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Anchoring: a valid explanation for biased forecasts when rational predictions are easily accessible and well incentivized?

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Abstract: Behavioral biases in forecasting, particularly the lack of adjustment from current values and the overall clustering of forecasts, are increasingly explained as resulting from the anchoring heuristic. Nonetheless, the classical anchoring experiments presented in support of this interpretation lack external validity for economic domains, particularly monetary incentives, feedback for learning effects and a rational strategy of unbiased predictions. We introduce an experimental design that implements central aspects of forecasting to close the gap between empirical studies on forecasting quality and the laboratory evidence for anchoring effects. Comprising more than 5,000 individual forecasts by 455 participants, our study shows significant anchoring effects. Without monetary incentives, the share of rational predictions drops from 42% to 15% in the anchor's presence. Monetary incentives reduce the average bias to one-third of its original value. Additionally, the average anchor bias is doubled when task complexity is increased, and is quadrupled when the underlying risk is increased. The variance of forecasts is significantly reduced by the anchor once risk or cognitive load is increased. Subjects with higher cognitive abilities are on average less biased toward the anchor when task complexity is high. The anchoring bias in our repeated game is not influenced by learning effects, although feedback is provided. Our results support the assumption that biased forecasts and their specific variance can be ascribed to anchoring effects.

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

JEL classification: C90; D03; D80; G17

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1. Introduction

The anchoring heuristic (Tversky and Kahnemann 1974) is increasingly considered when explaining biased forecasts with examples including 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) and 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.[2]

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 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 casually adopt psychological biases as stylized facts without supportive experimental studies that implement economic conditions. In the classic psychological studies cited in support of anchoring in forecasting, subjects take uninformed and non-incentivized guesses ("How many African countries in the UN?"). Thus, anchoring cannot be seen as a deviation from the rational strategy. In 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 external validity might 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. Taking up the doubts concerning the transferability of anchoring, McAlvanah and Moul (2013) investigate anchoring "in the wild" (ibid. p. 88) for the case of horseracing bookmakers. They find anchoring effects, stating that they are robust for an economic domain as the experienced bookmakers face real financial incentives for unbiased predictions under time pressure.

[2] 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).

However, 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 a rational 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 improve the external validity of the anchoring heuristic for 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 rounds' correct value to enable learning effects, as well as provide the external anchor for the current round. In this setting, we investigate the influence of monetary incentives, cognitive abilities, task-specific risk and cognitive load on the extent of the anchoring bias. In contrast to previous forecasting experiments (Leitner and Leopold-Wildburger 2011 provide a review), a correct prediction is considerably easy to achieve.[3] Unlike regular anchoring experiments, we facilitate the rational 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 juridical context supporting the assumption that forecasting experts are 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.

The only experimental study of anchoring in a forecasting context was presented by Critcher and Gilovich (2008), who investigated the influence of incidental anchors in real life; for example, 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.

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[3] 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).

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.

Blankenship et al. (2008) examine the effect of increased cognitive load, i.e. a systematic mental overload of subjects, by establishing time pressure and making the task more complex. They find significant anchoring effects once high cognitive load is established, which supports Wegener et al. (2001) as well as Wegener et al. (2010) in their assumption that at least two anchoring heuristics exist: one that occurs under high cognitive load and another that occurs under low cognitive load. They argue that different levels of cognitive effort 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 bring about 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, cognitive load and learning effects in the context of anchoring. Despite the deliberately simple rational strategy for unbiased predictions, we find significant anchoring effects. Monetary incentives reduce the average anchoring bias to around one third compared with non-monetary conditions. Increased cognitive load doubles the average anchoring bias, while increased risk quadruples the distortion when compared to monetary conditions. The variance of forecasts is smaller when higher risk or cognitive load is induced. Participants with higher cognitive capabilities are less prone to the influence of external anchors in a setting with higher cognitive load. Despite the feedback in every round, the anchoring bias is not reduced by learning effects.

