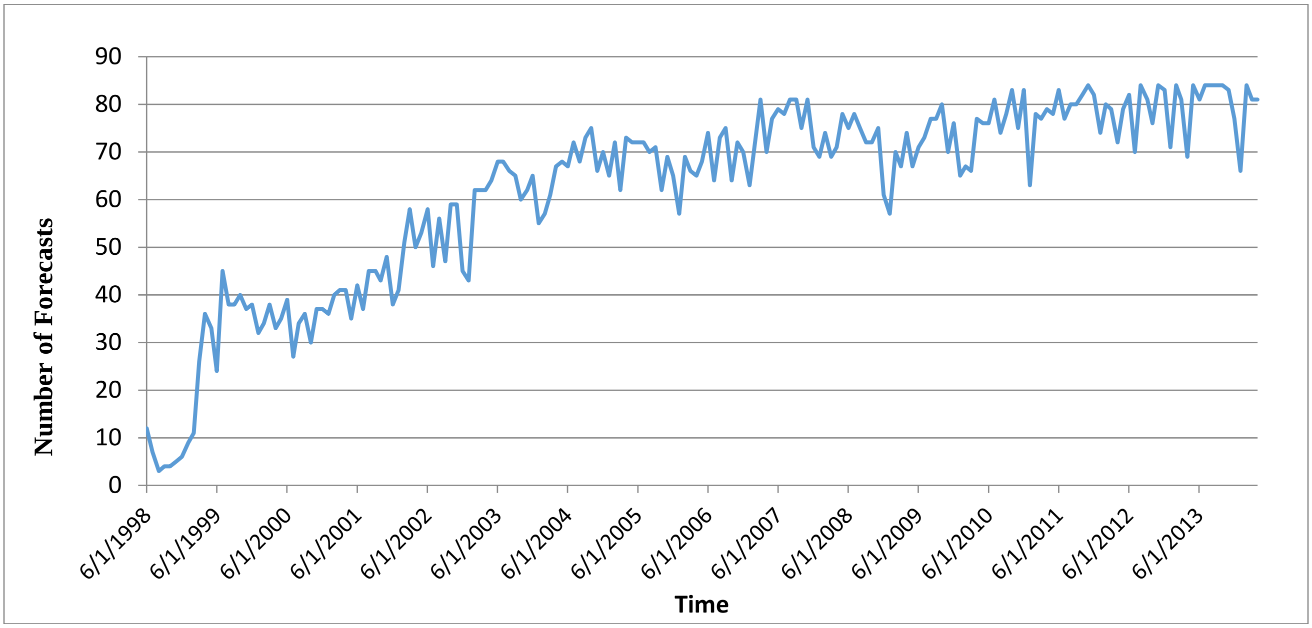


**Fig. 1** Number of PMI forecasts: June 1998 to April 2014

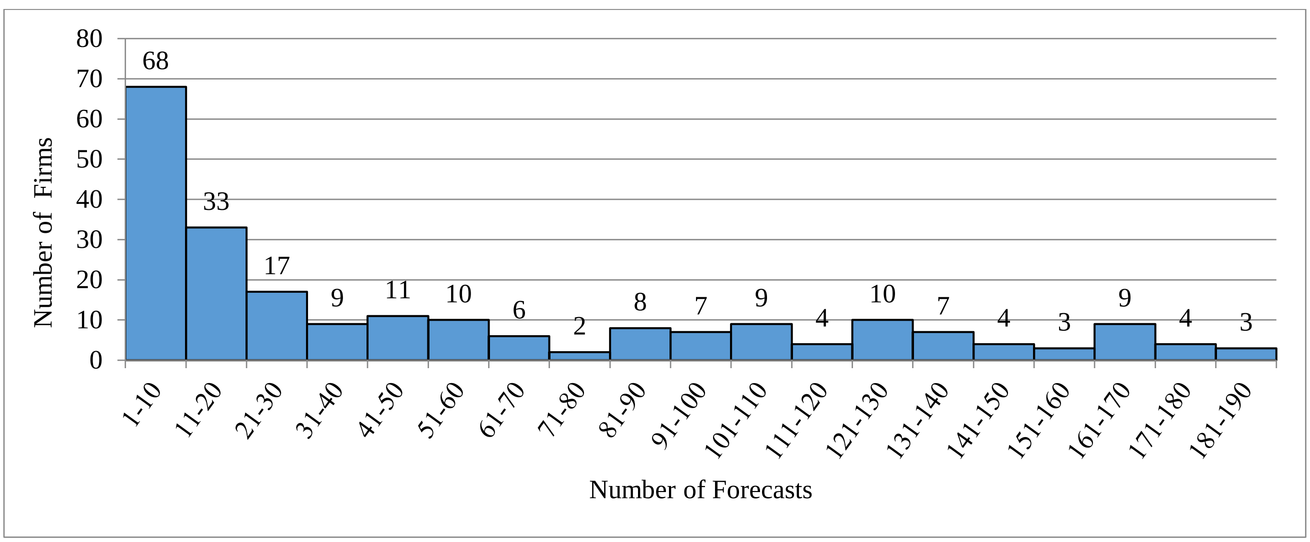


**Fig. 2** Number of forecasts per firm

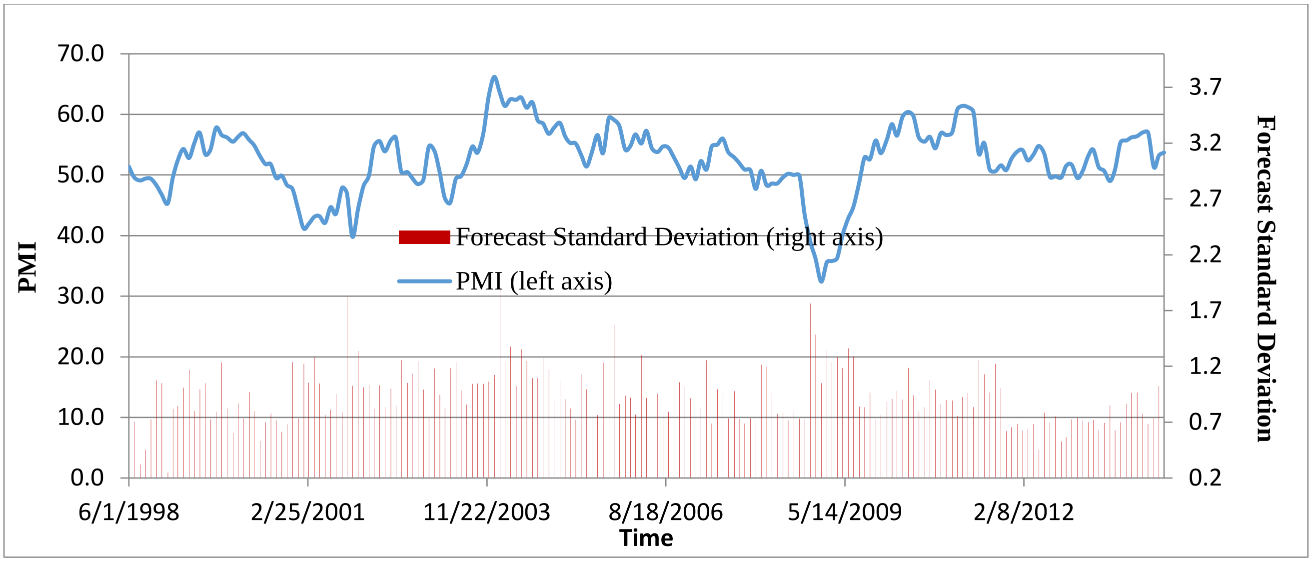


**Fig. 3** Announced PMI and forecast volatility

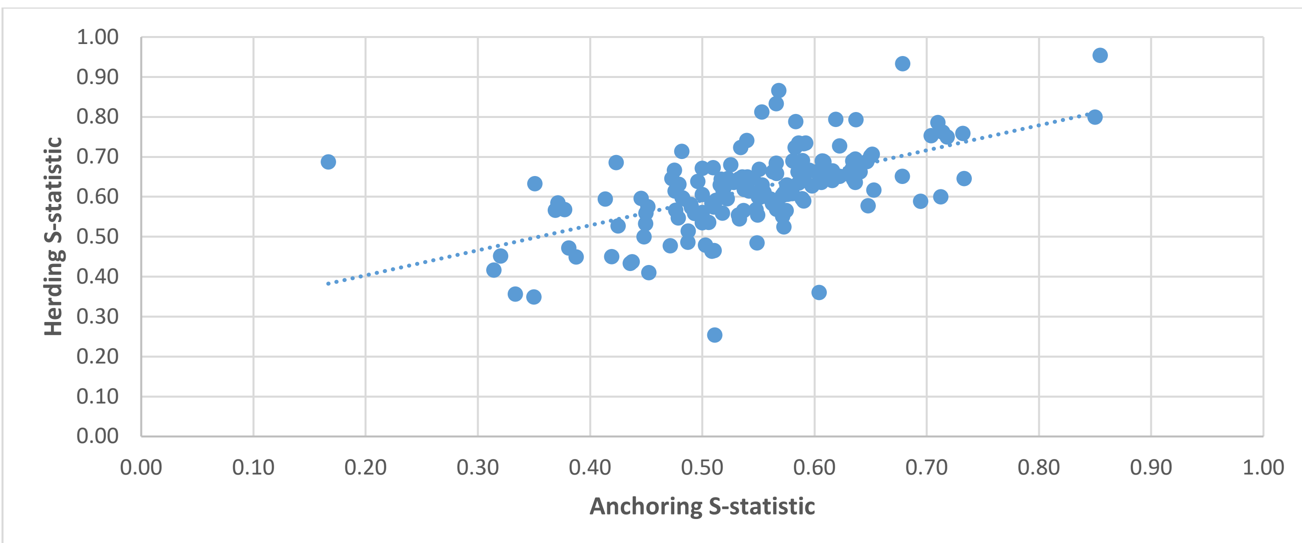


**Fig. 4** Relationship between biases

Table 1
Summary statistics

| | FE | | AFE | | APFE | |
|---|---|---|---|---|---|---|
| **Consensus Forecasts** | | | | | | |
| N | 191 | | 191 | | 191 | |
| Mean | 0.12 | | 1.53 | *** | 2.98 | *** |
| Std. Deviation | 1.99 | | 1.27 | | 2.53 | |
| **Individual Forecasts** | | | | | | |
| N | 11,842 | | 11,842 | | 11,842 | |
| Mean | 0.21 | *** | 1.73 | *** | 3.35 | *** |
| Std. Deviation | 2.21 | | 1.38 | | 2.75 | |
| **Naive Forecasts** | | | | | | |
| N | 190 | | 190 | | 190 | |
| Mean | 0.01 | | 1.84 | *** | 3.62 | *** |
| Std. Deviation | 2.39 | | 1.52 | | 3.10 | |

