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Abstract: The anchoring-and-adjustment heuristic has been studied in numerous experimental settings and is increasingly drawn upon to explain systematically biased decisions in economic areas as diverse as auctions, real estate pricing, sports betting and forecasting. In these cases, anchors result from publicly observable and aggregated decisions of other market participants. However, experimental studies have neglected this social dimension by focusing on external, experimenter-provided anchors in purely individualistic settings. We present a novel experimental design with a socially derived anchor, monetary incentives for unbiased decisions and feedback on performance to more accurately implement market conditions. Despite these factors, we find robust effects for the social anchor, an increased bias for higher cognitive load, and only weak learning effects. Finally, a comparison to a neutral, external anchor shows that the social context increases the bias, which we ascribe to conformity pressure. Our results support the assumption that anchoring remains a valid explanation for systematically biased decisions within market contexts.

Keywords: anchoring; conformity; heuristics and biases; incentives; laboratory experiment

JEL classification: C9;D8;Z2

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1. INTRODUCTION

The anchoring heuristic is one of the most thoroughly investigated behavioral biases. Following Tversky and Kahnemann's (1974) seminal paper, a considerable body of experimental literature has evolved, that assumes its "robust and pervasive influence" (Furnham and Boo 2011, p. 39). However, while anchoring has been investigated comprehensively for individualistic decisions, its social dimension has been neglected to date (Furnham and Boo, 2011). This shortcoming connects to the recent doubts on the universal prevalence of behavioral biases under economic conditions; an argument that has been put forth by List and Millimet (2008), Levitt and List (2007) and Loomes et al. (2003) who argue that monetary incentives connected with feedback can reduce behavioral anomalies through learning effects. Presenting experimental evidence on anchoring effects for willingness-to-pay/-accept, recent studies point to a lack of robustness under economic conditions (Fudenberg et al., 2012; Maniadis at al., 2011; Alevy et al., 2010 for a field experiment; Tufano, 2010; Simonson and Drolet, 2004). As economic transactions take place in social settings that foster learning effects through monetary incentives and the observation of other market participants in repeated tasks, doubts on the unconditional robustness of the anchoring bias seem reasonable.

We thus argue that experimental studies of "social anchors" are necessary to more accurately investigate actual anchoring-situations in market contexts. For an example of these social anchors, consider forecasters who anchor their predictions on the publicly available consensus values (Fujiwara et al., 2013; Campbell and Sharpe, 2009). All individual forecasts that constitute the respective consensus values are publicly observable, as is the most recent consensus forecast. Thus, the anchor values are constituted endogenously through the aggregation of prior decisions, while there are strong monetary incentives for unbiased predictions. We assume that this derivation of real-world anchors is applicable to a wide range of economic situations prone to anchoring effects. Endogenous anchors with an observable, social formation thus promise additional external validity in comparison to the classical external experimenter-provided anchors.

Consequently, we aim at establishing for the first time the behavioral impact of a social context on anchoring effects. Our basic expectation is that the implementation of a social anchor setting fosters a bias-reduction through monetary incentives, feedback and learning effects, which are the core elements of the market serving as a "catalyst for rationality and filter for irrationality" (List and Millimet, 2008, p.1). However, behavioral research on conformity-seeking behavior (see e.g. Klick and Parisi, 2008) may suggest that the social derivation of anchor values may ultimately increase the individual adherence to anchor values compared to experimenter-provided external anchors. Our results thus serve at more closely determining whether market conditions have a debiasing effect or even aggravate anchoring effects through conformity pressure.

More specifically, besides adding evidence to the discussion on market forces and biases, we aim at commenting on the growing body of empirical studies in various economic settings that assume anchoring to be the driving force behind systematic distortions in the behavior observed. Recent examples of this trend include art and online auctions (Beggs and Graddy, 2009; Dodonova and Khoroshilov, 2004), real estate purchases (Bucchianeri and Minson, 2013) and sports betting (Johnson et al., 2009; McAlvanah and Moul, 2013). Another large strand of literature draws on prediction behavior with time series data drawn from financial forecasts (Fujiwara et al. 2013), earnings forecasts (Cen et al., 2013), macroeconomic forecasts (Bofinger and Schmidt, 2003; Campbell and Sharpe, 2009) and sales forecasting (Lawrence and O'Connor, 2000). While anchoring does seem like a plausible explanation for the empirical patterns in the respective studies, their experimental base remains inadequate by featuring the classical non-incentivized decisions, external experimenter-given anchors, neither feedback on performance, nor information on other participant's decisions, all of which run contrary to market conditions. For anchoring to hold as an interpretation regarding actual markets, laboratory validations are required that encompass the central features of the decision situations potentially prone to biased decisions.

To further the discussions in the two strands of literature presented, we implement a simple estimation task that allows us to measure the effect of a socially derived anchor while providing economic conditions, i.e. information on the other players' decisions, feedback for learning effects and strong monetary incentives for unbiased decisions. Unlike the classical anchoring studies, we implement a relatively simple rational strategy of taking unbiased decisions. Accordingly, if social anchors have an impact even when avoiding them is rather simple and profitable, we suggest that their actual influence is bound to increase in a more complex decision situation. To account for this notion, we run a second experiment with increased cognitive load. In both experiments, the anchor values result from the aggregated decisions of all participants and contain no additional task relevant information. We thus introduce a "social anchor", whereby the decisions of all other subjects and the resulting average value are displayed. The average value subsequently serves as the anchor for the following round. To qualify the relevance of the social anchor, we finally compare its impact to results from Meub et al. (2013) who feature an identical experimental setting, but implement a classical external anchor.

In the following, we review the relevant literature to deduct our behavioral hypotheses.

