Exploring the Impact of Cognitive Uncertainty on Nudge Effectiveness: The Case of Anchoring

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Abstract

The inherent uncertainty in the world has led to the development of various mechanisms for managing it. Some authors suggest that this uncertainty underpins many heuristics and biases in human decision-making. Heuristics are principles or rules of thumb that guide human decisions and are relatively predictable, making them crucial to the success of nudging strategies. This study explores the relationship between uncertainty and nudging, specifically focusing on the well-known anchoring nudge. We hypothesise that people's confidence levels can help predict the effectiveness of an anchor. Participants were asked to estimate multiple means for a series of sequentially shown numbers with varying underlying distributions to mimic different levels of uncertainty. Our findings indicate that while participants could accurately assess the uncertainty and its impact on their estimates, the anchoring nudge did not bias their estimates downward as expected. Interestingly, the treated group reported unjustified higher confidence in their decisions, suggesting that the nudge influenced the very confidence meant to predict its efficacy. This study contributes to the anchoring literature and highlights how small contextual and design changes can lead to unexpected outcomes in robust phenomena.

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Introduction

Motivation

Richard H. Thaler and C. Sunstein introduced and popularized the concept of Nudge, empirically showing that subtly influencing the choice architecture, i.e., the context in which choices are presented, can have surprisingly large effects on how people make decisions (Thaler & Sunstein 2021). Since its introduction into economics, it has been applied in various policy and business settings. It is argued that one of the main contributions of the authors was to present a lingua franca between the academic worlds of economics and psychology. People acting irrationally is no secret in the psychology literature, and these irrationalities have been substantially studied under the term *cognitive biases* (Tversky & Kahneman, 1974). These biases contradict the assumption of a perfectly rational agent found in almost all economic models. Decades of research have uncovered an extensive list of biases that describe how people actually make decisions, where some textbooks (Baron, 2007) list more than 50. Such findings are a necessary part of the model for human decision-making, and many efforts have been made to uncover the underlying cause for such cognitive biases. Understanding more about different biases, like the underlying cognitive mechanisms behind them, their predictive power, and various contextual changes that influence their occurrences is essential in understanding Nudging. Nudges could be simply explained as different policies that work by exploiting these cognitive biases. Understanding these cognitive biases is the key to predicting if a Nudge will work or not.

M. Hilbert (2012) summarized some theories on why biases occur in human decision-making: Earlier explanations focus on the biological limitations in our information processing capacity leading to a concept known as "bounded rationality" (Simon, 1955). The dual-process theory (Kahneman, 2011) suggests that we use our fast and intuitive System 1 in order to reduce the cognitive load of decisions. This leads us to utilize mental shortcuts/rules of thumb known as heuristics (Goldstein & Gigerenzer, 2002; Kahneman, Slovic, & Tversky, 1982; Shah & Oppenheimer, 2008) when making decisions. Such heuristics are being exploited by nudges in a predictive way (R. Thaler and C. Sunstein 2008, Ariely, 2008). Emotional and moral causes have also been proposed (Loewenstein, Weber, Hsee, Welch, & Ned, 2001; Pfister & Böhm, 2008), as well as various social influences (Wang, Simons, & Bredart, 2001; Yechiam, Druyan, & Ert, 2008).

A modern line of research connects the concept of cognitive uncertainty as one of the key underlying mechanisms that link many biases observed commonly in behavioural economics and cognitive psychology literature (Enke & Graeber, 2023; Hilbert, 2012). They argue that these biases arise due to the inherent complexity of economic decisions, prompting people to make noisy decisions and rely on heuristics as guidance for these decisions. On top of that, they argue that cognitive uncertainty can be a measurable proxy for this noisiness in decision-making, thus becoming an important factor in predicting and explaining behaviour (Enke & Graeber, 2023).

In this paper, we will focus on cognitive uncertainty, its role in the decision-making process in the context of decision-from-experience tasks (DfE, which will be explained in the next segments), and how it mediates the effectiveness of one of the most widely used nudges, *Anchoring.*

Literature review

Cognitive uncertainty

Uncertainty can be generally divided into two categories: aleatory and epistemic. Aleatory uncertainty is represented as the fundamental uncertainty of the environment and is usually quantified by the true standard deviation/variance. Traditional economic models usually account for this type of uncertainty when an agent is making a decision. However, there is also a human dimension, represented by epistemic uncertainty, which deals with the available information to the agent and the extent to which that information is integrated into the decision-making process. Epistemic uncertainty is further divided into Brunswikian and Thurstonian uncertainty (Juslin & Olsson, 1997). Brunswikian uncertainty arises from limited data samples leading to greater uncertainty, which decreases as more data is observed and Bayesian updating refines the estimates. Thurstonian uncertainty accounts for cognitive limitations in integrating new information, emphasizing that decision-making depends on both the quantity of information and the agent's ability to process it effectively.

This paradigm relates specifically to the case of Decision from Experience (DfE). In DfE participants get to personally experience the information they need to use to make a specific decision (e.g. see a series of numbers and then make a decision based on them). This contrasts with the setting of Decision from Description (DfD), where all the relevant data for a decision is summarised and reported all at once (e.g. the statistics of these numbers like the mean or SD is already given and based on this a decision should be made). A DfE task can have more environmental reliability for scenarios where people only experience a sample of evidence for a phenomenon and need to use that knowledge for subsequent decisions. In this setting, both epistemic and aleatory uncertainty play an important role. This paper uses a DfE experimental design.

Disentangling these two aspects of epistemic uncertainty in a DfE setting was the theme of S. Olschewski and B. Scheibehenne's (2023) paper. More precisely they tested how epistemic uncertainty affects risk taking and how people's metacognitive awareness of the uncertainty is connected. They show that the increase in SD for a distribution from which a series of numbers are drawn influences the uncertainty levels positively. They also demonstrate that people are generally aware of how much they do not know (metacognitive uncertainty) and integrate this into their risk-taking behaviour. Such findings point to a bright side, we are fallible beings but are in general aware of how fallible we are i.e. how much we don't know. (S. Olschewksi & Scheibehenne, 2023). By making participants elicit the degree of confidence they have in their decision, a proxy for metacognitive uncertainty awareness is established. This has been shown to be a useful tool as it holds substantial predictive power in predicting systematic biases in economic decisions (Enke & Graeber, 2023).

Since cognitive uncertainty holds predictive power of biases, and exploring these biases is how nudges are effective then a natural question arises, does cognitive uncertainty have any predictive power in nudge effectiveness? More precisely research has found that in recent Bayesian cognitive noise models participants tended to regress to an intermediate cognitive default (middle ground value) (Enke and Graeber 2023). This is quite similar to the anchoring and adjustment heuristic, or simply known as the *Anchoring nudge*. The key question is will an Anchoring nudge be successful in influencing this cognitive default thus leading people with higher uncertainty to regress more strongly to a changing middle-ground value. More specifically will this occur in a DfE configuration similar to that carried out by S. Olschewski and B. Scheibehenne in their (2023) study?

