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CAN ANCHORING EXPLAIN BIASED FORECASTS? EXPERIMENTAL EVIDENCE

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(previously entitled "Anchoring: a valid explanation for biased forecasts when rational predictions are easily accessible and well incentivized?")

Abstract: Biased forecasts, particularly the inadequate adjustment from current values and excessive clustering, are increasingly explained as resulting from anchoring. However, experiments presented in support of this interpretation lack economic conditions, particularly monetary incentives, feedback for learning effects and an optimal strategy of unbiased predictions. In a novel forecasting experiment, we find monetary incentives to substantially reduce and higher task complexity and risk to increase the bias. Anchors ubiquitously reduce the forecasts' variance, while individual cognitive abilities and learning effects show debiasing effects only in some conditions. Our results emphasize that biased forecasts and their specific variance can result from anchoring.

Keywords: anchoring; cognitive abilities; forecasting; heuristics and biases; incentives; laboratory experiment

JEL classification: C90; D03; D80; G17

1. Introduction

The anchoring heuristic (Tversky and Kahnemann, 1974) is increasingly considered to explain biased forecasts with examples including as diverse as financial forecasts (Fujiwara et al., 2013), real estate price forecasts (Northcraft and Neale, 1987; Bucchianeri and Minson, 2013), sports betting (Johnson et al., 2009; McAlvanah and Moul, 2013), earnings forecasts (Cen et al., 2013), macroeconomic forecasts (Nordhaus, 1987; Frankel and Froot, 1987; Bofinger and Schmidt, 2003; Campbell and Sharpe, 2009; Hess and Orbe, 2013) or sales forecasting (Lawrence and O'Connor, 2000). The findings point to two core empirical patterns: an excessive influence of current values and a clustering of forecasts, reflected in a low overall variance. The underlying mechanism is typically described as in Harvey (2007, p.17), who states that forecasters tend to "use the last data point in the series as a mental anchor and then adjust away from that anchor to take account of the major feature(s) of the series. However, as adjustment is typically insufficient, their forecasts are biased." Given that almost 40 years of psychological studies show the robustness of anchoring (cp. Furnham and Boo, 2011 for a review), it provides a reasonable explanation for biased individual forecasts.[1] There is, however, substantiated criticism concerning the immediate applicability of psychological evidence to explain economic data. On a general level, markets are expected to rule out behavioral biases as individuals gain expertise and face real financial stakes (Levitt and List, 2007; List and Millimet, 2008). Persistent biases subsequently result from specific laboratory conditions and experimenter demand effects, and ultimately hold little relevance outside the lab (Zizzo, 2012; for anchoring, see Chapman and Johnson, 1999). In the specific

[1] Another prominent explanation of systematically biased forecasts points to reputational concerns of forecasters trying to strategically conceal their inability to predict future values. This results in strong incentives for herding behavior among forecasters. For this approach, see e.g. Ottaviani and Sorensen (2006) or Lamont (2002) and the experimental study by Ackert et al. (2008).

case of anchoring, this is suggested in the field experiments of Alevy et al. (2010) and Fudenberg et al. (2012), who show only minor anchoring effects on subjects' willingness-to-pay/-accept. Their results resonate well with Clark and Friesen's (2009) criticism of economists' tendency to adopt psychological biases as stylized facts without supportive experimental studies that implement economic conditions. Consider the classic psychological studies cited in support of anchoring in forecasting, in which subjects take uninformed and non-incentivized guesses ("How many African countries in the UN?"). In these settings, anchoring ultimately cannot be seen as a deviation from the rational strategy. By contrast, anchoring might actually increase – if only slightly – the likelihood of a correct guess when subjects lack task specific knowledge and are not provided any information. While the applicability of these results to economic domains might still hold for situations of purely intuitive decision-making, it is insufficient proof for forecasting settings where distinctly non-intuitive decision processes and strong incentives for correct predictions prevail.

Accordingly, controlled laboratory studies are needed to systematically assess the robustness of anchoring in forecasting settings. This includes timely feedback to enable learning effects, a chance of correct predictions by providing an optimal strategy of avoiding the anchor, a non-intuitive high cognitive effort task and finally monetary incentives. Our experimental design implements these factors. We thus close the gap between economic empirical studies on anchoring and the respective psychological lab-based studies in order to enable the application of anchoring to economical domains. We introduce a simple numerical forecasting task that distinctly facilitates unbiased decisions as the rational strategy. The respective last values of the time series serve as anchors and thus have a dual function: they reveal the previous periods' correct value to enable learning effects, as well as provide the anchor value for the current period. In this setting, we investigate the influence of monetary incentives, cognitive abilities, task-specific risk and task complexity on the extent of the anchoring bias. In contrast to previous forecasting experiments (see Leitner and Leopold-Wildburger, 2011 for a review), a correct prediction is considerably easy to achieve.[2] Unlike regular anchoring experiments, we facilitate the optimal strategy to test for anchoring under conditions that offer an easily accessible strategy of unbiased forecasts. While this evidently contradicts the complexities of actual forecasting, we argue that a test of anchoring in forecasting should implement a low-complexity task. If anchoring occurs when avoiding it is simple and incentivized, we assume that its impact on actual forecasts in a complex environment is even more relevant.