Traditional anchoring studies feature an externally given anchor and the additional question of whether participants expect the respective value to be higher or lower than the anchor in numerous variations (see Furnham and Boo, 2011 for a comprehensive review). Furthermore, a basic anchoring effect is shown by Wilson et al. (1996), who find anchoring even without the higher/lower question. Another result (e.g. by Epley and Gilovich 2005) is that self-generated anchors also lead to robust anchoring effects. Critcher and Gilovich (2008) show how even incidental numbers in the subject's environment bias estimations. However, closest to the investigation of social anchoring is the experiment in Phillips and Menkhaus (2010). They show that an endogenous anchor, constituted by the average results of the respective last round, leads to anchoring effects on the willingness to pay and accept in an auction. They explain the ensuing deterioration of prices in their auction as resulting from the norm of starting a negotiation at the anchor, in this case the average price.

With regard to a socially constituted anchor, the aspect of behavioral conformity may affect results. The human "meta-preference for conformity" (Klick and Parisi, 2008, p. 1319) has individuals seeking to conform to the actions of others, ultimately to gain advantages through their affiliation to social groups. Conformity is well-documented in social psychology (see Cialdini and Goldstein, 2004 for a review) and has been applied to economics in various contexts; for instance, as a determinant for contributions to public goods (Carpenter, 2004; Giovinazzo and Naimzada, 2012), regarding coordination externalities in heterogeneous groups (Grajzl and Baniak, 2012), group creativity (Goncalo and Duguid, 2012) or auctions (Beraldo et al., 2013), with Dequech (2013) providing a comprehensive institutional perspective. As our anchor values are explicitly presented as the average prediction of a group, the subconscious drive to adapt to the observed behavior of the other members may enhance anchoring effects, although there is no monetary benefit to conformity.

Conversely, a rational strategy with monetary incentives for unbiased decisions may reduce anchoring. Although Chapman and Johnson (2002, p.125) state that "incentives reduce anchoring very little if at all" (referring to the studies of Tversky and Kahnemann, 1974; Wilson et al., 1996 and Epley and Gilovich, 2005), Wright and Anderson (1989) as well as Simmons et al. (2010) show that incentives reduce anchoring if subjects have task familiarity or are provided clues in terms of the direction of adjustment for their initial predictions. Meub et al. (2013) show that monetary incentives reduce anchoring to one-third of its strength when compared to a non-incentivized setting. We argue that the ambiguous outcomes regarding the impact of incentives reflect the availability of a simple rational strategy in the respective experiments. Once given the realistic opportunity and incentives, subjects tend to act more rationally, which is one of the standard observations in economic experiments (see e.g. Smith and Walker, 1993; Rydval and Ortmann, 2004).

While learning effects in repeated tasks have not yet been investigated concerning their effect on anchoring, a number of studies have shown experts' susceptibility to anchoring. For instance, this has been investigated for car mechanics (Mussweiler et al., 2000), real estate agents (Northcraft and Neale, 1987) and legal experts (Englich and Mussweiler, 2001 and Englich et al., 2005; 2006). Accordingly, Furnham and Boo (2011) summarize that expertise fails to prevent anchoring. However, task specific knowledge has been shown to reduce anchoring by Wilson et al. (1996), as well as by Wright and Anderson (1989). The divergent results on task familiarity point to different processes that elicit anchoring effects (see Crusius et al., 2012). Thus, expert statements may be biased as anchor-consistent knowledge is activated in a cognitively effortful process, whereas in more simple tasks, anchors are used intuitively as a cue to the right answer (Wegener et al., 2001; 2010). Given that the decision situations investigated in empirical anchoring studies can be expected to feature non-intuitive settings, respective experimental studies need to implement cognitively effortful tasks to uphold external validity. Connected to this is the effect of cognitive load on subject's decision quality. Blankenship et al. (2008) show that a mental overload through time pressure and task complexity increases anchoring.

We contribute to the literature reviewed by furthering the knowledge on the effects of anchoring in a social context. This enables us to comment both on the robustness of anchoring under market conditions and on the interpretation of empirical studies that draw on anchoring. Our results show that a socially derived anchor does in fact trigger the anchoring bias, whereby higher cognitive load increases a subject's reliance on the anchor values. When compared to a neutral anchor in an otherwise identical setting, the social anchor has a stronger biasing effect. Thus, the social dimension increases anchoring, which we explain as resulting from conformity pressure. The comprehensive information on the derivation of the anchor and its factual uselessness for individual estimations elicits only weak learning effects. Overall, we state that under market conditions, anchoring effects are increased through implicit conformity pressure, which supports the validity of the empirical studies on anchoring.

The remainder of this paper is organized as follows. Section 2 presents the experimental design, section 3 introduces our behavioral hypotheses and results are presented in section 4, before section 5 concludes.

2. EXPERIMENTAL DESIGN

We report two experiments, both of which comprise a control and an anchor treatment. For all treatments, we implement an estimation task, whereby we ask participants to predict future values. These values result from various determinant values incorporated in a simple formula, which is common knowledge and remains constant during the experiment. One of the determinants is an unknown, uniformly distributed random variable. We thus implement an element of risk, which prevents participants from calculating future values exactly.

The first experiment (henceforth: BASIC) implements the formula $x_t=a_t+b_t-c_t+d_t$. x_t is the value participants are asked to predict, while a_t, b_t, c_t are the known determinants and d_t is the random variable that is uniformly distributed over the interval [-25,25]. The determinants for the anchor treatments (henceforth anchor) are randomly generated within each period on an individual level and shown to participants on the screen.[1] Accordingly, every subject has a different correct value to predict, which is common knowledge. At the end of every round, subjects are shown their individually correct value, the estimations of all other subjects and the average value resulting from these estimations. In the subsequent round, the previous average value is shown to participants as the anchor value on the screen. Note that the display of all estimations and the average prediction, i.e. the social anchor, does not have any additional informational value to the subjects. Participants are further asked whether the value in the current round will be higher or lower than the anchor value, which implements the standard experimental paradigm of anchoring (Tversky and Kahnemann, 1974). The control treatment has an identical design, albeit without the anchor values and the feedback screen.[2] In all treatments, subjects have one minute to calculate the values; there are fifteen rounds.