Anchoring

The widely recognised form of anchoring, known as the anchoring and adjustment heuristic, was introduced by Kahneman and Tversky in 1974 through their seminal work on decision-making under uncertainty. Participants were given an arbitrary percentage derived from spinning a wheel of fortune in their study. Subsequently, they were asked whether the percentage of African nations that are part of the United Nations was higher or lower than the given number. The study revealed that if participants received a low number (e.g., 10%) from the wheel, their average estimation (25%) was smaller—i.e., closer to the arbitrary anchor—compared to the high anchor condition (e.g., an anchor of 65% resulted in a mean estimation of 45%).

This initial finding spurred a vast literature on the topic, demonstrating that the anchoring effect is prevalent across various domains, including general knowledge (Epley & Gilovich, 2001; McElroy & Dowd, 2007; Mussweiler & Englich, 2005), probability estimates (Chapman and Johnson, 1999), legal judgments (Englich & Mussweiler, 2001; Englich & Soder, 2009), forecasting (Critcher & Gilovich, 2008), and negotiation (Galinski & Mussweiler, 2001). These studies underscore the robust presence of the effect ranging from controlled laboratory settings to real-world field applications (Furnham & Boo, 2011).

Further, nuanced findings have revealed different types of anchors. Researchers have examined informative versus uninformative anchors, and extreme versus realistic anchors, and the anchoring effect has remained robust in most studies, albeit with varying effect sizes (Furnham & Boo, 2011).

Cognitive explanations

The results of anchoring are a well-documented phenomenon, although the exact cognitive mechanisms remain not fully understood. Currently, there is no unified theory on precisely how anchoring works, but there are five major, non-mutually exclusive theories that attempt to explain the underlying processes. Given the inherent complexities of the human brain, developing a unified theory of anchoring is challenging. However, having five non-mutually exclusive theories can be valuable if we can map each specific theory to the context of the problem, which the current literature lacks (Turner & Schley, 2016).

For the purposes of this paper, *the Anchoring and Adjustment theory* appears to be the most suitable for the experimental design and the underlying mechanisms being influenced. Furthermore, we are not focused on predicting the exact extent of the anchoring nudge (e.g., 20% underestimation for the treatment group), but rather on the direction and significance of the effect. Therefore, having a high-level understanding of the cognitive processes, as provided by the aforementioned theory, is sufficient for the purpose of this study. Such a high-level approach is widely employed in many traditional anchoring experiments, regardless of the domain (Turner & Schley, 2016).

Adjustment and anchoring theory

It is hypothesized that individuals use the given anchor as a starting point in their judgment process and then fail to sufficiently adjust their estimate away from the anchor, thereby causing the anchoring effect (Kahneman & Tversky, 1974; Epley & Gilovich, 2006). Within this paradigm, two main sub-theories attempt to explain why the adjustment is insufficient.

Some researchers argue that individuals have a set of possible values, and as soon as they reach a value within this set, they settle for it (Epley & Gilovich, 2006; Quattrone, 1982; Quattrone, Lawrence, Finkel, & Andrus, 1984). Others believe that attention plays a critical role. Many tasks in anchoring studies are cognitively demanding and deplete cognitive resources. It is believed that adjusting from the anchor is an elaborate process where, after each adjustment, a decision must be made about whether to continue adjusting or stop. This process is costly in terms of attention, and when the cumulative cost of attending reaches a certain threshold, the adjustment process halts (Epley, 2004; Epley & Gilovich, 2006; Gilbert, 2002).

In this study, the anchor is designed to be suitable for both explanations within the Anchoring and Adjustment theory. Therefore, regardless of whether attention depletion or a spectrum of possible values is the true cause of the effect, the anchoring should occur (more on this in the study design segment).

Theoretical framework, hypothesis and contribution

In this paper, we aim to adopt the DfE study design from the paper by S. Olschewski and B. Scheibehenne (2023) to investigate how metacognitive uncertainty mediates the effectiveness of an anchoring nudge. By presenting numbers with different standard deviations, we introduce varying levels of complexity, which is hypothesised to be the underlying cause of noisy and biased decision-making. In the context of Bayesian decision-making, as designed in our study, it has been demonstrated that individuals tend to regress to an intermediate cognitive default. We hypothesize that this cognitive default can be influenced downward by an anchoring nudge.

Given that individuals generally have a fairly accurate estimation of their uncertainty, which can be seen as their subjective perception of complexity (Enke & Graeber 2023), we believe that the complexity introduced by changes in SD will then affect this uncertainty. This implies that assessing individuals' levels of uncertainty holds significant predictive value for the nudge's effectiveness as the literature points out that cognitive uncertainty predicts biases across various economic decisions (Enke & Graeber 2023). Based on this premise, we will test the following hypotheses:

H1: There will be a positive effect of the level of SD on participants' estimation mistakes, i.e Higher SD will lead to larger absolute deviations from the true mean.

H2: There will be a negative effect of the level of SD on confidence elicitation (used as a measure of metacognitive uncertainty), i.e. High SD condition leads to lower confidence.

H3: Introducing an anchor will lead participants to systematically underestimate the true value.

H4: The effectiveness of the nudge will be greater in cases of low confidence than in cases of high confidence.

The first two hypotheses are smaller-scale replications of the study by S. Olschewski and B. Scheibehenne (2023), while H3 and H4 build upon their results by introducing a nudge.

Our contribution to the anchoring literature is threefold. First, the anchoring and adjustment nudge have been predominantly tested in static environments (Remus & Kottemann, 1995) (e.g., DfD-type tasks). Here, we aim to contribute to the less common line of research where the nudge is applied to a decision made in a DfE setting. Second, an anchor is usually employed at the beginning of the decision-making process, where agents need to adjust away from the nudge according to the Adjustment and Anchoring theory. However, in our study, since we hypothesize that the decision-making process resembles a Bayesian updating mechanism, participants first experience some value and are nudged afterwards. This can be seen as forming a prior about a phenomenon before the nudge comes into play. Such a situation may be more ecologically valid for cases where people already have some evidence (knowledge) collected about a topic before making a decision. Lastly, we aim to provide further evidence if cognitive uncertainty has predictive power for biases, hence adding to the debate that many, initially thought of as distinct anomalies, have a common underlying cause. This in turn can be used to add to the theories that aim to explain the cognitive mechanisms behind the Anchoring heuristic. All together our findings will provide additional evidence for the general robustness and understanding of this well-known phenomenon.

Methodology and experiment design

General Setup

The main experimental design was based on the study by S. Olschewski and B. Scheibehenne (2023), already incorporating some of their findings. The entire study can be divided into three main parts:

1. Introduction to the study, including an explanation of key concepts and test rounds.

2. The main experiment consisted of four trials.

3. Short demographic survey.

On average, the entire experiment lasted under 10 minutes.

Main Experiment

Participants were shown a series of six numbers drawn from a distribution with a specified mean and standard deviation (SD). The numbers were displayed sequentially, each appearing on the screen for 1000 ms before disappearing. Based on these six numbers, participants were asked to estimate what they believed the true population mean of the distribution was. The interface for inputting their estimates varied between the control and the treatment (anchoring nudge) conditions, which will be discussed in more detail later.

After stating their estimate, participants were asked to indicate how confident they were that their estimate was within ±5 of the true mean. Confidence elicitation was done on a scale from 0% to 100% in 10% increments, where 0% indicated no confidence at all and 100% indicated complete confidence that they had estimated the correct population average within the range of ±5.