In the following, the respective literature is reviewed to deduct our behavioral hypotheses. Tversky and Kahnemann's (1974) seminal paper presented the 'anchoring-and-adjustment' heuristic, from which numerous studies have evolved that show a pervasive influence of anchoring in decision-making. The aspects tested are diverse and range from factual knowledge (Blankenship et al., 2008; Wegener et al., 2001) to probability calculations (Chapman and Johnson, 1999) to price estimations after monetary reforms (Amado et al., 2007). Task-specific expertise is shown to be irrelevant for the anchoring bias, as in Englich and Soder (2009), for a judicial context supporting the assumption that forecasting experts may be equally susceptible to anchor heuristics. Overall, the influence of the anchoring heuristic proved to be "exceptionally robust, pervasive and ubiquitous" (Furnham and Boo, 2011, p. 41) regarding experimental variations.

[2] There are many time series forecasting experiments investigating individual prediction behavior (see Harvey, 2007 for a literature review). However, these studies are not designed to capture anchoring itself. While they point to anchoring as a potential explanation of behavior, the designs do not give specific evidence comparable to previous research on anchoring. They are also defined by excessive complexity of the forecasting tasks and varying sources of information. As we are not interested in these aspects, but rather the anchoring effect itself, we refrain from basing our setting on the classic forecasting experiments. For examples of time series forecasting experiments, see e.g. Bolger and Harvey (1993); Lawrence and O'Connor (1995); Becker et al. (2005, 2007, 2009); Leitner und Schmidt (2006); Reimers and Harvey (2011).

There are only two experimental study of anchoring in forecasting contexts so far. Critcher and Gilovich (2008), investigated the influence of incidental anchors in real life; e.g. by attempting to forecast the capabilities of athletes with high and low shirt numbers. They find that subjects are subconsciously biased by the closest incidental anchor in their environment for their estimations. Meub and Proeger (2015) test the influence of endogenous, socially derived anchors and find that forecasters are more strongly biased towards such anchors than to neutral, experimenter-given anchor values.

Regarding incentives for accurate predictions, Tversky and Kahnemann (1974), Wilson et al. (1996) and Epley and Gilovich (2005) offer prizes as rewards for the most accurate, unbiased estimations but find only minor effects of such an incentive. Chapman and Johnson (2002) summarize these findings, concluding that "incentives reduce anchoring very little if at all" (p.125). Wright and Anderson (1989) find a reduction in the bias using performance-related financial incentives, if subjects are familiar with the tasks. Simmons et al. (2010) show that incentives for accuracy work, once subjects are given certainty about the correct direction of adjustment for their initial predictions. We interpret these contradictory findings as resulting from a varying availability of strategies for solving the given tasks and the information at hand. Once participants are given the realistic chance of issuing more accurate predictions, monetary incentives are able to reduce anchoring effects. This is in line with standard assumptions concerning the introduction of monetary incentives in economic experiments (see e.g. Smith and Walker, 1993), which are expected to induce more rational behavior.

There are two contradictory results concerning the role of cognitive abilities in anchoring. Stanovich and West (2008) do not find a correlation between the susceptibility to anchoring and higher cognitive abilities, based upon individually stated SAT results. Oechssler et al. (2009) come to the same conclusion using the cognitive reflection test (Frederick, 2005). Using a corporate cognitive ability test, Bergman et al. (2010) find a significant reduction of anchoring in subjects with higher cognitive abilities. Similar to Oechssler et al. (2009), we choose to draw on the CR-test, as it can be completed in a short period of time and has been shown to be a good predicator of cognitive abilities, particularly regarding mathematical abilities (Frederick, 2005).

Blankenship et al. (2008) examine the effect of increased cognitive load, i.e. a systematic mental overload of subjects and find significant anchoring effects, which supports Wegener et al. (2001; 2010) who argue that different levels of cognitive effort can induce anchoring, albeit due to different mechanisms. On the one hand, in simple tasks, the anchor is used intuitively as a cue to the correct answer; on the other, the anchor works in the framework of a more complex thinking process by activating anchor-consistent knowledge. Therefore, anchor biases can occur in the context of intuitive decisions and analytically challenging tasks. While the observable result is identical, the cognitive processes that elicit anchoring need to be differentiated in respect of the context investigated (Crusius et al., 2012). Consequently, a valid test of anchoring in forecasting has to implement high-cognitive-effort tasks that more closely resemble the actual cognitive processes of forecasting, in contrast to the classical anchoring studies that mostly induce intuitive responses. Accordingly, the anchoring task has to foster non-intuitive decisions, yet provide a fairly simple rational strategy of unbiased decisions.

We contribute to the literature reviewed above by presenting new evidence on the influence of incentives for unbiased predictions, cognitive abilities, task complexity and learning effects in the context of anchoring. Despite the deliberately simple payoff-maximizing strategy for unbiased predictions, we find significant anchoring effects. Monetary incentives reduce the average anchoring bias to around one half compared with non-monetary conditions. Increased task complexity quadruples the average anchoring bias when compared to the simple definition of the task, while higher risk increases the bias most effectively. The variance of forecasts is smaller in the anchor condition for all experiments. Participants with higher cognitive capabilities are less prone to the influence of anchors in settings with a simple definition of the task and low risk. Despite the feedback in each period, the anchoring bias is only reduced by learning effects in the case of high underlying risk. In sum, we show that the core findings regarding biased forecasts – a lack of adjustment from current values and clustering – might very well be attributed to anchoring effects.