Notes: FE are forecast errors computed as Announced – Forecast; AFE are absolute forecast errors; APFE are absolute percentage forecast errors, i.e. absolute forecast errors scaled by the announced value and multiplied by 100. Naïve forecast is an AR(1) change in the announced, i.e. $A_t - A_{t-1}$. *** are significant at 1% or better.

Table 2
Forecast errors in times of uncertainty

| Economic State | Consensus APFE | | | Individual APFE | | | Naïve APFE | | | Mean Forecast Dispersion |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Standard Deviation | N | Mean | Standard Deviation | N | Mean | Standard Deviation | |
| Full Sample | 191 | 2.9840 | 2.5159 | 11,842 | 3.3464 | 2.7535 | 191 | 3.6267 | 3.1720 | 0.9337 |
| Recessions | 28 | 4.2274 | 3.5090 | 1,721 | 4.6818 | 3.8731 | 28 | 5.4366 | 4.8700 | 1.0880 |
| Crisis | 30 | 3.3760 | 3.2487 | 2,194 | 3.8576 | 3.4766 | 30 | 4.3539 | 3.9785 | 1.0020 |
| EPUI | 89 | 3.4319 | 2.8972 | 5,544 | 3.7988 | 3.1058 | 89 | 3.9824 | 3.5197 | 0.9515 |

Notes:
Recessions are based on NBER dates; Crisis is the period 2007:1 to 2009:6 that captures the worst of the credit crisis. EPUI is the Economic Policy Uncertainty Index (Baker, Bloom and Davis, 2013). Periods when the EPUI increased are considered periods of elevated uncertainty.

Table 3
Herding test using an evolving consensus

| Day(s) Prior to Announcement | N | Prob $(F_t>A_t \mid z_+)$ | Prob $(F_t<A_t \mid z_-)$ | S | Lower 95% | Upper 95% | Bias |
|---|---|---|---|---|---|---|---|
| -7 | 1020 | 0.4790 | 0.7681 | 0.6235 | 0.5906 | 0.6565 | Anti-herding |
| -6 | 918 | 0.6100 | 0.5488 | 0.5794 | 0.5446 | 0.6142 | Anti-herding |
| -5 | 1057 | 0.6497 | 0.5686 | 0.6091 | 0.5775 | 0.6408 | Anti-herding |
| -4 | 1686 | 0.5366 | 0.7441 | 0.6404 | 0.6152 | 0.6655 | Anti-herding |
| -3 | 2504 | 0.5997 | 0.6737 | 0.6367 | 0.6159 | 0.6575 | Anti-herding |
| -2 | 443 | 0.7921 | 0.5521 | 0.6721 | 0.6227 | 0.7215 | Anti-herding |
| -1 | 750 | 0.6384 | 0.7027 | 0.6705 | 0.6321 | 0.7090 | Anti-herding |
| 0 | 1253 | 0.5728 | 0.6371 | 0.6050 | 0.5751 | 0.6349 | Anti-herding |