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 round.[4] One determinant is a random variable which is uniformly distributed over the interval [-25,25]. Its realizations are unknown and change every round, 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 round as an external anchor, and are asked whether the value of the current round 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. Subjects in the respective control groups are not shown the realized value of the previous round 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 external anchor of the previous value does not contain any additional information for the current round. 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 forecast without monetary incentives. Participants were asked to participate in a classroom experiment. Beforehand, every subject receives instructions[5] along with the formula, as well as ten forms for entering his or her calculation in each round. 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 round 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 round's realized value (in anchor treatment only) are displayed on a

[4] 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.

[5] The introductions were in German. A translation is provided in Appendix.

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 rounds.
The second experiment ("monetary") introduces a monetary incentive for accurate predictions. The experiments 2-4 are conducted using the software 'z-tree' (Fischbacher 2007) and carried out in an experimental lab.[6] The formula and determinants remain identical, likewise the cognitive reflection test before the actual experiment. The time for calculating the current value remains one minute per round, with fifteen rounds played in the second experiment. The payoff in each round 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 round is eighty cents minus the absolute difference between the respective forecast and the correct value in cents.
The forth experiment ("cognitive load") 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 round, a_t, b_t ,c_t, d_t are the known determinants in round t.
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 cognitive load). A naïve strategy of predicting the previous round'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 cognitive load). 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 round'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. 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,

[6] 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.

54% were female. Table 1 provides an overview of the different experiments and the numbers of participants.[7]

Experiment		Variation			Number of participants		
No.	**denomination**	**monetary**	**risk**	**cognitive load**	**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	cognitive load	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 external 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 cognitive load 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 external anchor.

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. In order to test this assumption, we formulate Hypothesis 2:

Hypothesis 2 (*"*Differences in variance*").* The external 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:

[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 treatments were conducted earlier on and yielded more attendees, while control treatments were conducted after the anchor treatments where attendance was weaker. However, our analysis of treatment comparison is not influenced or biased by these differences in any way.

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, in order to check whether subjects are prone to the anchoring bias. Furthermore, we compare treatment effects between experiments to identify the driving forces of the anchoring bias. Second, we look for differences in the variance of predictions between the treatments. Third, results are evaluated regarding influences of cognitive abilities. Fourth, we comment on learning effects in our experiment.

4.1 Rationality and anchoring bias

Recall that showing the correct value of the previous round in the treatment group does not change the profit-maximizing strategy of forecasting the expected value. Additionally, subjects in the control group do not answer the higher/lower-question.[8] If forecasts in the anchor treatments are biased toward the values of previous rounds, we interpret this as evidence in support of Hypothesis 1.

Table 2 summarizes the main data for treatment comparison, indicating the mean absolute deviation of predictions from the expected values, the fraction of optimal forecasts and the share of subjects acting rationally by treatments for all experiments.[9] Forecasts equal to the expected value are characterized as optimal. A subject is defined as rational if not more than one forecast deviates from the expected value. Given that the previous round's values are by

[8] In experiment 1, 77% of the higher/lower-questions were answered correctly (87% in experiment 2, 77% in experiment 3 and 68% in experiment 4).

[9] Our dataset contains 253 missing values (predictions) because subjects did not enter a value in the respective round. Additionally, the dataset is corrected for subjects' forecasts if the task was obviously misinterpreted. We assume this to be true if the forecast of subject i in period t (y_{it}) is smaller than 25 or negative (y_{it}<25), i.e. subjects tried to forecast the random determinant and not the realized value. Thus, 265 observations were deleted. Furthermore, we remove outliers, i.e. forecasts deviating by more than three times the maximum realization of the random determinant from the expected value. Accordingly, for experiments 1, 2 and 4, observations are defined as outliers and dropped if $y_{it}<[E(x_t)-3*25]$ or $y_{it}>[E(x_t)+3*25]$. For experiment 3, we chose a smaller multiplier for the interval due to the greater range of the random determinant. In this case, we drop forecasts if $y_{it}<[E(x_t)-2*75]$ or $y_{it}>[E(x_t)+2*75]$. In total, we removed 100 observations defined as outliers by the criterion described, which leaves us with a total of 5,342 forecasts.

design first shown in the second period in the treatment group, we exclude values for the very first period. However, the results also hold when including the first period.