The remainder of this paper is organized as follows: in section 2, we describe the experimental design; section 3 introduces our behavioral hypotheses, section 4 presents the results and section 5 concludes.

2. Experimental Design

We implement a forecasting task whereby participants are asked to predict future values using a simple formula comprising several determinants. The formula is known to participants and remains constant throughout the experiment. Subjects have to predict the correct value using this given formula and the determinants that change each period.[3] One determinant is a random variable which is uniformly distributed over the interval [-25,25]. Its realizations are unknown and change every period, thus we induce an element of risk into the forecasting task. Its expected value is zero. The formula is $x_t=a_t+b_t-c_t+d_t$; x_t being the value participants are asked to predict, a_t, b_t, c_t are the known determinants and d_t is the random variable.

Each of our four experiments comprises two treatments. In the anchor treatments, subjects are shown the realized value of the previous period as an anchor, and are asked whether the value of the current period will be higher or lower than the anchor value. In this way, the standard paradigm of traditional anchoring (Tversky and Kahnemann, 1974) is implemented. The design basically demands participants to give a directional forecast first, then a point forecast.

[3] Subjects in the classroom experiment were allowed to use a pocket calculator, whereas in the lab they were able to use the Windows calculator implemented in the z-Tree program.

Subjects in the respective control groups are not shown the realized value of the previous period and accordingly are not asked the higher/lower question.

The rational strategy for payoff maximization is the calculation of the expected value using the formula and determinants. Given that the expected value of the random determinant is zero, it should not affect predictions. Moreover, the anchor of the previous value does not contain any additional information for the current period. Therefore, any bias toward the anchor value can be qualified as not rational.

In our first experiment ("basic"), we test if anchoring occurs when participants make forecasts without monetary incentives. Participants were asked to participate in a classroom experiment. Beforehand, every subject receives instructions[4] along with the formula, as well as ten forms for entering his or her calculation in each period. Instructions are read aloud prior to the experiment. Before starting their calculations, subjects are asked to do the cognitive reflection test (Frederick, 2005) in a maximum of six minutes, two minutes for each question. Subsequently, the calculations begin. Note that the calculations are intentionally fairly easy to solve. For instance, the calculation in the first period is 100 + 40 – 50 = 90; a task that every participant should be able to complete. Each round lasts one minute, during which the determinants and the last period's realized value (in anchor treatment only) are displayed on a PowerPoint sheet and read aloud. Participants are asked to write down their estimations on their forms. In the anchor treatment, they are additionally asked to estimate whether the current value is higher or lower than the previous value. Each treatment has ten periods.

The second experiment ("monetary") introduces a monetary incentive for accurate predictions. The experiments 2-4 are conducted using z-tree' (Fischbacher, 2007) in an

[4] The original instructions were in German; a translation is provided in the appendix.

experimental lab.[5] The formula and determinants remain identical, as does the cognitive reflection test before the actual experiment. The time for calculating the current value remains at one minute per period, with fifteen periods played in the second experiment. The payoff in each period is fifty cents minus the absolute difference between the respective forecast and the correct value in cents. Payoffs cannot become negative. Subjects are given an additional Euro for correctly answering all three CRT questions at the beginning.

The third experiment ("risk") increases the underlying risk by tripling the range of the random determinant's interval. Accordingly, the (d_t)'s are realizations of a random variable uniformly distributed over the interval [-75,75]. The expected value remains at zero. In order to account for the higher variance of d_t, the payoff in each period is eighty cents minus the absolute difference between the respective forecast and the correct value in cents.

The forth experiment ("complex") reduces the time that subjects have to make predictions to 30 seconds and introduces a more complex formula. The formula can now be written as $x_t=a_t+b_t -0.5c_t+d^2_{t+} e_t$; e_t being the random variable, again uniformly distributed over the interval [-25,25]. x_t is the value participants are asked to predict in each period, a_t, b_t ,$c_{t,}$ d_t are the known determinants in period t. In the laboratory experiment, we assured participants' understanding of the instructions by running several control questions beforehand[6], in the classroom experiment we answered subjects' questions regarding the design before starting the experiment.

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[5] Since we run a new control group in each experiment, transferring the experiment to the lab should not lead to a misinterpretation of the results. This would only be true if the control and anchor groups were affected differently by the conditions in the lab.

[6] The questions for the laboratory experiments were: (1) What is your task in this game? (2) On which formula is the future value based? (3) What does your payoff in this game depend on? (4) What is your payment in a given period, if the future value is 150 and your estimation has been 140?

Given the realizations for all determinants, following the rational strategy of predicting the expected values of x_t yields on average 0.38€ (=50-12.1) per prediction in the monetary experiment (0.45€ in risk and 0.38€ in complex). A naïve strategy of predicting the previous period's values, i.e. anchoring in the most extreme way, would yield on average 0.20€ per prediction in monetary (0.33€ in risk and 0.22€ in complex). Bearing in mind that subjects make 15 forecasts in total, there is obviously a strong monetary incentive for unbiased predictions. However, relying on the anchor values generates some payoff due to the weak autocorrelation of values to be predicted. We thus capture a key feature of real time series data: although no additional information can be obtained by observing the previous period's values, the naïve forecast yields some success.