Table 4
Herding test by year

| Year | N | S | Lower 95% | Upper 95% | Bias |
|---|---|---|---|---|---|
| 1999 | 375 | 0.5858 | 0.5278 | 0.6438 | Anti-Herding |
| 2000 | 412 | 0.6701 | 0.6157 | 0.7244 | Anti-Herding |
| 2001 | 490 | 0.4953 | 0.4476 | 0.5431 | No bias |
| 2002 | 623 | 0.6388 | 0.5958 | 0.6818 | Anti-Herding |
| 2003 | 747 | 0.6408 | 0.6009 | 0.6807 | Anti-Herding |
| 2004 | 799 | 0.7358 | 0.6978 | 0.7737 | Anti-Herding |
| 2005 | 825 | 0.6303 | 0.5926 | 0.6681 | Anti-Herding |
| 2006 | 817 | 0.5819 | 0.5455 | 0.6183 | Anti-Herding |
| 2007 | 909 | 0.6707 | 0.6348 | 0.7066 | Anti-Herding |
| 2008 | 869 | 0.6276 | 0.5919 | 0.6634 | Anti-Herding |
| 2009 | 859 | 0.5882 | 0.5516 | 0.6249 | Anti-Herding |
| 2010 | 901 | 0.6157 | 0.5810 | 0.6504 | Anti-Herding |
| 2011 | 944 | 0.5979 | 0.5635 | 0.6323 | Anti-Herding |
| 2012 | 948 | 0.6840 | 0.6487 | 0.7193 | Anti-Herding |
| 2013 | 970 | 0.6181 | 0.5831 | 0.6530 | Anti-Herding |
| 2014 | 313 | 0.6718 | 0.6084 | 0.7352 | Anti-Herding |
| Full Sample | 11,181 | 0.6279 | 0.6181 | 0.6377 | Anti-Herding |

Table 5
Herding: Robustness Tests

| | N | S | Lower 95% | Upper 95% | Bias |
|---|---|---|---|---|---|
| A. Periods of High/Low Uncertainty | | | | | |
| No Recession | 9553 | 0.6328 | 0.6222 | 0.6435 | Anti-Herding |
| Recession | 1628 | 0.6020 | 0.5766 | 0.6274 | Anti-Herding |
| No Crisis | 9105 | 0.6219 | 0.6110 | 0.6328 | Anti-Herding |
| Crisis | 2076 | 0.6539 | 0.6312 | 0.6767 | Anti-Herding |
| Below mean EPUI | 6037 | 0.6368 | 0.6234 | 0.6502 | Anti-Herding |
| Above mean EPUI | 5144 | 0.6175 | 0.6031 | 0.6320 | Anti-Herding |
| B. Forecaster Experience (# of forecasts) | | | | | |
| 1 - 9 | 1676 | 0.6124 | 0.5869 | 0.6378 | Anti-Herding |
| 10 – 29 | 2553 | 0.6489 | 0.6283 | 0.6696 | Anti-Herding |
| 30 – 74 | 3479 | 0.6202 | 0.6026 | 0.6378 | Anti-Herding |
| 75 – 119 | 1844 | 0.6307 | 0.6066 | 0.6548 | Anti-Herding |
| > 119 | 1629 | 0.6240 | 0.5982 | 0.6498 | Anti-Herding |
| C. Forecaster Optimism | | | | | |
| Pessimistic | 4281 | 0.6060 | 0.5899 | 0.6221 | Anti-Herding |
| Neutral | 753 | 0.6590 | 0.6207 | 0.6972 | Anti-Herding |
| Optimistic | 4761 | 0.6420 | 0.6264 | 0.6576 | Anti-Herding |
| D. PMI Volatility | | | | | |
| Low | 6782 | 0.6930 | 0.6804 | 0.7056 | Anti-Herding |
| High | 4399 | 0.5286 | 0.5128 | 0.5443 | Anti-Herding |