[1] We avoid negative values to be predicted and keep the calculations fairly simple. For the anchor treatment in BASIC determinants were drawn from uniform distributions with $a_t \in [50,150]$, $b_t \in [51,150]$, $c_t \in [0,75]$, $d_t \in [-25,25]$. For COMPLEX: $a_t \in [60,150]$, $b_t \in [0,50]$, $c_t \in [0,75]$, $d_t \in [0,10]$, $e_t \in [-25,25]$. Also, subjects are allowed to use the Windows calculator implemented in Ztree (Fischbacher, 2007).

[2] Note that the control treatments are drawn from a prior experiment, described in Meub et al. (2013). In this case, the determinants were identical for all participants. Given that participants could not observe the other player's estimations, there was no need to implement individual determinants.

The second experiment (henceforth: COMPLEX) implements the same setting as BASIC, yet introduces a higher cognitive load. Subjects are now asked to make their estimations in 30 seconds and use the formula $x_t=2a_t-b_t -0.5c_t+d^2_t+e_t$, with e_t being the random variable that is again uniformly distributed over the interval [-25,25]. As before, x_t is the value that participants are asked to predict, while a_t, b_t, c_t, d_t are the known determinants in round t. As before, the control treatment does not include the anchor values and the feedback screen.

The payoff in every round for all treatments is fifty cents minus the absolute difference between the respective estimation and the correct value, i.e. $payoff_{it}=(50cent-|x_{it}-y_{it}|)$, where y_{it} denotes the prediction of subject i in round t. However, the payoffs in every round could not become negative. Consequently, the rational strategy for all treatments is the calculation of the respective expected value of x_t using the formula and the given determinants. Thus, subjects minimize the expected absolute deviation of their prediction from the correct value, which in turn results in maximizing the payoff. They do so by ignoring the random variable, as its expected value is zero.[3] The anchors shown to participants contain no additional information.

For both experiments, given the realizations of the respective random variable, following the rational strategy of predicting the expected values of x_t yields on average about 0.38€ per prediction. Since the anchor values are determined endogenously in BASIC and COMPLEX, potential gains by solely relying on the anchor value cannot be calculated ex-ante. Accordingly, we rely on the averages of the actual predictions and realizations of the determinants. For BASIC (COMPLEX), naïve anchoring would only lead to average gains of 0.19€ (0.13€) per period. Thus, there are quite strong monetary incentives for unbiased predictions.

Experiments were conducted in the Laboratory for Behavioral Economics at the University of Göttingen. Participants were recruited with ORSEE (Greiner, 2004) and were only allowed to participate in one session. Experiments were programmed using z-Tree (Fischbacher, 2007). There were six sessions for anchor in December 2012 with 58 (57) participants in BASIC (COMPLEX) and 3(4) sessions for control in June 2012 with 44 (35) participants. To achieve homogenous group sizes in anchor, we kept the number of subjects in a session close to constant, as we had 18/19/20(20/20/18) participants for BASIC (COMPLEX). All sessions

[3] For example, consider for BASIC that $a_t=100$, $b_t=80$, $c_t=20$. Plugging in the values into the formula gives $x_t=100+100-40+d_t=160+d_t$. Since subjects now that all values within the interval of [-25,25] are equally likely realizations of the random variable d_t, they optimally assume d_t to be zero and predict 160 as the future value.

lasted around thirty minutes. Participants earned €5.89 on average. They were on average 22.7 years old, with 59% being female.

3. HYPOTHESES

Our setting in principal uncovers the anchor itself as useless and thus fosters rational decisions that maximize payoffs. Given, however, that both anchoring and conformity pressure have been shown to profoundly influence human decisions, we hypothesize that subjects are biased to the social anchors. Observation of other players is thus expected to only inefficiently reduce anchoring. Cognitive load is expected to increase the reliance on anchor values. We thus formulate hypothesis 1:

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

Furthermore, we are interested in learning effects. We hypothesize that the comprehensive information on both the anchor and the other player's decisions, as well as the repetition of the identical task, leads to the buildup of task-specific knowledge. As a number of anchoring studies claim that this does not prevent anchoring, we hypothesize that learning effects fail to reduce social anchoring.

Hypothesis 2 ("Learning effects"). The anchoring bias is not reduced by learning effects.

Lastly, we are interested in the magnitude of the anchoring effects triggered by social anchors. By comparing the effects to a treatment that features a neutral anchor drawn from Meub et al. (2013), we can estimate which anchor type more strongly affects decisions. As conformity pressure appears likely to influence subjects' decisions, we hypothesize that the social anchor has a stronger impact.

Hypothesis 3 (*"neutral- versus social anchor"*). Subjects are more strongly biased towards a social anchor.

4. RESULTS

We present the experimental results in four subsections. First, we compare performance between treatments in terms of prediction accuracy. Second, we investigate if these differences point to an anchoring bias. Third, we test for learning effects. Fourth, we compare the results of the anchor treatments to a neutral, exogenous anchor in an otherwise similar setting to measure the relevance of the social anchor. This enables us to disentangle the basic underlying anchoring bias and additional effects potentially triggered by the social anchor.

4.1 OVERALL PERFORMANCE AND RATIONALITY

We analyze overall performance by considering subjects' prediction accuracy and rationality conditional on experiment and treatment. Recall that the profit-maximizing strategy of estimating the expected value is identical for all experiments and treatments, as the average prediction of the previous round does not contain any additional information. Moreover, only subjects in the treatment groups answer the higher/lower-question, which also does not affect rational behavior.[4]

Table 1 summarizes the mean absolute deviation of predictions from the expected values and the share of optimal estimations by treatments for all experiments.[5] Predictions equal to the expected value are characterized as optimal.[6]

[4] In BASIC (COMPLEX) 73% (68%) of the higher/lower-questions were answered correctly.