	1 (basic)			2 (monetary)		
	Control	**Anchor**	**test statistic (p-value)**	**Control**	**Anchor**	**test statistic (p-value)**
Average absolute deviation	10.2 (13.66)	13.1 (12.32)	-6.490*** (0.0000)	5.8 (10.18)	6.9 (8.77)	-4.394*** (0.0000)
Share optimal forecasts	0.428	0.151	(0.0000)	0.574	0.435	(0.0000)
Share rational subjects	0.279	0.061	(0.001)	0.50	0.235	(0.013)
	3 (risk)			**4 (cognitive load)**		
	Control	**Anchor**	**test statistic (p-value)**	**Control**	**Anchor**	**test statistic (p-value)**
Average absolute deviation	20.0 (24.74)	17.2 (17.4)	-0.56 (0.5752)	12.7 (17.21)	13.8 (16.53)	-2.107** (0.0351)
Share optimal forecasts	0.41	0.297	(0.0000)	0.402	0.32	(0.0082)
Share rational subjects	0.20	0.10	(0.224)	0.13	0.023	(0.113)

Table 2: Treatment comparison

Note: Test-statistics for the average absolute deviation derived by a two-sided Wilcoxon rank-sum test; p-values in parentheses. (*** p<0.01, ** p<0.05, * p<0.1). For the share of optimal forecasts and the share of rational subjects a two-sided Fisher's exact is applied and the respective p-values are shown.

The fraction of optimal forecasts is higher for every experiment in the control group. For example, in basic, the average absolute deviation is increased by around 28% when the anchor value is shown (19% in monetary, 9% in cognitive load). In risk, there is no significant difference of the average absolute deviation between treatments, although there is a higher fraction of optimal forecasts. This can be explained by the anchor value's tendency to reduce the variance of deviations. There are more optimal decisions in the control groups, but the non-optimal ones deviate more from the expected value. These results will be discussed in more detail in the context of comparing the variance of forecasts over treatments (subsection 4.2).

However, one might interpret differences across treatments as accruing from the representativeness bias (Kahnemann and Tversky 1973). The distribution of forecasts in the treatment groups might reflect the distribution of the value to be forecasted.[10] 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;

[10] 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.

Harvey et al. 1997; Harvey 2007). We therefore have to show 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 adequately 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.

$$y_{it} = \gamma_1 E(x_t) + \theta_1[A_i(E(x_t)-x_{t-1})] + \theta_2[E(x_t)-y_{it-1}] + u_{it} \qquad (1)$$

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 round. 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 round x_{t-1} and the expected value in the current round $E(x_t)$ 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 $\theta_1 < 0$. Additionally, we control for the influence of the deviation of the previous round's forecast y_{it-1} from the expected value of the current round $E(x_t)$ (forecast_deviation). Again, $\theta_2 < 0$ indicates a bias toward the forecast of the previous round, whereas in the absence of this bias θ_2 is equal to zero.[11]

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 an insignificant effect on the values forecasted ($\theta_1 = \theta_2 = 0$). 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, heteroskedasticity, serial correlation in the idiosyncratic errors and cross-sectional dependence.

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

Notwithstanding, there are differences between the experiments in terms of the average quality of the forecast. A smaller marginal effect of a change in the expected value, i.e. a smaller γ_1 for $\gamma_1 < 1$, has to be associated with a lower average quality of the forecasts and less rational behavior. In monetary, the subjects adjust best compared to the other experiments and optimal on average according to a change in the expected value. The forecasting quality drops if there are no monetary incentives (basic) or the underlying risk is increased (risk). The

[11] This control variable is required due to the possible correlation of forecasts made in consecutive rounds. Since the forecasts and realized values of previous rounds are definitely correlated, this would lead to an omitted variable bias and the inconsistent estimation of all other coefficients.

[12] We checked the robustness of our results by only considering the first ten rounds played. This check was due to the temporal restriction in the classroom experiment, in which we were only able to play ten rounds. However, estimating Eq. (1) by the same procedure as in Table 3 with only the first ten rounds does not relevantly alter our results. Moreover, we estimated Eq. (1) while controlling for a treatment-specific influence of the expected_value. Again, we find a significant influence of the deviation in the anchor value for all experiments, whereby the magnitude of the coefficients changes only slightly.

lowest quality on average is realized if the cognitive load is increased by a more complex definition of the task (cognitive load).