Each trial sequence consisted of three parts: showing a series of six numbers, requesting an estimate of the population mean, and eliciting confidence levels. There were four trials in total, each with numbers drawn from different distributions (more details on this in the stimulus creation segment). On average, these four trials took a total of 5 minutes.

Introduction to the Study

It was assumed that participants did not initially know the difference between a sample mean and a population mean. Before the main experiment started, participants went through a detailed training phase. During this phase, they were introduced to the experimental interface and given an extensive explanation of the difference between the sample mean and population mean, with frequent reminders to estimate the population mean. Participants answered two practice questions: the first asked them to estimate a sample mean from a series of numbers, and the second asked them to estimate a population mean. Feedback was provided for their answers during the practice rounds, but not during the main experiment. This training phase lasted approximately 5 minutes.

Survey

The survey was administered at the end of all the trials and consisted of four questions. Participants were asked to:

1. Input their exact age.

2. Indicate their gender.

3. State their annual after-tax earnings in EUR by selecting one of the proposed ranges (0-5,000; 5,001-15,000; up to 60,000; and above 60,000).

4. Indicate their highest completed educational level (High School or bellow, Bachelor’s degree, Master’s degree, Phd or equivalent)

These survey questions were inspired by the 2023 paper by Lin and Schlein, which showed that age, gender, income, and education level significantly affect susceptibility to anchoring nudges. On average, participants took 30 seconds to complete this survey.

Stimuli Creation

The six numbers shown to the participants were drawn from predetermined distributions. Each of the four trials had its own distribution, with two trials assigned to numbers drawn from low SD distributions and the other two from high SD distributions. In total, there were four normal distributions with different parameter pairs. The low SD condition included one pair with a mean of 400 and SD of 10, and a second pair with a mean of 80 and SD of 5. For the high SD condition, the pairs were mean = 300 and SD = 60, and mean = 100 and SD = 50. The coefficient of variation between the low SD condition and the high SD condition is exactly in the ratio of 1:8, which aligns with the boundaries of the CV from the original study.

It is important to note that these are population parameters, hence the six randomly drawn numbers could have different sample means and SDs. To control for this, several series of randomly drawn numbers were constructed per theoretical distribution, each with their sample values allowed to deviate by a maximum of 5% from the underlying distribution population parameters. This ensures that the presented sequences were representative of the respective underlying distribution, similar to the original study. Additionally, the numbers shown from these series were randomized, along with the trials, so participants randomly saw numbers drawn from either a low SD condition distribution or a high SD condition distribution.

S. Olschewski and Scheibehenne (2023) found that the sample size of numbers drawn from the initial distribution had no significant effect on estimation accuracy. This could be attributed to the well-documented recency and primacy effects in cognitive psychology. These effects demonstrated that when a series of numbers (or words) are shown to participants they tend to recall the beginning and the end of the number series (Tan & Ward, 2000). This explanation fits well with what S. Olschewski and Scheibehenne (2023) found. According to their study, showing 24 numbers versus 4 numbers did not significantly affect participants' estimation accuracy. This finding is also evidence for Thurstonian uncertainty, where the size of numbers shown was not well-integrated and therefore did not cause perfect Bayesian updating to occur, reducing uncertainty levels (decrease in the Brunswickian uncertainty). Based on this finding, we decided not to vary the sample size of the drawn numbers, as it had the added benefit of reducing the duration of the experiment.

Treatment

Our main extension of the S. Olschewski and Scheibehenne (2023) paper was the introduction of an anchoring nudge. This treatment was randomly assigned to participants and was implemented during the population mean estimation phase of a trial (the number sequences and confidence elicitation were identical for the control and treatment groups). In the control group, participants only had an empty box where they were to write their best guess of the true population mean. The treated participants were given a series of ranges to choose from, and then after selecting a specific range, they wrote their precise estimate within the bounds of the chosen range.

The following example illustrates one of the anchors from the study:

For a distribution with a true mean of 300, participants had the option to choose one of the following ranges:

1. 150-187

2. 188-225

3. 226-262

4. 263-300

5. Above 300

After choosing, for example, the 188-225 range, they had to write in an empty box on the right side of the selected range their precise estimate within the boundaries of the selected range (it was technically impossible to write a number outside the boundaries of the chosen range).

Several features of this anchor design are noteworthy. Firstly, the anchor is designed to be a low value (e.g., 150), expected to have a downward effect on the mean estimation. Secondly, the anchor was set to be half the true value, making it a realistic anchor since the number falls within the domain of plausible answers. Scholars argue that realistic anchors are more effective than extreme, implausible ones (e.g 5-10) (Mussweiler & Strack, 2001a). This anchor is also an informative anchor, meaning it holds some relevance to the correct solution (unlike the initial Kahneman and Tversky spin-the-wheel anchor, which had no relevance to the percentage of African nations in the United Nations). This informative feature has been shown to positively affect participants' susceptibility to the nudge's effectiveness (Hastie et al., 1999; Marti & Wissler, 2000; Englich et al., 2005; Strack & Mussweiler, 1997). Additionally, the ranges are typically non-round numbers, which have been shown to be perceived as more credible (Jain et al., 2020), further adding to the information relevance argument.

Finally, the sequential trajectory of the ranges was deliberately designed to exploit the anchoring and adjustment cognitive theory behind this nudge. Participants are hypothesized to start with a low, yet informative and plausible anchor (e.g., 150) and adjust away from it by considering other values. When they reach either the first values from their plausible set or experience attention fatigue, they will settle for that range and an estimate within it, thus systematically biasing the estimation downward closer to the anchor value.

It is important to note that for each of the four possible means, the anchors are designed to be of the same proportion, i.e., starting from half the size of the true mean value (e.g., for mean 400, the ranges start from 200).

Data analysis

Participants

A total of 194 people clicked on the experiment. Of these, 101 left the experiment before the introduction part was over. Five participants were removed due to incomplete data, leaving a total of 88 participants who completed the entire experiment (estimated the mean four times, elicited their confidence four times, and completed the survey). Out of the 88 participants who finished the experiment, 55 were randomly allocated to the control group, while 33 were allocated to the treatment group. The average age of the participants was 25.18 years, with 51 participants being female. The educational levels were primarily dominated by master's and bachelor's degrees, with 37 participants each. The remaining participants included 9 with high school education or below and 5 with a PhD or equivalent. Most participants fell into the following income ranges: 20 participants in the 0-5000 EUR range, 22 in the 5001-15000 EUR range, and 23 in the 15001-30000 EUR range, while a minority of participants, 6 and 9, were in the higher 45001-60000 EUR and above 60000 EUR income ranges, respectively.

Balancing Checks

After promptly cleaning the data from incomplete entries, we conducted some preliminary analyses. Firstly, we performed balancing checks between the categorical variables (and age) found in the demographic survey at the end of the experiment. This analysis was necessary to uncover if some demographic subgroups (e.g., males or highly educated individuals) were overrepresented in either the treatment or control group. If this situation arose, it could pose challenges for subsequent analysis.