[5] The dataset contains 181 missing values (78 in the treatment groups and 103 in the control groups) when subjects did not enter a value in the respective round. Additionally, the dataset is corrected for subjects' predictions if the task was obviously misinterpreted. We assume this to be true if the estimation of subject i in period t (y_{it}) is smaller than 25 or negative (y_{it}<25), i.e. subjects tried to estimate the random determinant and not the future value. Thus, 162 observations (8 in the treatment groups and 154 in the control groups; for anchor (control) 6(128) in BASIC and 2(26) in COMPLEX were recoded as missing values. We assume that the higher number of predictions showing misunderstanding of the task in the control group is due to the lack of feedback or correction by observing others as in the treatment group. This leaves us with 2670 individual decisions.

[6] The optimality criterion is eased for predictions that deviate by a maximum of 0.5 points in the treatment groups. This adjustment is necessary as the expected values were not integers in all rounds of COMPLEX and thus deviations of 0.5 only reflect the restriction for subjects having to round entered values to be integers. Accordingly, we round down absolute deviations by 0.5 points in such cases.

Experiment		BASIC		COMPLEX	
		control	anchor	control	anchor
absolute deviation	**mean** (std. dev.)	**8.42** (21.27)	**11.62** (23.71)	**32.48** (102.04)	**28.12** (42.62)
	mean corrected (std. dev.)	**5.75** (9.47)	**8.61** (13.47)	**17.74** (29.73)	**23.90** (31.29)
	median	0	4	10	11
	75%	10	13	25	35
	95%	30	50	100	109
share optimal		0.56	0.33	0.37	0.10

Table 1: Treatment comparison subject to prediction accuracy.

Note: Values for mean corrected originate from treating values greater than the 97.5th percentile as outliers excluded from the calculation.

The prediction accuracy and the share of optimal predictions are higher for BASIC. More interestingly, there are significant differences between anchor and control. As a measure for overall prediction accuracy, the median absolute deviation clearly indicates that subjects' performance is worse when they are shown the social anchor (K-sample test; for BASIC chi2(1)=25.5955 with p=0.000, for COMPLEX chi2(1)=13.9095 with p=0.000). Considering the share of optimal predictions, we also find a significantly better performance for the control groups (Fisher's exact; p=0.000 for both experiments). As mean corrected shows, the mean absolute deviation is somewhat misleading, given that results are driven by outliers in the control treatments, particularly in COMPLEX. Applying a Wilcoxon-Rank-Sum test on mean corrected points at significantly better performance in control (for BASIC z=-6.441, p=0.000; for COMPLEX z=-5.744, p=0.000).

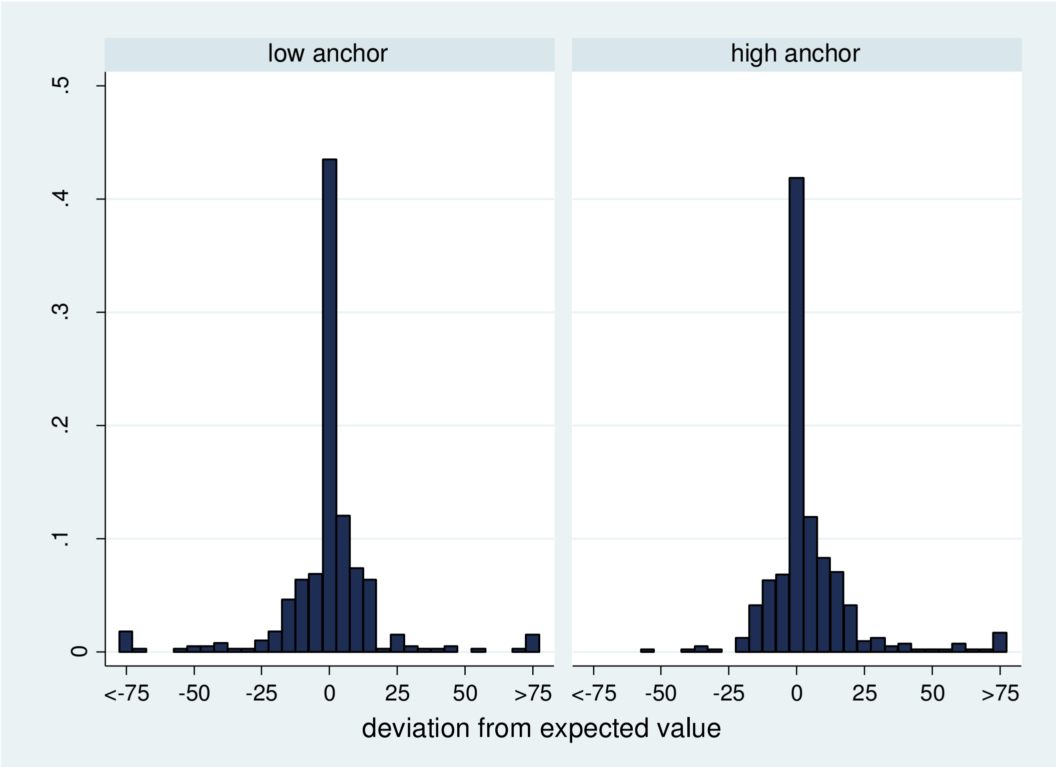
We conclude that the social anchor has a strong impact on overall prediction accuracy. These differences are economically relevant since the average absolute deviation, once corrected for outliers, increases by around 50% in BASIC and around 35% in COMPLEX. The share of optimal predictions is 23 percentage points higher in control of BASIC and 27 p.p. for COMPLEX. However, differences in performance do not necessarily indicate an anchoring bias.[7] Therefore, we further investigate the distinct distribution of deviations from the expected values.