Experiment 1 was conducted at the University of Göttingen in May 2012. Participants were undergraduate students in multiple tutorials of an introductory course in economics. Due to our procedure, control and treatment groups were conducted in different tutorials. The experiment took on average eighteen minutes.

The lab-based experiments took place in twenty six sessions from May to July 2012 and were conducted in the Laboratory for Behavioral Economics at the University of Göttingen. Participants were recruited using the online recruiting system ORSEE (Greiner, 2004) and were only allowed to participate in one session, which lasted around thirty minutes. On average, each participant earned €6,86. Overall, participants were on average 23.3 years old, 54% were female. Table 1 provides an overview of the different experiments and the numbers of participants.[7]

[7] Note that in basic, the treatment-specific difference in number of participants is due to the number of participants in the respective tutorials; in the laboratory experiments, differences occur because anchor treatment sessions were conducted earlier on and yielded more attendees, while control treatment sessions were conducted

No.	experiment	Variation			Number of participants		
		monetary	risk	complexity	control	anchor	total
1	basic	no	low	low	58	115	173
2	monetary	yes	low	low	44	53	97
3	risk	yes	high	low	39	53	92
4	complex	yes	low	high	35	58	93
	Total				176	279	455

Table 1: Summary of experiments and participants.

3. Hypotheses

Given that anchoring has been shown to be "extremely robust" (Furnham and Boo, 2011, p. 41) in various settings, we expect a significant bias towards the anchor values within our forecasting design.

Following Wright and Anderson (1989) and Simmons et al. (2010) and thus discarding Epley and Gilovich (2005), Wilson et al. (1996) and Tversky and Kahnemann (1974), monetary incentives can be expected to reduce anchoring, since a rational strategy is available. Increased task complexity and risk exposure should further increase anchoring as subjects might act more intuitively (Blankenship et al., 2008). However, the existence of a simple rational strategy along with monetary incentives can be expected to induce more rational behavior on average (Rydal and Ortmann, 2004); also, time pressure might lead to better decisions as in Kocher and Sutter (2006). The two opposing tendencies of rational strategy versus anchoring bias are addressed in Hypothesis 1:

Hypothesis 1 *("Rationality and anchoring bias")*. Subjects' forecasts are biased towards the anchor.

after the anchor treatment sessions where attendance was weaker. However, our analysis of treatment comparison is not influenced by these differences in any way as the number of observations is sufficiently high.

Based H1, we hypothesize that a systematic bias towards the anchor value can lead to a smaller variance of the forecasts in the treatment group. Therefore, the anchor heuristic would help to explain the empirical result of clustered forecasts. To test this assumption, we formulate Hypothesis 2:

Hypothesis 2 (*"*Differences in variance*").* The anchor reduces the variance in forecasts.

Furthermore, we examine the influence of subjects' cognitive abilities on the extent of the anchoring bias. Therefore, we aim at furthering the ongoing discussion concerning the susceptibility to anchoring depending on cognitive abilities (see Bergman et al., 2010). Consequently, we formulate Hypothesis 3:

Hypothesis 3 ("Cognitive abilities and anchoring bias"). Higher cognitive abilities reduce the anchoring bias.

Finally, we are interested in the relevance of learning effects. As the task is repeated and feedback is given in the treatment groups, learning effects are fostered. However, studies on experts in a judicial context (Englich et al., 2005; Englich and Soder, 2009) and in time series forecasting (Harvey et al., 1994; Harvey and Fisher, 2005) suggest that anchoring is independent of participants' prior knowledge or learning effects. Accordingly, we formulate Hypothesis 4:

Hypothesis 4 ("Learning effects"). The anchoring bias is not reduced by learning effects.

4. Results

We structure the following results according to our Hypotheses. First, we investigate prediction accuracy for each experiment to check if subjects are prone to the anchoring bias. Furthermore, we compare treatment effects between the experiments to identify determinants of the anchoring bias. Second, we look for differences in the variance of predictions between the treatments. Third, the results are evaluated regarding the influence of cognitive abilities and fourth, we comment describe learning effects.

4.1 Rationality and anchoring bias

Recall that showing the correct value of the previous period in the treatment group does not alter the profit-maximizing strategy of forecasting the expected value. The same holds true for the higher/lower-question, which is only answered by subjects in the treatment group.[8] If forecasts in the treatment group are biased toward the values of previous periods, we interpret this as evidence in support of the anchoring bias (Hypothesis 1).

Table 2 summarizes the main data for the comparison of our treatments, indicating the absolute deviation of predictions from the expected values and the fraction of optimal forecasts. Forecasts equal to the expected value are characterized as optimal. All values are calculated treating each subject as one observation only. Our dataset contains 253 missing values (predictions) when subjects did not enter a value in the respective period.[9]

[8] In basic 77% of the higher/lower-questions were answered correctly (87% in monetary, 77% in risk and 68% in complex).