For the categorical variables of gender, income, and education, we performed a Chi-square goodness of fit test and Fisher's exact test for those subcategories that had a sample size below the threshold of 5 observations per subcategory for the Chi-square test statistic. This threshold helps avoid distortions in findings and minimizes Type 1 and Type 2 errors. For cases where this threshold was not met, we chose to implement Fisher's exact test instead of merging the two subcategories because the number of subcategories was not particularly large (Cleophas & Zwinderman, 2016). In summary, our results show that all of the categorical variables are not statistically overrepresented in either of the two groups. The exact representation tables (frequency) can be found in the appendix, while the test statistics are summarized in Table 1 below:

Category	Chi-square test: p-value	Fischer's exact test: p-value
Gender	0.4235	0.5401
Income	0.5118	0.5418
Education	0.6958	0.7094

Table 1

Based on these p-values, the null hypothesis (H0) is not rejected; therefore, there is no statistical difference between the frequency of these demographic subcategories between the control and treatment groups. Age was measured as a continuous variable; hence, we used a different approach. The Shapiro-Wilk test indicated that age is not normally distributed (SW = 0.68306, p-value = 0.0000). Therefore, to compare the mean age between the treatment and control groups, we used the non-parametric Mann-Whitney U Test (Wilcoxon rank-sum test). We do not reject the null hypothesis, concluding that there is no age group overrepresented in either of the two groups (W = 1115.5, p-value = 0.06756). Note: the H0 is not rejected under the 5% significance level; however, there is one outlier in age in the control group (63 years old), which raises the average age of the control group enough to approach this boundary condition.

H1 and H2: Hypotheses from the Initial Paper

For hypotheses H1 and H2, we aimed to replicate the initial findings of the authors (S. Olschewski & Scheibehenne, 2023). Here, we are interested in the mistakes participants made in their mean estimation, regardless of whether they were overestimations or underestimations (H1). For this reason, the absolute difference between the true mean and their estimation is used as a measure of mistakes. Only the participants in the control group were used in this level of analysis, as they faced conditions similar to the participants of the initial paper, i.e., no nudge that could potentially influence their estimations in the low vs. high SD condition, as well as their confidence elicitations for the two conditions.

Participants' average absolute deviations from the true values do not follow a normal distribution for the two cases (High SD condition: SW = 0.75782, p-value = 3.748e-08; Low SD condition: SW = 0.48345, p-value = 1.25e-12). We again utilized a non-parametric approach for the mean comparison between the two conditions. This time, we used the Wilcoxon Signed Rank Test, which is more suited to our case since each participant was subjected to both conditions, and this test takes that into account. The results show a significant difference between the average mistakes in the two conditions (V = 1399.5, p-value = 1.357e-07). Just like in the original study, participants tended to make larger mistakes in the high SD conditions. More precisely, in our experiment, the participants' average mistake was 22.75 (SE = 2.94) in the high SD condition, while the low SD condition yielded a much lower average mistake of 5.56 (SE = 1.49). This is summarized in Figure 1A.

Participants' confidence elicitations follow a normal distribution (High SD: SW = 0.98035, p-value = 0.503; Low SD: SW = 0.9451, p-value = 0.01405). Hence, we used a classical paired t-test for mean comparison to test our H2. Just like in the previous case, our H2 is also not rejected, because there is a significant difference between the confidence elicitation in the 2 conditions (t = -8.4577, p-value = 1.813e-11; Cohen’s d = -1.14). Participants tended to be more confident in the low SD condition (M = 54.82, SE = 2.95) and elicited smaller confidence percentages on average in the high SD condition (M = 39.27, SE = 2.52), as summarized in Figure 1B.

Figure 1A:

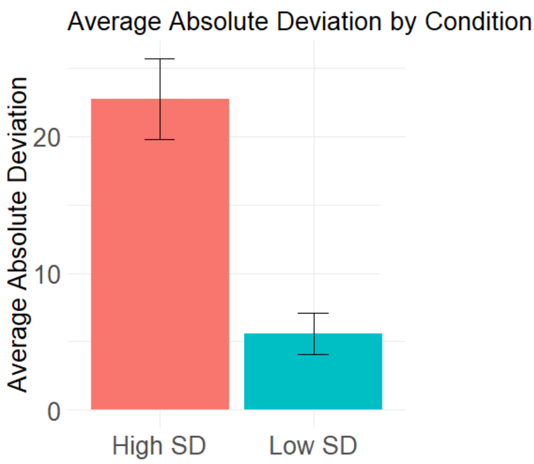
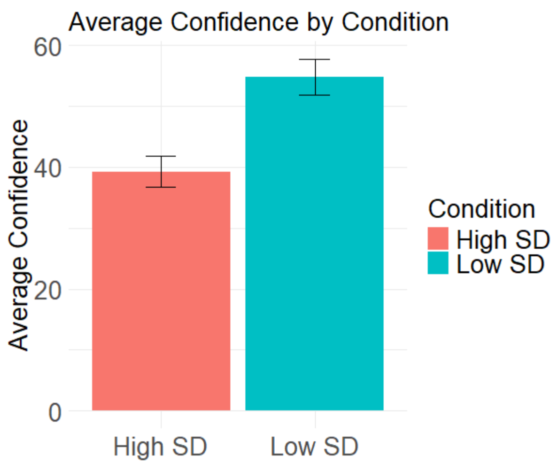


Figure 1B:



This aligns with the original findings that people are generally aware of their own uncertainty and thus can predict their mistakes, as seen in the link between confidence and estimation mistakes.

H3 and H4: Analysis of the Extension-Introduced Anchor

To determine if the Nudge had any effect on the estimation of the treated participants, we conducted a series of analyses with varying levels of complexity, thus approaching the issue from different angles. The first and most simplistic analysis we conducted was a basic comparison of the average estimation between the treated group and the control group to see if the nudge had an underestimating effect.

Upon testing for normality, only the estimation for the distribution (M = 100, SD = 50) followed a normal distribution, while the other three did not. Accordingly, we used both a t-test and the Mann-Whitney U Test. The results are summarised in the following table.

	M:400 & SD:10		M:80 & SD:5		M:300 & SD:60		M:100 & SD:50	
Metric	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value
Control	397	0.17	79	0.049*	297	0.32	95	0.65
Treatment	393		77		298		92	

Table 2

The only significant difference found was between the mean estimation of the Low SD case, with a mean of 80 and SD of 5, although this is at the very edge of the criteria of 5%. In other cases, the raw numbers show a small downward effect (in most cases) in the treatment group, but this is not statistically significant. This prompted us to conduct a more comprehensive analysis, introducing various control variables to help isolate the effects of the treatment.

Regression model:

For this level of analysis, we decided to use a random intercept model, a subset of the mixed-effects model. In this model, a random intercept is assigned to each participant while the effects of predictor variables (their slopes) are fixed across all participants, allowing us to interpret these results in a general sense across the entire sample. Introducing a random intercept is suitable for our experimental setting as it captures each participant's unique baseline tendency, controlling for individual differences. For instance, some participants may systematically overestimate or underestimate averages due to an innate difficulty with numbers or other personal characteristics. By accounting for these individual differences with a varying intercept, we mitigate the bias that might arise. Keeping the slopes fixed enables us to extract the general effects of our independent variables, ensuring our results are robust and reflective of general trends rather than specific idiosyncratic behaviours. The configuration of our model is as follows (Note this is not the theoretical model with the random, fixed elements and error terms shown . The model is bellow compatible with the table output that follows, as we are only interested in the general fixed effects):

Model 1: $Y_i = \alpha_1 + \beta_1$(M_400_SD_10) + β_2(M_80_SD_5) + β_3 (M_300_SD_60) + β_4(Confidence_Percentage) + β_5(Group_Dummy) + β_6(Group_Dummy * Confidence_Percentage) + β_7(Gender_Male) + β_8(Education_High_School_or_below) + β_9(Education_Masters) + β_{10}(Education_PhD_or_equivalent) + β_{11}(Income_0_50000) + β_{12}(Income_5001_15000) + β_{13}(Income_30001_45000) + β_{14}(Income_45001_60000) + β_{15}(Income_Above_60000) + β_{16}(Age)

Where the dependent variable Y_i stands for *Directed deviation* which calculated by the difference between the True Mean and the Estimated mean.