[7] An alternative explanation might be seen in the representativeness bias (Kahnemann and Tversky, 1973). The distribution of predictions might reflect the distribution of the equation's random determinant. Forecasters have been shown to display the tendency of replicating the distribution of a time series' noise. Therefore, they

4.2 A SYSTEMATIC ANCHORING BIAS

If predictions in the treatment groups are systematically biased toward the averages of previous rounds, we interpret this as evidence in support of Hypothesis 1.The following graphs show the distribution of deviations from the expected values.

Figure 1: Distribution of predictions for BASIC

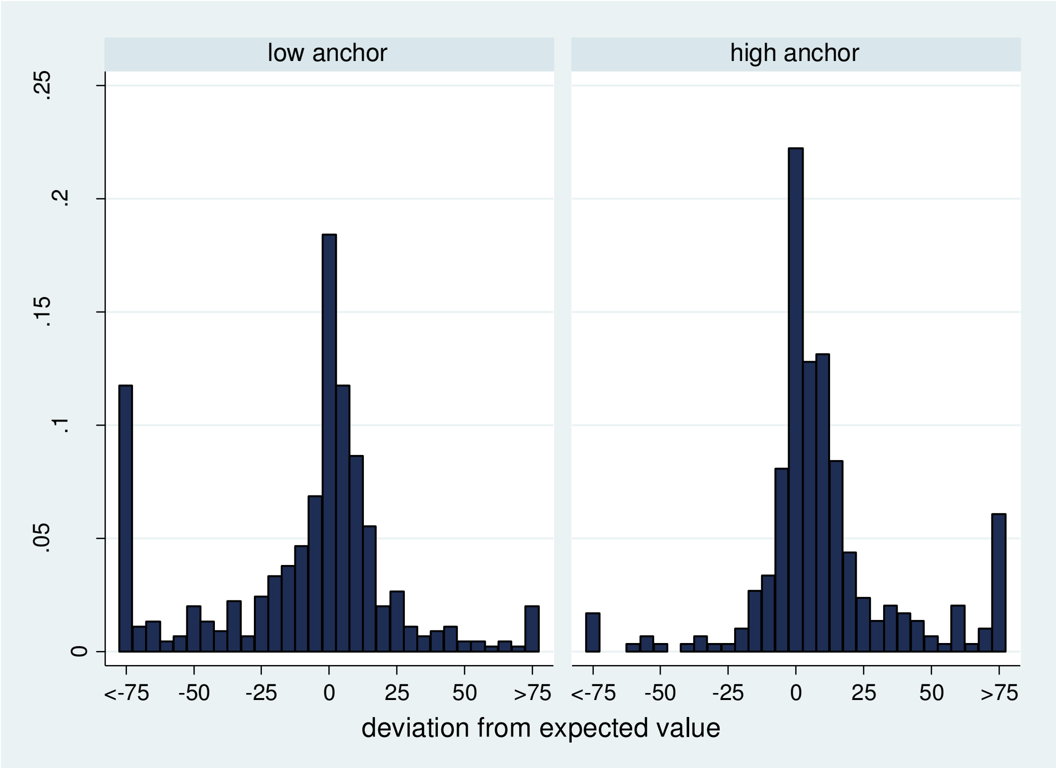


In BASIC, there are no apparent differences in the distribution of the deviations from the expected value for the treatment group with respect to the direction of the anchor value shown.

By contrast, in COMPLEX, we find the typical pattern resulting from a systemic anchoring bias: for low anchor values, more predictions are too low, i.e. smaller than the expected value. Considering the right hand side shows the same pattern for the case of high anchor values. However, the distributions of deviations conditional on the anchor direction in the treatment groups significantly differ for both experiments (Two-sample Kolmogorov-Smirnov test; for BASIC corrected p-value=0.080, for COMPLEX corrected p-value=0.000).

incorporate the uncertainty rather than ignoring it for an optimal prediction (Harvey, 2007). Subjects in treatment groups might be more prone to the representativeness bias since they are also confronted with the noise in the predictions given by the other subjects.

Figure 2: Distribution of predictions for COMPLEX



For a more profound analysis and quantification of the anchoring bias, we test for a specific anchoring pattern in the estimations by running a regression.

Equation (1) presents the model to explain the subjects' predictions. Let y_{it} denote the estimation of subject i at period t, and x_t the realized value at time t, with $E(x_t)$ giving its expected value.

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

In the given context, an optimal prediction 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 average prediction of the previous round, denoted as $\bar{y}_{t-1}$. We include the term θ_1[$(E(x_t)-\bar{y}_{t-1})$] (anchor_deviation) to control for an anchoring bias, measuring the deviation of the average prediction of the previous round $\bar{y}_{t-1}$ and the expected value in the current round $E(x_t)$. An unbiased estimation is given if $\theta_1=0$, whereas an estimation biased toward the anchor value is given if $\theta_1 < 0$.

In sum, information is used efficiently if a regression of Eq. (1) results in an estimation of γ_1 that is not significantly different from 1. At the same time, all other variables should show an insignificant effect on the values predicted. In this case, there would be no evidence supporting H1, but rather indicating that on average and ceteris paribus estimations are made optimally and are unbiased.

Additionally, we extend the model to allow for learning effects, an aspect discussed in subsection 4.3. Therefore, we introduce an interaction term for the anchoring bias picking up changes after the first five periods, i.e. for the last ten periods, as well as for the last five periods: the dummy variables to identify the periods are denoted as P^{10} and P^{5} respectively. We can write the regression model as follows:

$$y_{it} = \gamma_1 E(x_t) + \theta_1[E(x_t)-\bar{y}_{t-1}] + \theta_2[(E(x_t)-\bar{y}_{t-1})P^{10}{}_t] + \theta_3[(E(x_t)-\bar{y}_{t-1})P^{5}{}_t] + u_{it} \quad (2)$$

Table 2 provides the results of a pooled OLS regression on our unbalanced panel dataset of Eq. (1) and Eq. (2), applying robust Driscoll and Kraay standard errors.