[9] Given that the previous periods' values are by design first shown in the second period in the treatment group, we checked all results with respect to dropping the forecasts for the very first period. However, all results remain valid when relying on this reduced data set and thus we report our results based on the full data set including all forecasts.

		basic		monetary		risk		complex	
		control	**anchor**	**control**	**anchor**	**control**	**anchor**	**control**	**anchor**
average absolute deviation	**mean (sd)**	26.57 (34.19)	19.40 (17.28)	10.81 (16.71)	8.09 (7.13)	23.86 (23.11)	18.36 (13.15)	35.88 (57.02)	19.41 (12.13)
	median (p-value)	14.15	14.31	3.33	6.87	23.93	20.47	22.43	17.96
	75th pct.	24.44	22.44	10.83	12	35.33	27.83	37.23	26
	95th pct.	94.8	59	46	21.87	89.14	43.08	194.29	44
share optimal	**mean (sd)**	33.79 (38.43)	14.7 (25.28)	53.64 (42.58)	43.52 (39.60)	38.63 (38.36)	30.38 (35.9)	28 (35.1)	27.36 (26.83)
	median (p-value)	15	0	60	26.67	20	10	6.67	13.33
	75th pct.	60	20	1	86.67	73.33	60	66.67	40
	95th pct.	1	90	1	1	1	1	93.33	80

Table 2: Descriptive statistics for treatment comparison

The descriptive statistics show two main effects of the anchor values. First, subjects tend to forecast better on average due to the feedback of each previous round's correct value. This effect can be explained by the distinctive derivation of our anchor values, which hold some information on the expected values. As subjects are not fully capable of conducting the calculation of expected values to derive optimal forecasts, the reliance on previous rounds' values allows them to make better forecasts than those without anchor values. No such strategy is available in control groups where subjects do not receive any feedback, thus misinterpretations of the task are not resolved immediately. For example, subjects forecasting values smaller than 25 or even negative values, obviously trying to forecast the random determinant and not the actual value, can be found more often in control than in anchor.[10]

Second, the share of optimal forecast decreases in the presence of anchors. Accordingly, fewer subjects forecast the expected values due to the anchor values. Put simply, there are more optimal decisions in the control groups, but the non-optimal ones deviate from the expected value more strongly. These results will be discussed in more detail in the context of comparing the variance of forecasts over treatments (subsection 4.2).

[10] In basic (monetary/risk/complex) 16.7% (2.9/2.2/7.5) of forecasts are smaller than 25 in control, compared to 6.5% (0.4/1.4/2.7) in the treatment group.

However, one might interpret differences across treatments as accruing from the representativeness bias (Kahnemann and Tversky, 1973), whereby the distribution of forecasts in the treatment groups might reflect the distribution of the value to be forecasted.[11] This is due to the tendency of forecasters to replicate the distribution of a time series' noise, thus incorporating the uncertainty rather than ignoring it for an optimal prediction. (Harvey, 1995; Harvey et al., 1997; Harvey, 2007). We therefore have to demonstrate that deviations from the expected value are systematically related to the anchor values and do not stem from non-optimal behavior evoked by the representativeness bias. We test for a specific anchoring pattern in the forecasts of the treatment groups by running a regression.

Equation (1) presents the model to explain the subjects' forecasts. Let y_{it} denote the forecast of subject i at time t, and x_t the realized value at time t, whereby $E(x_t)$ gives its expected value. A_i is a dummy, which is 1 for subjects in the treatment group.

$$y_{it} = \gamma_1 E(x_t) + \theta_1[A_i(E(x_t)-x_{t-1})] + u_{it} \qquad (1)$$

In the given context, an optimal forecast of x_t can be explained by the expected value (expected_value) $E(x_t)$ only, i.e.(γ_1=1). However, we are interested in a potential bias caused by the anchor value, which is the realized value of the previous period. We include the term $\theta_1[A_i(E(x_t)-x_{t-1})]$ (anchor_deviation) to control for an anchoring bias. It measures the deviation of the realized value of the previous period x_{t-1} and the expected value in the current period $E(x_t)$ for subjects in the treatment group (A_i=1). An unbiased forecast is given if θ_1=0, whereas a forecast biased toward the anchor value is given if $\theta_1 < 0$.

In sum, information is used efficiently if a regression of (1) results in an estimation of γ_1, which is not significantly different from 1. At the same time, all other variables should show

[11] The distribution of the values to be forecasted is common knowledge in both treatments. Nevertheless, the representativeness bias might be more relevant in the treatment groups because the noise in the realizations is far more obvious when feedback is given.

an insignificant effect on the values forecasted ($\theta_1 = 0$). In such a case, there would be no evidence for H1, indicating that on average and ceteris paribus forecasts are made optimally and are unbiased.

Table 3 provides the results of a fixed-effects regression on our unbalanced panel dataset of Eq. (1), applying robust Driscoll and Kraay standard errors. Hence, we control for unobservable heterogeneity, heteroscedasticity, serial correlation in the idiosyncratic errors and cross-sectional dependence.

Experiment	**(1)**	**(2)**	**(3)**	**(4)**
	basic	monetary	risk	complex
expected_value	**0.766*** **	**0.964*** **	**0.922*** **	**0.760*** **
	(0.025)	(0.012)	(0.039)	(0.100)
anchor_deviation	**-0.058** **	**-0.038*** **	**-0.145*** **	**-0.152* **
	(0.023)	(0.012)	(0.04)	(0.086)
constant	**16.31*** **	**5.097*** **	**12.83*** **	**28.29** **
	(2.231)	(1.173)	(3.973)	(9.779)
F-Statistic (γ_1=1)	**88.68*** **	**8.95** **	**4.03* **	**5.73** **
Prob. > F	(0.000)	(0.010)	(0.066)	(0.033)
Observations	1505	1351	1280	1163
No. of Groups	171	97	92	93

Table 3: Fixed-effects regression of Eq. (1) with forecast (y_{it}) as dependent variable.