Table 6
Anchoring test by year

| Year | N | Prob ($F_t$>$A_t$\|$z_+$) | Prob ($F_t$<$A_t$\|$z_-$) | S | Lower 95% | Upper 95% | Bias |
|---|---|---|---|---|---|---|---|
| 1999 | 375 | 0.4485 | 0.6975 | 0.5730 | 0.5208 | 0.6251 | Anti-anchoring |
| 2000 | 412 | 0.8755 | 0.2927 | 0.5841 | 0.5342 | 0.6341 | Anti-anchoring |
| 2001 | 490 | 0.5085 | 0.4413 | 0.4749 | 0.4303 | 0.5195 | Unbiased |
| 2002 | 623 | 0.5457 | 0.4454 | 0.4956 | 0.4546 | 0.5365 | Unbiased |
| 2003 | 747 | 0.4498 | 0.2308 | 0.3403 | 0.3009 | 0.3797 | Anchoring |
| 2004 | 799 | 0.6727 | 0.6625 | 0.6676 | 0.6285 | 0.7066 | Anti-anchoring |
| 2005 | 825 | 0.5753 | 0.5992 | 0.5872 | 0.5516 | 0.6229 | Anti-anchoring |
| 2006 | 817 | 0.7500 | 0.3798 | 0.5649 | 0.5302 | 0.5996 | Anti-anchoring |
| 2007 | 909 | 0.4986 | 0.5287 | 0.5137 | 0.4797 | 0.5476 | Unbiased |
| 2008 | 869 | 0.6646 | 0.6647 | 0.6647 | 0.6220 | 0.7073 | Anti-anchoring |
| 2009 | 859 | 0.3361 | 0.5898 | 0.4630 | 0.4263 | 0.4996 | Anchoring |
| 2010 | 901 | 0.3176 | 0.6949 | 0.5063 | 0.4699 | 0.5427 | Unbiased |
| 2011 | 944 | 0.5038 | 0.7013 | 0.6026 | 0.5700 | 0.6351 | Anti-anchoring |
| 2012 | 948 | 0.6730 | 0.5494 | 0.6112 | 0.5787 | 0.6437 | Anti-anchoring |
| 2013 | 970 | 0.3686 | 0.8193 | 0.5939 | 0.5616 | 0.6263 | Anti-anchoring |
| 2014 | 313 | 0.5298 | 0.4894 | 0.5096 | 0.4522 | 0.5670 | Unbiased |
| Full Sample | 11,842 | 0.5308 | 0.5926 | 0.5617 | 0.5526 | 0.5709 | Anti-anchoring |

Table 7
Anchoring: Robustness tests

| | N | S | Upper 95% | Lower 95% | Bias |
|---|---|---|---|---|---|
| A. Periods of High/Low Uncertainty | | | | | |
| No recessions | 10121 | 0.5724 | 0.5624 | 0.5824 | Anti-Anchoring |
| Recessions | 1721 | 0.5613 | 0.5368 | 0.5859 | Anti-Anchoring |
| No crisis | 9648 | 0.5709 | 0.5607 | 0.5811 | Anti-Anchoring |
| Crisis | 2194 | 0.5742 | 0.5518 | 0.5967 | Anti-Anchoring |
| Below mean EPUI | 6447 | 0.5891 | 0.5765 | 0.6017 | Anti-Anchoring |
| Above mean EPUI | 5395 | 0.5535 | 0.5399 | 0.5671 | Anti-Anchoring |
| B. Different Anchors | | | | | |
| Anchor = prior period consensus | 11830 | 0.5148 | 0.5055 | 0.5241 | Anti-Anchoring |
| Anchor = prior own forecast | 10171 | 0.5224 | 0.5122 | 0.5325 | Anti-Anchoring |

Table 8
Forecast bias and forecast accuracy

| Dependent Variable | N | α | β | $R^2$ |
| --- | --- | --- | --- | --- |
| | | (Anti-)Herding | | |
| Absolute Error | 188 | 1.4878 | 0.3424 | 0.0333 |
| | | (0.0000) | (0.0122) | |
| Absolute Percent Error | 188 | 0.0289 | 0.0061 | 0.0226 |
| | | (0.0000) | (0.0396) | |
| | | (Anti-)Anchoring | | |
| Absolute Error | 192 | 1.6150 | 0.1629 | 0.0054 |
| | | (0.0000) | (0.3093) | |
| Absolute Percent Error | 192 | 0.0310 | 0.0031 | 0.0045 |
| | | (0.0000) | (0.9301) | |

Notes: p-values in parentheses.