Equation	**(1)**	**(1)**	**(2)**	**(2)**
Experiment	**BASIC**	**COMPLEX**	**BASIC**	**COMPLEX**
expected_value	**1.0138*****	**1.0033*****	**1.0138*****	**1.0059*****
	(.0051)	(.0046)	(.0051)	(.0039)
anchor_deviation	**-.0934*****	**-.2188*****	**-.1145*****	**-.2618****
	(.0129)	(.0454)	(.0080)	(.1048)
anchor_deviation*P10			**.0261**	**.0358**
			(.0161)	(.1015)
anchor_deviation*P5			**.0094**	**.0580*****
			(.0296)	(.0169)
F-Statistic (γ_1=1)	**7.25****	**0.50**	**7.34****	**2.25**
Prob. > F	(.0184)	(.4911)	(.0179)	(.1573)
F-Statistic (θ_2= θ_3 =0)			**1.69**	**5.93****
Prob. > F			(.2229)	(.0148)
F-Statistic (θ_1= θ_2= θ_3=0)			**102.87 *****	**110.76*****
Prob. > F			(.0000)	(.0000)
Observations	802	748	802	748
No. of Groups	58	57	58	57

Table 2: OLS regression of Eq. (1) and Eq. (2) with estimations (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 both 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 average estimation of the previous period.[8] For a decreasing (increasing) expected value in t compared to the average prediction in t-1, subjects in the treatment groups give significantly higher (lower) estimations. This has to be interpreted as a systematic inability to ignore the average estimation of the previous round. Additionally, subjects in BASIC fail to predict optimally on average, given that the marginal effect for the expected value (γ_1>1) indicates a general overestimation of the values to be predicted.

Besides the significance of the bias, its relevance has to be addressed. Based on the average absolute difference of the anchor values and the expected values of 37.5 points in BASIC (60.3 in COMPLEX), the estimated marginal effect of -0.093 (-0.219) amounts to a ceteris paribus bias of 3.4875 (13.2057) points on average. This corresponds to 2.1% (6.5%) of the average correct values. The cognitive load evidently has a strong influence on anchoring, as the magnitude of the bias is tripled for COMPLEX. As already indicated by Figure 1, there are only small effects caused by the anchor value in BASIC, although an estimated bias for each prediction of all individuals in each round of 2.1% has to be considered as economically relevant.

We conclude that the additional, albeit useless, information shown in the treatment groups creates a general noise in subjects' estimations. The social anchor values have an overall significant and relevant impact, especially when cognitive load is high. On average, subjects are unable to ignore the averages determined by the predictions of all players, as the rational strategy would suggest. Note that the anchoring bias is not only driven by subjects performing poorly who subsequently draw on these values, since the share of optimal predictions

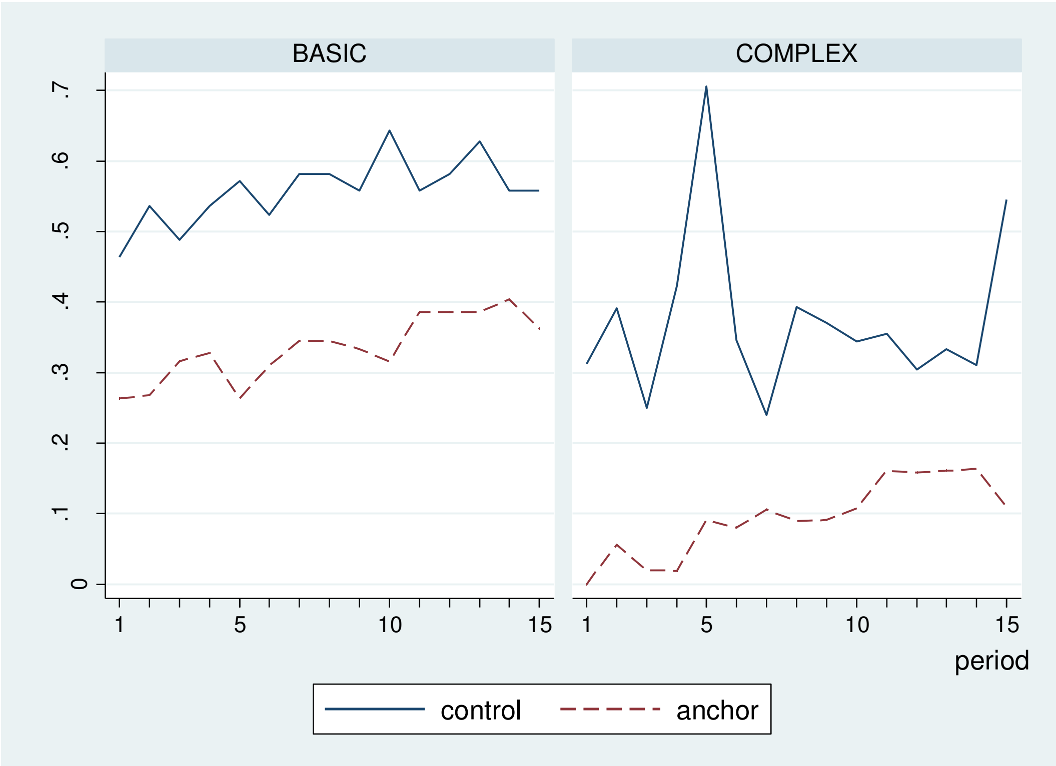
[8] In the following, we describe two main tests for the robustness of our results. First, we control for the influence of the deviation of the previous round's estimation y_{it-1} from the expected value of the current round $E(x_t)$. This control variable might be required due to the possible correlation of predictions made in consecutive rounds. Since the individual and the average estimation of previous rounds are positively correlated, this would lead to omitted variable bias. We find a significant marginal effect of the difference between last round's prediction and the current expected value. However, the effects are rather small (-.0417 in Eq. (1) for BASIC, -.0796 in Eq. (1) for COMPLEX, -.0412 in Eq. (2) for BASIC, -.0892 in Eq. (2) for COMPLEX). Most importantly, the anchor value's deviation and the interaction term in COMPLEX remain highly significant for all models, although marginal effects of the anchor deviation are slightly lower (-.0414 in Eq. (1) for BASIC, -.1533 in Eq. (1) for COMPLEX, -.0646 in Eq. (2) for BASIC, -.2452 in Eq. (2) for COMPLEX). Second, we test the robustness of our results with respect to outliers, as they might drive the results. Therefore, we exclude all predictions that deviate by more than three times the maximum value of the random determinant, i.e. if $y_{it}<[E(x_t)-3*25]$ or $y_{it}>[E(x_t)+3*25]$. Again, the anchor deviation is still significant for all models. Unsurprisingly, marginal effects of the anchor deviation are estimated to be somewhat smaller (-.0456 in Eq. (1) for BASIC, -.1005 in Eq. (1) for COMPLEX, -.0806 in Eq. (2) for BASIC, -.0896 in Eq. (2) for COMPLEX).