Note: Robust Standard Errors in parentheses; for F-Statistics p-value in parentheses. (*** p<0.01, ** p<0.05, * p<0.1)

For all experiments, we find a significant effect of the deviation in the anchor value.[12]

Notwithstanding, there are differences between the experiments with regard to the average quality of the forecast. A smaller marginal effect of a change in the expected value, i.e. a

[12] We checked the robustness of our results by only considering the first ten periods played. This check was due to the temporal restriction in the classroom experiment, in which we were only able to play ten periods. However, estimating Eq. (1) by the same procedure as in Table 3 with only the first ten periods does not relevantly alter our results.

smaller γ_1 for $\gamma_1 < 1$, has to be associated with a lower average quality of the forecasts and less optimal behavior. In monetary, the subjects adjust best compared to the other experiments and almost optimal on average according to a change in the expected value. The forecasting quality drops if there are no monetary incentives (basic), the underlying risk is increased (risk) or task complexity is increased (complex).

For all experiments, we find a negative and significant effect of the deviation in the anchor value ($\theta_1 < 0$), which has to be interpreted as an on average bias towards the realized value of the previous period in forecasts by the treatment group, as compared to the control group. For a decreasing (increasing) value in t compared to t-1, subjects in the treatment group give significantly higher (lower) forecasts. This fact has to be considered as a systematic inability to ignore the realized value of the previous period and a substantial anchoring bias.

Besides the significance of the bias towards the anchor value, its relevance can be addressed. Based on the average absolute difference of the anchor values and the expected values of 24.6 points in basic (20.4 in monetary, 32.9 in risk, 20.4 in complex), the estimated marginal effect of -0.058 (-0.038, -0.145 and -0.152) amounts to a ceteris paribus bias of 1.427 (0.775, 4.771 and 3.101) points on average. This corresponds to 1.51% (0.8%, 5.0% and 3.2%) of the average values to be forecasted.[13]

Obviously, implementing monetary incentives diminishes the influence of the anchoring bias. In monetary, the average bias in the treatment group is around half of the bias in basic. In comparison to monetary, higher underlying risk substantially increases the extent of the bias

[13] The differences in the average deviation of the anchor value and realized values in experiments 2, 3 and 4 accrue from the lower number of periods being played in experiment 1, along with small adjustments as part of the formula modification in experiment 4 and changed realized values for the unknown determinant in experiment 3 due to the greater range of the interval of the random variable. The changes in experiment 4 became necessary to avoid subjects' calculations of the expected values from becoming too complicated.

by a factor of about 6. Establishing a higher task complexity quadruples the extent of the bias compared to monetary.

We conclude that the anchoring bias has a significant and relevant impact on subjects' forecasts. The information given is not used optimally. On average, subjects are unable to ignore the values of the previous periods as the optimal strategy would suggest. Consequently, the empirical finding of forecasts biased towards the respective current values can – at least partly – be explained by the anchoring bias. Therefore, we interpret our results as presenting strong evidence in favor of H1.

4.2 Variance of forecasts

In order to test for differences in the variance of forecasts (H2), we present the standard deviation over experiments and treatments, as well as the Brown and Forsythe statistic resulting from the procedure to test for equality in group variances in Table 4.

		Std. dev.		Tests (H_0: equality)	
		control	anchor	B/F-statistic (W50)	B/F-statistic (W0)
1	basic	46.53	33.02	33.73	45.38***
2	monetary	32.89	24.75	12.9	13.01***
3	risk	44.5	31.88	27.6	32.71***
4	complex	106.46	36.5	26.83	35.88***

Table 4: Summary of standard deviations and Brown/Forsythe statistics

Note: Asterisks representing p-values of the B/F-statistic testing the null of equal variances. (*** p<0.01, ** p<0.05, * p<0.1) W50 denotes the results from the test procedure using the median; W0 when using the mean.

We find a significantly smaller standard deviation in the anchor treatments for all experiments. Consequently, there is strong evidence in favor of H2. The uniformity or low variance of forecasts shown in empirical studies of forecasting time series might be explained to some extent by a systematic anchoring bias. The differences across treatments can be explained by subjects turning to the anchor values trying to cope with the challenging task. However, recall that the anchor value causes a higher frequency of deviations from optimal forecasts, which in turn tend to be smaller compared to the control group.

Since subjects align their forecasts to the anchor values, a substantial share of private information might not be revealed in actual forecasting markets and information disclosure might be inefficient on the aggregate level. Accordingly, forecasters acting homogenously might not be a sign of unambiguous information of high quality but rather reflect analysts trying to cope with too little information or driven by the same bias.

4.3 Cognitive abilities

To test for the influence of cognitive abilities on the anchoring bias, we classify subjects using a procedure proposed by Oechssler et al. (2009), according to which subjects correctly answering two or more questions of the CR-Test are classified as having "high cognitive abilities" (HCA), and otherwise as having "low cognitive abilities" (LCA). In total, 29% of the subjects answered none of the questions correctly, 24% got one question right, 23% two questions and 23% all three questions. Accordingly, 53% of the subjects were grouped as having LCA, and 47% as having HCA. We expect LCA subjects to be more prone to the anchoring bias, due to their tendency of answering more intuitively (H3).