Experiment	**(1)**	**(2)**	**(3)**	**(4)**
	basic	monetary	risk	cognitive load
expected_value	**0.853***** (0.030)	**0.986***** (0.010)	**0.841***** (0.025)	**0.766***** (0.045)
anchor_deviation	**-0.100***** (0.022)	**-0.045**** (0.019)	**-0.130***** (0.029)	**-0.101*** (0.048)
forecast_deviation	**0.012** (0.031)	**-0.020** (0.017)	**0.066** (0.041)	**0.024** (0.016)
constant	**15.44***** (2.92)	**2.904***** (0.91)	**21.52***** (2.121)	**23.00***** (4.623)
F-Statistic (γ_1=1) **Prob. > F**	**23.24***** (0.001)	**1.85** (0.197)	**40.27***** (0.000)	**26.89***** (0.000)
Observations	1344	1314	1245	961
No. of Groups	159	96	92	92

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 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 round.

Besides the significance of the bias towards the anchor value, its relevance needs to 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 cognitive load), the estimated marginal effect of -0.1 (-0.045, -0.13 and -0.101) amounts to a ceteris paribus bias of 2.46 (0.92, 4.28 and 2.06) points on average. This corresponds to 2.53% (0.94%, 4.3% and 2.11%) 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 one third of the bias in basic. In comparison to monetary, higher underlying risk more than quadruples the extent of the bias. Establishing a higher cognitive load through a more complex definition of the task at hand more than doubles 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 rounds, as the rational strategy would suggest. The empirical

[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 rounds being played in experiment 1, together 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 becoming too complicated.

finding of forecasts being frequently biased towards the respective current values can be motivated 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.

Experiment		**Std. dev.**		**Tests (H_0: equality)**	
no.	**denomination**	**control**	**anchor**	**B/F-statistic (W50)**	**B/F-statistic (W0)**
1	basic	24.41	22.22	0.3 (0.58)	0.65 (0.419)
2	monetary	23.6	22.32	1.61 (0.205)	1.61 (0.204)
3	risk	37.42	29.51	18.96*** (0.000)	22.52*** (0.000)
4	cognitive load	28.55	24.67	9.88*** (0.002)	9.84*** (0.002)

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

Note: Asterisks representing p-values (in parentheses) 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 smaller standard deviation in the anchor treatments for all experiments. The difference in basic and monetary turns out not to be significant at the conventional levels of significance. For risk and cognitive load, both test procedures point to a significantly lower variance in the anchor treatments. In the presence of monetary incentives and high underlying risk or high cognitive load, we conclude that the anchoring bias causes a smaller variance in the forecasts. Consequently, we find mixed results regarding H2. The uniformity or low variance of forecasts revealed by empirical studies might be explained to some extent by a systematic anchoring bias. The anchor value causes a higher frequency of deviations from rational forecasts, which in turn tend to be smaller compared to the control group.

4.3 Cognitive abilities

To test for the influence of cognitive abilities on the anchoring bias, we group subjects using the rule 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, owing to their tendency to answer intuitively (H3).

We find HCA subjects to predict more accurately and act rationally more often. For basic (monetary/risk/cognitive load), the average absolute prediction error for HCA pooled over treatments is 10.5 points (4.6/14.2/10.5), while for LCA it is 13.3 points (8.7/25.1/17.0). The difference between LCA and HCA subjects in the control group amounts to 0.1 points

(2.0/14.9/10.5). For the treatment group, the difference is given by 3.2 points (6.2/9.9/4.5).[14] However, we are interested in the specific effect on the anchoring bias of having higher cognitive abilities.

Therefore, we modify Eq. (1) such that it allows 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.

$$y_{it} = \gamma_1 E(x_t) + \theta_1[A_i(E(x_t)-x_{t-1})] + \vartheta_1[A_i HCA_i(E(x_t)-x_{t-1})] + \theta_2[E(x_t)-y_{it-1}] + u_{it} \qquad (2)$$