significantly deteriorates at the same time. Therefore, we interpret our results as presenting strong evidence in favor of H1.

4.3 LEARNING EFFECTS

In H2, we hypothesized that learning effects should be absent as task-specific knowledge generally fails to prevent biased decisions. There is evidence in support of learning effects when considering the regression results of Eq. (2) for COMPLEX. For BASIC, an F-test on the interaction terms of the anchor deviation and the last ten and last five periods fails to reject the null of no-joint-significance (p-value=0.2229). However, for COMPLEX, the results clearly indicate a reduction of the anchoring bias as the game proceeds. Figure 3 presents the development of the share of optimal predictions over periods, which supports the notion that there are slight learning effects.

Figure 3: Share of optimal predictions over periods.



The graphs points to learning effects for both experiments, given that the share of optimal predictions increases gradually over time, although such evidence is weaker for BASIC.[9] In

[9] The extremely high share of optimal predictions in period five of the control group in COMPLEX is due to the expected value being equal to 100. Thus, many subjects applying a rule of thumb hit the expected value, rather by accident than through a correct calculation.

the first period of COMPLEX, there are no optimal predictions in the treatment group, while the share of optimal predictions in the last five periods amounts to more than 10%.

In sum, we find mixed evidence regarding H2. There are some learning effects regarding the general understanding of the game. While there seem to be no learning effects in terms of the reduction of the anchoring bias for BASIC, performance improves over time for COMPLEX, as the anchoring bias tends to weaken. However, learning effects are rather weak as the share of rational predictions is strictly lower for all periods compared to the control treatments. Also, the magnitude of the marginal effects of the anchor interaction terms are quite small.

4.4 COMPARING THE SOCIAL TO A NEUTRAL ANCHOR

Lastly, we compare the impact of the social anchor to the results of a similar anchoring experiment, drawn from Meub et al. (2013). This study comprehends two analogous treatments implementing the same calculation tasks as in BASIC and COMPLEX, but does not feature a social anchor. Instead, subjects are merely displayed the correct value after each round, which subsequently becomes the anchor value for the ensuing round. There is no social observation, only feedback on the correct value after each round. All other factors are identical.

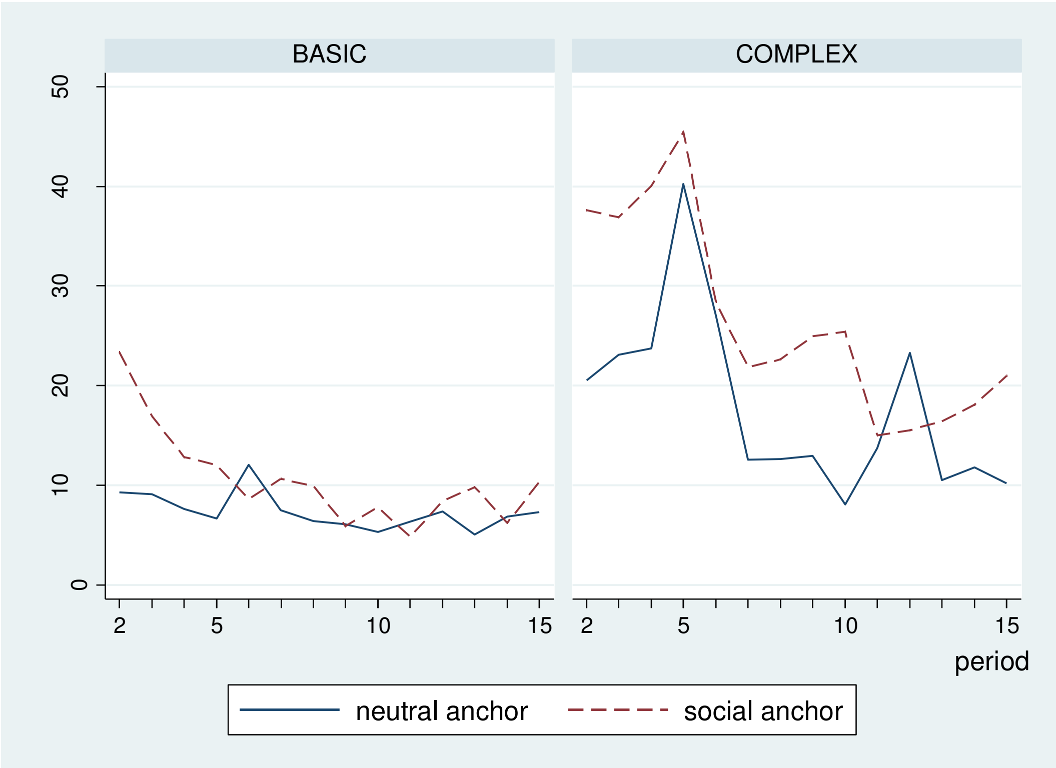
By comparing the two experiments, we aim to disentangle the impact of other behavioral influences towards the social anchor such as conformity pressure and a basic anchoring effect that is independent of the social context. Accordingly, Figure 4 shows the average absolute deviation over periods for the social and the neutral anchor.