α_1 – fixed intercept

Controls

In order to control for the inherent effect of complexity on the Confidence elicitation and the mean estimation we introduced four dummy variables, that represent the Mean & SD pair of a distribution for a particular trial. This control has the additional benefit of taking into account the innate difficulty of calculating an average of numbers that come from a distribution with a mean of 400 vs a mean of 80. Put in other words, it is cognitively more difficult for some people to estimate an average where the true mean is 400 than 80 even if both are part of the low SD i.e low complexity case. These dummy variables control for this.

The second set of controls are demographic variables collected with a survey at the very end of the experiment. All but the variable Age are coded as dummies. The controls are summarized below:

- M_400_SD_10 = dummy variable for the distribution of Mean 400 and SD 10
- M_80_SD_5 = dummy variable for the distribution of Mean 80 and SD 5
- M_300_SD_60 = dummy variable for the distribution of Mean 300 and SD 60

- M_100_SD_50 = dummy variable for the distribution of Mean 100 and SD 50 (omitted to avoid multicollinearity)
- Gender_Male = Dummy representing the Male Gender
- Gender_Female_Other = Dummy representing the Female Gender and Other (
- Education_High_School_or_below = Dummy representing High School or bellow as the highers completed educational level
- Education_ Bachelors = Dummy representing Bachelor's degree as the highest completed educational level (omitted to avoid multicollinearity)
- Education_ Masters = Dummy representing Masters degree as the highest completed educational level
- Education_ PhD_or_equivalent = Dummy representing Phd or above degree as the highest completed educational level
- Income_0_50000 = Dummy representing the bracket of annual before tax income expressed in EUR
- Income_5001_15000 = Dummy representing the bracket of annual before tax income expressed in EUR
- Income_15001_30000 = Dummy representing the bracket of annual before tax income expressed in EUR (omitted)
- Income_30001_45000 = Dummy representing the bracket of annual before tax income expressed in EUR
- Income_45001_60000 = Dummy representing the bracket of annual before tax income expressed in EUR
- Income_Above_60000 = Dummy representing the bracket of annual before tax income expressed in EUR

Independent variables of main interest

The 3 independent variables of main interest:

- Confidence_Percentage = Represents the elicited confidence in the estimation (10% increments from 0% to 100%)
- Group_Dummy = A dummy variable that represents the Control (coded as 0) and Treatment (coded as 1)
- Confidence_Percentage*Group_Dummy = Interaction term

The coefficient of the Group_Dummy variable is used to test H3 while the interaction term will help in investigating our 4th and last hypothesis.

Main Results

The regression results are summarised in the table below(random intercept in the appendix).

Fixed effects:	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	19.0484	14.7233	79.8788	1.2938	0.1995
M_400_SD_10	0.9100	4.2307	273.1923	0.2151	0.8299
M_80_SD_5	-1.6040	4.2992	281.3153	-0.3731	0.7094
M_300_SD_60	-2.7269	4.1088	256.6634	-0.6637	0.5075
Confidence_Percentage	-0.1422	0.0965	197.9938	-1.4726	0.1424
Group_Dummy	-1.2002	8.8216	207.0926	-0.1361	0.8919
Gender_Male	6.3183	3.9547	75.1687	1.5977	0.1143
Education_High_School_or_below	-6.8725	6.5771	75.4353	-1.0449	0.2994
Education_Bachelors	-0.1682	4.0410	72.5560	-0.0416	0.9669
Education_PhD_or_equivalent	6.4322	10.1235	72.4912	0.6354	0.5272
Income_0_5000	1.7744	8.1757	73.8081	0.2170	0.8288
Income_15001_30000	-0.6136	4.6873	73.6542	-0.1309	0.8962
Income_45001_60000	2.1178	7.7995	73.4920	0.2715	0.7867
Income_Above_60000	9.2166	10.8543	72.5277	0.8491	0.3986
Age	-0.5162	0.4119	72.4174	-1.2534	0.2141
Confidence_Percentage:Group_Dummy	0.0541	0.1547	258.2841	0.3499	0.7267

Table 3

In short none of our variables of interest have been shown to significantly influence the dependent variable. When changing the reference categories, no significant effect was preset as well. This prompts some additional analysis that may help uncover why this was the case.

Additional analysis:

Our dependent variable measures the directed deviation; therefore, it has both underestimations (positive values) and overestimations (negative values) There could be the case that purely by chance some of these estimations cancelled out. We will now test 2 additional models where we keep the same independent variables as in Model 1 but only change the dependent variable to measure the overestimation and underestimation cases separately. This approach has 2 major drawbacks and therefore was not considered for conducting the main analysis. The first flaw is that it reduces the already small sample size. The second, and more important is that by separating the dependent variable we can also separate the same participant that happened to overestimate in some cases and underestimate in others. This is, we acknowledge a big mistake, but the reason for doing this additional analysis is to see if under ideal circumstances there is an effect of the treatment. If we were to find an effect, then a more nuanced hypothesis about the nudge could be investigated.

Underestimation case

Model 2: $Y_i = \alpha_1 + \beta_1(M\_400\_SD\_10) + \beta_2(M\_80\_SD\_5) + \beta_3(M\_300\_SD\_60) + \beta_4(Confidence\_Percentage) + \beta_5(Group\_Dummy) + \beta_6(Group\_Dummy * Confidence\_Percentage) + \beta_7(Gender\_Male) + \beta_8(Education\_High\_School\_or\_below) + \beta_9(Education\_Masters) + \beta_{10}(Education\_PhD\_or\_equivalent) + \beta_{11}(Income\_0\_50000) + \beta_{12}(Income\_5001\_15000) + \beta_{13}(Income\_30001\_45000) + \beta_{14}(Income\_45001\_60000) + \beta_{15}(Income\_Above\_60000) + \beta_{16}(Age)$

Where Yi are the underestimation cases (true mean – estimated mean >0)

This regression yielded some surprising results. When focusing on our main variables of interest it shows that Confidence_Percentage is in a negative relation with the amount of underestimation (β_Confidence_Percentage = -0.29; p-value: 0.0076). This is consistent with the literature that people are good at estimating how much they do not know (S. Olschewski and Scheibehenne, 2023) and that the underestimate on average less, i.e. are closer to the true value is reflected in the rise of their confidence. It is worth mentioning that the mistakes w the largest in the case of M:300, SD=60 (β_300_60 = 23.7023, p-values = 3.2e-05) which also is consistent with a high SD and large population mean causing a larger mistake rate. This was also the case when the reference dummy was changed, meaning that higher SD and Mean pairs induce larger underestimation mistakes (see Appendix). What was the largest surprise was the effect of our Treatment. We need to mention that the Treatment, coded as Group_Dummy, would be only considered significant if we were to change the criteria from 5% to 10%, hence increasing the probability of Type 1 error. Having this in mind the sign of the treatment goes against our initial hypothesis (β_Group_Dummy = -16.1973; p-value: 0.0733) indicating that underestimation was smaller in the treatment condition than in the control condition. The interaction term also provided interesting results and was significant at the 10% criteria (β_Confidence:Percentage_Group_Dummy = 0.2950, p-value: 0.0651) giving an interpretation that participants that were treated and reported higher confidence levels made larger underestimation mistakes than the control group that elicited the same confidence. It is important to stress that these findings are considered significant only when the criteria are changed and when we consider the underestimation cases, where separating the data in this way holds the above-mentioned risk.