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	cognitive load
expected_value	**0.853***** (0.031)	**0.986***** (0.010)	**0.841***** (0.025)	**0.766***** (0.045)
anchor_deviation	**-0.106***** (0.026)	**-0.073***** (0.01)	**-0.144***** (0.028)	**-0.179**** (0.079)
anchor_deviation_HCA	**0.019** (0.042)	**0.0459** (0.033)	**0.0252** (0.024)	**0.140**** (0.060)
forecast_deviation	**0.012** (0.031)	**-0.021** (0.017)	**0.0664** (0.041)	**0.024** (0.016)
constant	**15.44***** (2.924)	**2.888***** (0.901)	**21.56***** (2.106)	**22.98***** (4.592)
F-Statistic ($\theta_1 = \vartheta_1 = 0$) Prob. > F	**10.71***** (0.006)	**29.81***** (0.000)	**12.83***** (0.001)	**2.71** (0.104)
Observations	1344	1314	1245	961
No. of groups	158	96	92	92

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)

Again, we find a significant effect on the forecasts of the deviation in the anchor value from the expected value for subjects in the treatment groups. The marginal effect or bias tends to be smaller for subjects in the HCA group; individually though, HCA is only significant in cognitive load. The average marginal effect on forecasts in cognitive load of a one-unit change in the deviation in the anchor values from the expected value is estimated to be -0.179 in the LCA group and only -0.0395 in the HCA group.

[14] The control group in basic shows an average absolute prediction error of 10.1 points (4.9/15.7/7.4) for HCA subjects and 10.2 points (6.9/30.6/17.9) for LCA; the treatment group in basic shows an average absolute prediction error of 10.8 points (4.4/12.6/11.9) for HCA subjects and 14.0 points (10.6/22.5/16.4) for LCA.

Overall, we find a non-optimal, biased behavior, even in the HCA group on average. Nevertheless, the extent of the bias tends to be lower in the HCA group, at least in the presence of a more complex definition of the task. Therefore, we also find evidence in support of H3 and conclude that cognitive abilities have an influence on the susceptibility to the anchoring heuristic.

4.4 Learning effects

We hypothesized that learning effects should be absent if anchoring subconsciously influences subjects as a behavioral bias. We find evidence in support of H4, which can best be seen when again considering the share of optimal forecasts or the average absolute deviation only for the last 5 rounds. For basic (monetary/risk/cognitive load), we find 43% (58.2/45.2/40.6) of forecasts to be rational in the control group and only 15% (45.7/32.2/32.7) in the treatment group. The average absolute deviation amounts to 9.7 (5.4/17.2/13.4) in the control group and 12.9 (6.6/17.5/13.0) in the treatment group. These numbers essentially resemble the results shown in Table 1 when considering all periods.

5. Conclusion

The present article extends the applied empirical studies on anchoring in various fields of forecasting with a counterpart laboratory study. Therefore, we implement economic conditions in an anchoring experiment to provide external validity for an economic domain. 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 existence of a rational strategy with monetary incentives, feedback and repeated decisions. On average, higher risk and cognitive load increase anchoring, which supports our notion that anchoring is bound to increase for actual forecasting where the cognitive load and complexity is higher. 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 external anchor among individuals performing well on the cognitive reflection test, at least if the task complexity is high. Finally, anchoring tends to reduce the variance of 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 cognitive load in a complex and 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 round. The determinant D varies arbitrarily between -25 and 25 from round to round.

Formula:

$$\textbf{value} = \mathbf{A + B - C + D}$$

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

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x^{th} Round

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

Please tick the box:

higher	lower

2. Please enter your estimation:

Note: Question 1 does not apply for the control group. The original instructions were in German.

Instructions for Laboratory Experiments (Experiments 2-4).

The Game

In this game, you will estimate a value in each round. There are a total of 15 rounds in which you will give your estimation. In each round, 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 round. The determinant D {Exp4: E} varies arbitrarily between -25 and 25 {Exp3: -75 and +75} in each round; you do not know its exact value.
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 round of the game. {Exp2-4 Anchor Treatments: As soon as all players have submitted their estimation at the end of each round, the correct value for each round will be displayed. In the following round, you will also have to estimate whether the value will be higher or lower than that of the preceding round.}
Before the 15 rounds 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 round, you will have one minute {Exp4: 30 seconds} to enter your estimations and click on OK to confirm them.
Please note: If you do not enter a number within this minute and confirm it with OK, your payment in the corresponding round 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 round. 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.

Example: 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 round 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. The original instructions were in German.

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