As can be seen from the graphs, there are only small differences between the social and neutral anchor in BASIC, whereby subjects facing the social anchor perform slightly worse in the first five rounds. For COMPLEX, we find subjects in the neutral anchor treatment to perform better, with the exception of period 12.[10] Overall, performance is better, since the average absolute deviations pooled for all periods is 7.9 (11.6) for the neutral anchor (social anchor) in BASIC and 17.5 (28.2) in COMPLEX. A Mann-Whitney test shows significant

[10] The somewhat extreme values of period five and twelve for the neutral anchor in COMPLEX can be ascribed to the experimental design. Since subjects in the neutral anchor treatment could not observe each other and were presented the same determinant values for their calculation and the same anchor values, specific characteristics in some rounds affect all estimations homogenously. Thus, there is more noise on average between periods, which cancel out in the social anchor treatment with individual determinant values. For example, in period five and twelve of COMPLEX, the determinant d is at its maximum and has to be squared to calculate the expected value, which causes high individual deviations from the expected value if subjects fail to do so.

differences between the social and neutral anchor treatment for BASIC (z=-2.374, p=0.0176) and COMPLEX (z=-5.680, p=0.0000).

Figure 4: Average absolute deviations over periods by anchor setting.



Additionally, running a similar analysis for the neutral treatment as in subsection 4.3, Meub et al. (2013) show the same pattern of a systematic anchoring bias. For BASIC, the anchoring bias amounts to 0.94% of the average value to predict, compared to 2.1% for the social anchor. In COMPLEX , the average bias is 2.11% for the neutral treatment and 6.5% for the social anchor.

We conclude that subjects facing a social anchor are even more prone to the anchoring bias than those facing a neutral anchor. This result holds although the anchor is obviously useless for correct estimations in our setting, since it is common knowledge that every subject receives individual, random values for the determinants. Apparently, a social environment increases anchoring rather than reducing it through additional information on the anchor itself. We ascribe this effect to the observation of other players and hypothesize that it subconsciously activates subjects' "meta preference for conformity" (Klick and Parisi, 2008, p. 1319). Thus, the average values lead subjects to conform to the perceived group norm. While our design gives evidence for the social anchoring effect, it does not provide unambiguous proof for an interpretation based on conformity pressure. However, we find evidence in support of H3, i.e. a stronger effect of social anchors.

5. CONCLUSION

In line with Furnham and Boo (2011), this study argues that research on the anchoring bias has neglected to consider its social dimension and focused on purely individualistic choices instead. This limits the external validity of the experimental anchoring studies, as actual markets feature extensive opportunities for learning through observation of the other economic agents. By implementing an observational framework with socially derived endogenous anchors, our setting more closely resembles the decisions faced by subjects in the markets commonly investigated in empirical studies, such as auctions or forecasting. Further, by implementing strong monetary incentives and feedback on performance, we are able to present arguments as to whether lab-implemented market forces may serve as a filter for irrational decisions (List and Millimet, 2008).

In spite of monetary incentives, a simple rational strategy and feedback on performance, we find a strong anchoring bias resulting from the socially derived anchor, which increases along with higher task complexity. There are only small learning effects in the case of high cognitive load. Thus, the obvious derivation of the anchor values through the prior decisions of other subjects does not succeed in eliminating the bias. Finally, the comparison to a neutral anchor shows that, overall, a social anchor leads to substantially stronger effects than a classical external one. We explain this as resulting from the implicit pressure of conforming to the average decisions of all other subjects, despite its factual irrelevance.

Our study thus does not support the notion that market conditions may generally serve as a remedy for behavioral biases. We argue that they may instead foster other influences, such as conformity pressure towards consensus values. Consequently, our results lend experimental support to the empirical studies that report biases towards social anchors in economic contexts. We suggest that their interpretation is valid, given that market conditions in our study not only fail to eliminate the bias, but rather increases it. To gain a more profound understanding of anchoring in social contexts, further experimental studies should more closely investigate the interdependencies of anchoring and other behavioral influences, such as conformity pressure.

APPENDIX

Instructions for BASIC and COMPLEX. The differences between experiments and treatments are indicated in braces. The original instructions were in German and are available from the authors upon request.

The Game

In this game, you will estimate a value in each round. There are 15 rounds in which you will give your estimation. In each round, the correct value results from the determinants **A, B, C and D** {COMPLEX: A, B, C, D and E}. The determinants A, B and C {COMPLEX: A, B, C and D} will be displayed to you in each round. The determinant D {COMPLEX: E} varies arbitrarily between -25 and 25 in each round; you do not know its exact value.

The formula to calculate the value is:

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

This formula is valid for every round of the game. {BASIC, COMPLEX - anchor treatments: As soon as all players have submitted their estimation at the end of each round, the estimations of all the other players will be displayed, as well as the resulting average estimation. Starting from the second round, you will also have to estimate whether the value will be higher or lower than the average estimation of the preceding round.} In each round, you will have one minute {COMPLEX: 30 seconds} to enter your estimation and click on OK to confirm it.

<u>Please note</u>: If you do not enter a number within this minute {COMPLEX: these 30 seconds} 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 cents in each round, with the difference between your estimation and the correct value being deducted 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**.

The gains of each round are added together and paid to you after the end of the game. Furthermore, you will receive a basic payment of € 1.50.

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