Overestimation

Here we only changed the dependent variable such that negative values represent overestimation (true mean – estimated mean < 0) and the larger the negative value the larger the overestimation. Like in the previous case having a larger Mean and SD combination makes people overestimate on average more ($\beta_{300\_60} = -19.67088$; p-values = 0.00398) and this trend was persistent when the reference dummy was changed (see Appendix). However, we do not see any significant effect of confidence, treatment or the interaction between the two. This further makes us question the validity of the results made in the underestimation analysis.

Unexpected effect of the treatment on confidence

The unexpected same direction of both confidence (direction consistent with the literature) and treatment (direction inconsistent with our hypothesis), as well as the positive slope of the interaction term, has prompted us to further investigate the connection between them. We found, using the Whitney U non-parametric test that the mean difference between the confidence elicitation in the treatment group was statistically larger than in the control group. (Mean_Confidence_Treatment = 54%; Mean_Confidence_Control = 47% , W = 12071, p-value = 0.007584), Figure 2A. This was only further confirmed when the treatment was regressed on Confidence (b=6.97, p-value = 0.00584). When separating per High and Low SD condition we find that there is a statistically significant larger Mean Confidence estimate for the treated participant in the High SD condition (Mean_Confidence_Treated = 48.2, Mean_Confidence_Control = 39.3%; W = 2739.5, p-value = 0.006059) Figure 2B. The mean estimates for the Low SD condition are larger than in the High SD condition, but there is no significant difference between the treated and control group (although the mean of the treated is higher, 59.8% vs 54.8% for the control group; W = 3215.5, p-value = 0.2014). This further supports the claim that the nudge and confidence elicitation are somehow connected, especially in the case where uncertainty is larger, just not as it was initially hypothesised. The question that we need to ask ourselves is, is this increase in confidence justified, or in other words are people who are being treated actually correct in their estimations, therefore rightly so reporting higher confidence levels?

Figure 2A:

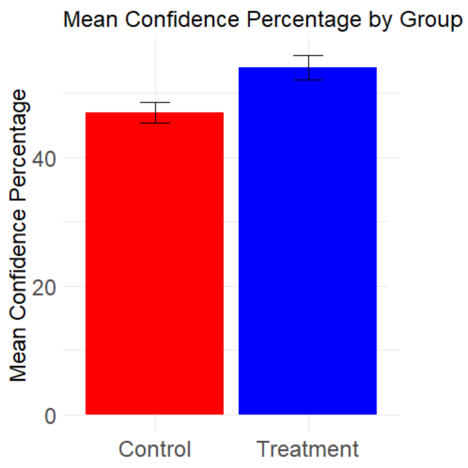
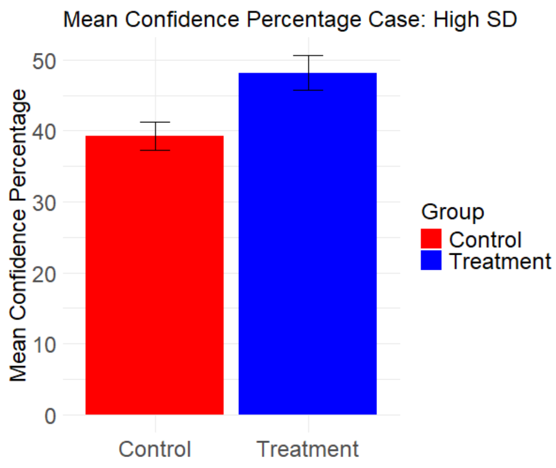


Figure 2B:



Correctness of estimations

A high-level analysis would suggest that there is no difference in the number of correct estimations. The correct estimation is considered to be an estimation that falls in the range of plus/minus 5 of the true value, regardless if it is an overestimation or underestimation (e.g. For the true mean of 80 a correct result is in the range between 75 and 85). For the Treated group, out of the total 132 estimations, 65 were false and 67 were correct. Similar percentages could be seen in the Control group where 118 estimations were correct and 102 were wrong. So, in both groups a rough 50-50 split. Since there was a significant difference in confidence for the high SD condition we investigate the correctness of the result here. The treated participants estimated 20 correct results out of 66 for the high SD case, while the control got 27 out of 100 right, hence the difference in correct answers between the two groups in the High SD case was statistically non-significant (X-squared = 0.43543, p-value = 0.5093).

This analysis leads us to the following important conclusion, although participants in the treated group reported higher confidence elicitation in the higher uncertainty condition, they do now have a larger amount of correct answers than their counterparts in the control group. This could hint at an unexpected hypothesis, the anchoring nudge presented in the described format changed the perceived confidence of the participants, which was particularly strong in the condition with higher uncertainty.

Discussion

Summary of the results

The results of the study show that, as expected by increasing the underlying uncertainty participants make larger mistakes in estimating the means. More importantly, they can objectively assess the uncertainty levels, and this is represented by confidence elicitations. The effect of the nudge was not significant, and even with a more nuanced analysis, the downward effect of the anchor is questionable. An unexpected result was that the anchor, as designed in our study may have affected people's confidence elicitations, making them more certain in their decision even if this was not justified by their correct response rates. Some of the potential explanations are discussed in the next subsegments.

Potential explanations of the results

One of the main aims of this paper was to contribute to the overall nudge literature and, through contextual changes, test the overall robustness of the anchoring nudge. The general existence of this phenomenon is a well-documented fact and was never in question. This leads us to follow two lines of reasoning. Firstly, in the context of our study—such as the DfE setting with mean estimations from a series of numbers drawn from different distributions—the anchoring nudge may not produce the commonly expected result of systematic skewness towards the anchor. Alternatively, the design of our nudge might not have been adequate for the described scenario. We will investigate the latter option in more detail, but based on this single study, no strong conclusions should be made, prompting the necessity for further research.

We see two possible explanations for why an anchor of this design did not work in the expected way, hinting at the possibility that by accounting for these "mistakes," the anchor could yield the desired results. The first one is the potential confounding factor of *the round number bias*, while the second is the *explicit design* of the anchoring nudge.

Round number bias

In our experiment, the true means/correct answers were round numbers (400, 80,100 and 300). Potentially, two heuristics were activated simultaneously: the anchoring and adjustment heuristic coupled with the round number bias. The round number bias is a broad phenomenon where people generally tend to prefer round numbers to non-round numbers. This heuristic was tested in multiple settings. Bastiaanse (2009) demonstrated that round numbers significantly increase the likelihood that the number is perceived as an approximation, while correct values are perceived to be more exact. In the context of inflation expectations, there was a connection between people estimating round numbers and when facing high uncertainty levels (Binder, 2014; Binder, 2015).