We find HCA subjects to predict more accurately and act optimally more often. For basic (monetary/risk/complex), the average absolute deviation for HCA pooled over treatments is 21.0 points (6.7/16.7/23.0), while for LCA it is 22.3 points (12.7/26.6/28.6). The difference between LCA and HCA subjects in the control group amounts to -0.1 points (5.6/12.5/7.3). For the treatment group, the difference is given by 6.7 points (6.0/10.2/1.5).[14] However, we are interested in the specific effect of higher cognitive abilities on the anchoring bias.

[14] The control group in basic shows an average absolute prediction error of 26.6 points (8.0/20.0/31.9) for HCA subjects and 26.5 points (13.6/32.5/39.2) for LCA; the treatment group in basic shows an average absolute prediction error of 14.6 points (5.7/13.5/18.8) for HCA subjects and 21.3 points (11.7/23.7/20.3) for LCA.

Therefore, we modify Eq. (1) such that it allows for the identification of a potential influence of a subject's cognitive abilities on the anchoring bias. HCA_i denotes a dummy for subjects classified as having high cognitive ability.

$$y_{it} = \gamma_1 E(x_t) + \theta_1[A_i(E(x_t)\text{-}x_{t-1})] + \vartheta_1[A_i HCA_i(E(x_t)\text{-}x_{t-1})] + u_{it} \qquad (2)$$

The impact of the deviation in the anchor values is now to be interpreted according to the subjects' cognitive abilities. θ_1 gives the marginal effect of a change in the deviation in the anchor values for subjects in the anchor treatment and the LCA group; $(\theta_1 + \vartheta_1)$ gives the marginal effect for the HCA group. The extent of the bias towards the anchor in the LCA group ($\theta_1 < 0$) is smaller for the HCA group if $\vartheta_1 > 0$. Table 5 illustrates the regression results of Eq. (2) using the analogue estimation routine as for Eq.(1).

Experiment	**(1)**	**(2)**	**(3)**	**(4)**
	basic	monetary	risk	complex
expected_value	**0.766*** **	**0.964*** **	**0.922*** **	**0.760*** **
	(0.025)	(0.012)	(0.039)	(0.100)
anchor_deviation	**-0.079** **	**-0.085*** **	**-0.162*** **	**-0.161**
	(0.027)	(0.010)	(0.033)	(0.102)
anchor_deviation_HCA	**0.073*** **	**0.077*** **	**0.033**	**0.016**
	(0.018)	(0.019)	(0.032)	(0.073)
constant	**16.31*** **	**5.095*** **	**12.83*** **	**28.28** **
	(2.235)	(1.172)	(3.975)	(9.780)
F-Statistic ($\theta_1 = \vartheta_1 = 0$)	**9.06*** **	**33.82*** **	**14.76*** **	**1.57**
Prob. > F	(0.009)	(0.000)	(0.000)	(0.244)
Observations	1505	1351	1280	1163
No. of groups	171	97	92	93

Table 5: Fixed-effects regression of Eq. (2) with forecast (y_{it}) as dependent variable

Note: Robust Standard Errors in parentheses; for F-Statistics p-value in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Except for complex, we find a significant effect of the anchor values. However, the marginal effect of the anchoring bias tends to be smaller for subjects in the HCA group; individually though, HCA is not significant for risk and complex. This effect is very strong for basic and monetary, where the bias is almost eliminated by subjects with high cognitive abilities. Nevertheless, the extent of the bias tends to be strong in the HCA group under high risk and a complex definition of the task. Therefore, we find mixed evidence in support of H3 and conclude that cognitive abilities might have an influence on the susceptibility to the anchoring heuristic depending on task specifics.

4.4 Learning effects

We hypothesized (H4) that learning effects should be absent if anchoring subconsciously influences subjects as a behavioral bias. In order to investigate potential learning effects, we extend our model of Eq. (1). We add an interaction term denominated as anchor_deviation_2, which allows to measure if the anchoring bias is different for the first and the second half of the game. We introduce the dummy variable P_i, which equals 1 for periods of the second half of the game. $\pi_1<0$ indicates a stronger influence of the anchor values in the second half of the game, $\pi_1>0$ hints at a weaker influence. We can formulate:

$$y_{it} = \gamma_1 E(x_t) + \theta_1[A_i(E(x_t)-x_{t-1})] + \pi_1[P_i\,(A_i(E(x_t)-x_{t-1}))] + u_{it} \qquad (3)$$

Table 6 gives the results of estimating Eq. (3) when relying on the same estimation procedure as before.