Our findings could be used to support some of these claims. In our experiment participants of the control group estimated 105 times a round number (out of 220 total estimations), and 52 were the correct round number. i.e true value of the mean. This could hint at the fact that the control group that didn’t have an anchoring bias, experienced the round number bias more strongly. When comparing the frequency of round vs non-round number estimations for the control group we see significantly fewer round number estimates in the low SD case (42 round number estimates vs 68 non-round estimates in the low SD case; X-squared = 6.1455, df = 1, p-value = 0.0132), where confidence is shown to be higher. This could be interpreted such that when people were more certain in their decision, they estimated an exact number, while when they were uncertain, they estimated round numbers, which happened to be half of the time the true answer. This hypothesis is in line with the evidence provided by Binder (2015).

The treatment group has a smaller overall percentage of round number estimates 47 out of 132. The same case is found in the low SD condition where there were 17 round number estimates in comparison to 49 non-round estimates(X-squared = 15.515, df = 1, p-value = 0.0001). One explanation could be found in the design of the nudge (we will cover this more in the next segment) whereby providing several ranges that usually ended with an exact number, the treated participants were influenced to believe that the true value is hidden somewhere between the ranges, and since exact numbers are more trustworthy choosing an exact number as the solution also gave a confidence boost. This nudge towards an exact value is in line with the proposed new hypothesis of the treatment influencing the confidence, as people perceive exact numbers as more trustworthy and by being offered to choose one it increased the elicited confidence.

What we want to emphasise is that our analysis was not intended to fully explain the round number heuristic, hence the analysis here is used to provide some evidence for a potential explanation of the results we got. In order to uncover the true effect of the round number bias in a setting similar to ours as well as its dynamics coupled with the anchoring bias additional and more rigorous research is necessary. The message we want to convey is that the mistake of making the true values round numbers potentially introduces a confounding element in the form of the round numbers bias, hence tampering with our results.

Explicit Anchor design

The second explanation could be found in the design of the nudge itself. The nudge consisted of multiple ranges/options, which is usually not the case as an anchor is typically only one number/range (Lin and Schlein, 2023). Our initial hypothesis was that participants would go through the ranges and adjust away from the anchor. However, since there were multiple ranges and numbers explicitly present, it could be that each number diminished the effect of the initial anchor, hence acting as an anchor itself. Coupled with the fact that the true value was hinted at by being at the very end of the presented range, this could explain the ineffectiveness of our design. In the anchoring and adjustment cognitive explanation that inspired the nudge, after seeing only one number that serves as an anchor, the adjustment process happens implicitly in the mind of the agent. Here, the adjustment process was explicitly shown in the range format, which could have made it easier to readjust therefore neutralizing the effect. The explicit ranges that were shown could have prompted participants to search for the solution among them and not cognitively search for a true value, hence choosing the one that looked the most suitable.

Potential joint effects

As previously noted, there may be an interconnection between round number bias, explicit anchor ranges, and elevated perceived confidence levels. This connection suggests that presenting explicit anchor ranges may influence participants to select exact numbers during their decision-making process. Consequently, choosing an exact number may enhance confidence in the decision, as such numbers are perceived to be more reliable and accurate estimations.

This suggests a causal direction opposite to our initial hypothesis, where instead of confidence mediating the treatment effect, the treatment creates an "illusion" of confidence. The term "illusion" is justified by the fact that the treatment group was no more successful in providing correct estimates than the control group. This leads us to believe that, although the fundamental uncertainty remains unchanged, introducing the nudge alters the perceived uncertainty. One of our key assumptions was the link between true uncertainty and confidence elicitations; however, evidence indicates that an anchoring nudge designed in this manner weakens this link and diminishes its predictive power.

Limitations and future research

Limitations

The first limitation is a smaller sample size which may have impacted the statistical significance of some results, particularly those additional analyses conducted after estimating Model 1. Selection bias might have been present, as indicated by the substantial number of participants who did not complete the experiment, possibly suggesting that only those highly motivated or comfortable with numerical tasks fully participated.

Another limitation is the number of mean estimates that the participants had to make. In the original study of S. Olschewski and Scheibehenne (2023), each participant gave 16 estimations with 16 confidence elicitation offering a wider range of distribution possibilities compared to our experiment. Coupling this limitation with the already investigated effect of only having round numbers as true means we get a large potential influence of the round number heuristic. Alternatively, if we had many more number series shown, with different round and non-round mean true values, this heuristic would have been washed away and negligible in influencing the effects. The decision to have only 4 trials was made primarily due to time constraints as introducing more trials would have added to the duration of the experiment and likely decreased the number of participants.

Further research

A general direction of further research would be to continue examining the contextual changes that affect the overall robustness of the Anchor heuristics. Addressing rigorously the problems with the anchor design features we put forward and giving more clarity on the exact way the anchor should be implemented (at the beginning vs at the end, or one range vs multiple) may prove to be a highly valued contribution in bettering our understanding of this phenomenon. Our experiment assumes that people follow a Bayesian updating decision-making process while incorporating cognitive inefficiencies (S. Olschewski and Scheibehenne, 2023). Turner and Schley (2016) created a model called the Anchoring Integration Model (AIM) that aims to predict the effect size of a particular anchor. They believe that an anchor provides additional data that influences prior beliefs, and this influence can be quantitatively predicted using Bayesian decision-making principles. This approach to understanding anchoring and being able to predict its precise effects creates a necessity for a better understanding of the true cognitive mechanisms behind it, hence contributing to overall understanding. We highly encourage pursuing this and similar research paths.

Practical implications

What this study has shown is that without having a well-understood cognitive theory behind how a nudge works, implementing what seems to be a simple design and compatible with some previous research may backfire. This further emphasises the point that having multiple theories of how an anchor works is not as big of a problem as our inability to map a particular theory to the defined context. Human decision-making is complex, and even in well-designed laboratory settings, interventions rarely have direct and unambiguous effects on the targeted group. In real-world scenarios, numerous factors simultaneously influence decisions; in our study, the round number bias may have impacted both the effectiveness of our nudge and the control group, complicating the differentiation of the treatment's true effects. Policymakers should be cautious when implementing well-known nudges as even a slight contextual change or modification to the nudge could lead to drastically different consequences. Having a sound theoretical framework of the underlying process behind a nudge and how these interplays with contextual changes is essential for achieving the targeted results.

Conclusion

The world is full of complexities that compel individuals to make decisions amidst varying levels of uncertainty. This fundamental complexity drives us to seek effective ways to manage it and is hypothesized to be the underlying cause of many heuristics. The good news is that people are fairly good at evaluating this complexity that causes the feeling of uncertainty hence we know well enough what to expect from our decisions, as demonstrated in our study. However, policymakers should exercise caution when attempting to leverage this connection for interventions. Our study highlights that even the most well-established and robust phenomena are highly sensitive to contextual changes and design modifications. Implementing interventions, such as the anchoring nudge in our case, can affect the very factor believed to predict the nudge's effectiveness—confidence elicitation as a proxy for uncertainty levels. This underscores the critical importance of a robust theoretical framework to understand the underlying mechanisms of the effects of interest.