Experiment	**(1)**	**(2)**	**(3)**	**(4)**
	basic	monetary	risk	complex
expected_value	**0.765*****	**0.963*****	**1.003*****	**0.775*****
	(0.026)	(0.012)	(0.041)	(0.096)
anchor_deviation	**-0.066****	**-0.038****	**-0.211*****	**-0.178***
	(0.028)	(0.014)	(0.038)	(0.092)
anchor_deviation_2	**0.010**	**-0.003**	**0.189*****	**0.108**
	(0.031)	(0.025)	(0.052)	(0.169)
constant	**16.36*****	**5.132*****	**4.865**	**26.94****
	(2.306)	(1.175)	(3.85)	(9.64)
F-Statistic ($\theta_1 = \pi 1 = 0$)	**4.01***	**4.93****	**22.23*****	**1.87**
Prob. > F	(0.062)	(0.026)	(0.000)	(0.193)
Observations	1505	1351	1280	1163
No. of groups	171	97	92	93

Table 6: Fixed-effects regression of Eq. (3) with forecast (y_{it}) as dependent variable

Note: Robust Standard Errors in parentheses; for F-Statistics p-value in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

We find that the anchoring bias is reduced for the second half of the game when the underlying risk is high, which contradicts hypothesis 4 and points to strong learning effects in that case. Consequently, we cannot rule out that learning effects reduce the anchoring bias in a forecasting setting. However, no such significant effect is apparent for the other experiments, although a similar tendency is suggested by the coefficient estimations in complex.

5. Conclusion

The present article presents a counterpart laboratory study to the applied empirical studies on anchoring in various fields of forecasting. Therefore, we implement economic conditions in an anchoring experiment to enable a better application to economic domains. In contrast to classic anchoring experiments, our study introduces a rational strategy and further captures central features of forecasts, specifically feedback and learning effects, time pressure, a high cognitive effort task and strong monetary incentives for avoiding the anchoring bias.

We find a strong anchoring bias despite the implementation of economic conditions. On average, higher risk and complexity increase anchoring, which supports our notion that anchoring is bound to increase for actual forecasting with highly complex estimation tasks. We advance the discussion on incentives for accuracy and show that monetary incentives reduce anchoring if a simple strategy for avoiding anchoring is available. We show a relevant reduction in the average orientation towards the anchor among individuals performing well on the cognitive reflection test only if the task complexity and the underlying risk are low. Learning effects substantially reduce the bias if the underlying risk is high. Finally, anchoring tends to reduce the variance of predictions and thus increases the homogeneity of forecasters' predictions.

Our results support the empirical studies that emphasize anchoring effects in forecasting. We find both a robust influence of the respective last correct value and clustered forecasts despite an accessible and incentivized strategy of avoiding it. It may be assumed that forecasters are generally exposed to significant levels of risks and uncertainty as well as high task complexity in a dynamic forecasting environment. Even if all relevant information were available to forecasters, as in our experiment, anchoring would prevent an optimal interpretation of data. Consequently, we assume that the effect of anchoring in forecasting demonstrated in our study is bound to increase for real-world predictions and can thus serve as a valid explanation for forecasters' lack of adjustment from current values.

Appendix

Instructions for Classroom (Experiment 1)

Instructions

In this game, you will estimate 10 values. Each value accrues from the determinants A, B, C and D. The determinants A, B and C will be shown to you in each period. The determinant D is a random number determined for each period and takes on a value between -25 and 25; you do not know this number.

Formula: **value = A + B – C + D**

<u>Speaking is not permitted during the game.</u> The game will take approximately 15 minutes. Of course, your data will be treated anonymously.

---

xth Period

1. Do you think that the value is higher or lower than the value of the preceding period?

Please tick the box:

higher	lower

2. Please enter your estimation:

Note: Question 1 does not apply for the control group.

Instructions for Laboratory Experiments (No. 2-4)

The Game

In this game, you will estimate a value in each period. There are a total of 15 periods in which you will give your estimation. In each period, the correct value results from the determinants **A, B, C and D** {Exp4: A, B, C, D and E}. The determinants A, B and C {Exp4: A, B, C and D} will be displayed to you in each period. The determinant D {Exp4: E} } is a random number determined for each period and takes on a value between -25 and 25 {Exp3: -75 and +75} in each round; you do not know this number.

The formula to calculate the value is:

value = A + B – C + D {Exp4: $A+B-0.5C+D^2+E$}

This formula is valid for every period of the game. {Exp2-4 Anchor Treatments: As soon as all players have submitted their estimation at the end of each period, the correct value for each period will be displayed. In the following period, you will also have to estimate whether the value will be higher or lower than that of the preceding period.}

Before the 15 periods start, you will answer three questions. You have two minutes to answer each question. The game will start once all players have completed this task.

In each period, you will have one minute {Exp4: 30 seconds} to enter your estimations and click on OK to confirm them.

<u>Please note</u>: If you do not enter a number within this minute and confirm it with OK, your payment in the corresponding period will be 0 Euros.

The Payment

Your payment is calculated according to the accuracy of your estimation with regard to the value. The payment is calculated as follows: you receive 50 {Exp3: 80} cents in each period. The difference between your estimation and the value is deducted from your payment in cents. It is not possible for your payment to become negative.

<u>Example:</u> value = 100

your estimation = 75

difference between your estimation and the value = 25

your payment: 50ct. – 25 ct. = **25ct**. {Exp3: 80ct. – 25 ct. = **55ct**.}

The gains of each period are added together and paid to you after the end of the game. Furthermore, you will receive € 1 for providing the correct answers to all three preceding questions, as well as a basic payment of € 1.50.

Note: Original instructions were in German. Differences in experiments are indicated by {Exp#:…}. If not indicated, differences apply to both anchor and control treatments.

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