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Appendix

Table 1 Checks and balances (frequencies):

Category	**Control**	**Treatment**
Female	34	17
Male	20	16
Other	1	0
0-5000	9	11
5001-15000	16	6
15001-30000	14	19
30001-45000	6	3
45001-60000	4	2

Above 60000	6	2
High School and bellow	5	4
Bachelors	24	13
Masters	24	13
PhD and equivalent	2	3

Table 2 underestimation:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	44.33735	15.48704	99.52965	2.862868	0.00511932**
M_400_SD_10	4.054865	4.838337	148.6134	0.83807	0.40333726
M_80_SD_5	-8.45294	4.647999	148.1217	-1.81862	0.07098965.
M_300_SD_60	27.7572	4.980242	145.682	5.573465	0.00000012***
Confidence_Percentage	-0.29055	0.106822	108.515	-2.71997	0.00760487**
Group_Dummy	-16.1973	8.962773	116.1029	-1.80717	0.07332504.
Gender_Male	3.586021	4.323669	83.50808	0.829393	0.40924651
Education_High_School_or_below	-14.7072	6.533891	67.98497	-2.2509	0.02762903*
Education_Masters	-2.92451	4.299523	76.40939	-0.68019	0.49843709
Education_PhD_or_equivalent	-0.40094	11.92057	107.1882	-0.03363	0.97323125
Income_0_5000	-8.81943	8.883419	90.5791	-0.9928	0.32345396
Income_30001_45000	-1.66721	8.077438	107.6015	-0.2064	0.83686622
Income_45001_60000	-5.7026	8.25224	96.0689	-0.69104	0.49120911
Income_Above_60000	-14.2066	11.30229	87.42466	-1.25696	0.21211493
Age	-0.24053	0.507477	120.7171	-0.47398	0.63637194
Confidence_Percentage:Group_Dummy	0.294966	0.158525	128.2669	1.860695	0.06507704.

Table 3 overestimation:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-13.6341098	19.7756542	87	-0.68943913	0.49238176
M_400_SD_10	5.73695803	7.02377061	87	0.81679177	0.41627846
M_80_SD_5	14.4954488	7.88234835	87	1.83897592	0.06933022.
M_300_SD_60	-19.6708752	6.64818323	87	-2.9588347	0.00397701**
Confidence_Percentage	-0.09492072	0.16264656	87	-0.58360113	0.56099868
Group_Dummy	-21.8396827	15.3346038	87	-1.42420913	0.15796295
Gender_Male	6.75637661	5.43475687	87	1.24317918	0.21714165
Education_High_School_or_below	-12.6088768	9.41107311	87	-1.33979162	0.18380221
Education_Masters	2.21501371	5.56802994	87	0.39780923	0.69174525

Education_PhD_or_equivalent	11.9862535	12.4006399	87	0.96658347	0.33643159
Income_0_5000	5.37987894	10.7583219	87	0.50006674	0.61829061
Income_30001_45000	0.0424277	8.24638125	87	0.00514501	0.99590667
Income_45001_60000	5.94868476	10.1158223	87	0.58805746	0.55801716
Income_Above_60000	0.62427893	16.2450059	87	0.03842898	0.9694337
Age	-0.23567233	0.61621947	87	-0.38244869	0.70306129
Confidence_Percentage:Group_Dummy	0.38337297	0.29494191	87	1.29982536	0.19709426

Some tables of overestimation when the reference dummies change:

	Estimate	**Std. Error**	**df**	**t value**	**Pr(>|t|)**
(Intercept)	-33.764	18.852	86.000	-1.791	0.077
M_400_SD_10	25.533	6.484	86.000	3.938	0.000
M_80_SD_5	34.335	7.571	86.000	4.535	0.000
M_100_SD_50	19.792	6.696	86.000	2.956	0.004
Confidence_Percentage	-0.095	0.164	86.000	-0.583	0.561
Group_Dummy	-21.639	15.430	86.000	-1.402	0.164
GenderMale	6.856	5.474	86.000	1.253	0.214
GenderOther	7.326	24.487	86.000	0.299	0.766
Education_High_School_or_below	-12.480	9.470	86.000	-1.318	0.191
Education_Masters	2.412	5.636	86.000	0.428	0.670
Education_PhD_or_equivalent	11.952	12.467	86.000	0.959	0.340
Income_0_5000	5.483	10.821	86.000	0.507	0.614
Income_30001_45000	0.080	8.291	86.000	0.010	0.992
Income_45001_60000	5.790	10.183	86.000	0.569	0.571
Income_Above_60000	0.606	16.331	86.000	0.037	0.971
Age	-0.231	0.620	86.000	-0.372	0.711
Confidence_Percentage:Group_Dummy	0.382	0.297	86.000	1.288	0.201

	Estimate	**Std. Error**	**df**	**t value**	**Pr(>|t|)**
(Intercept)	0.5717	20.7409	86.0000	0.0276	0.9781
M_400_SD_10	-8.8021	7.9075	86.0000	-1.1131	0.2688
M_300_SD_60	-34.3352	7.5709	86.0000	-4.5351	0.0000
M_100_SD_50	-14.5431	7.9255	86.0000	-1.8350	0.0700
Confidence_Percentage	-0.0954	0.1635	86.0000	-0.5833	0.5612
Group_Dummy	-21.6393	15.4300	86.0000	-1.4024	0.1644
GenderMale	6.8563	5.4736	86.0000	1.2526	0.2137
GenderOther	7.3263	24.4866	86.0000	0.2992	0.7655
Education_High_School_or_below	-12.4804	9.4705	86.0000	-1.3178	0.1911
Education_Masters	2.4118	5.6359	86.0000	0.4279	0.6698
Education_PhD_or_equivalent	11.9516	12.4666	86.0000	0.9587	0.3404
Income_0_5000	5.4833	10.8206	86.0000	0.5068	0.6136
Income_30001_45000	0.0796	8.2908	86.0000	0.0096	0.9924

Income_45001_60000	5.7899	10.1830	86.0000	0.5686	0.5711
Income_Above_60000	0.6055	16.3308	86.0000	0.0371	0.9705
Age	-0.2307	0.6197	86.0000	-0.3723	0.7106
Confidence_Percentage:Group_Dummy	0.3819	0.2965	86.0000	1.2880	0.2012

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	2.9835	22.1980	86.0000	0.1344	0.8934
M_400_SD_10	-8.8021	7.9075	86.0000	-1.1131	0.2688
M_300_SD_60	-34.3352	7.5709	86.0000	-4.5351	0.0000
M_100_SD_50	-14.5431	7.9255	86.0000	-1.8350	0.0700
Confidence_Percentage	-0.0954	0.1635	86.0000	-0.5833	0.5612
Group_Dummy	-21.6393	15.4300	86.0000	-1.4024	0.1644
GenderMale	6.8563	5.4736	86.0000	1.2526	0.2137
GenderOther	7.3263	24.4866	86.0000	0.2992	0.7655
Education_High_School_or_below	-14.8921	9.1460	86.0000	-1.6283	0.1071
Education_Bachelors	-2.4118	5.6359	86.0000	-0.4279	0.6698
Education_PhD_or_equivalent	9.5399	12.4815	86.0000	0.7643	0.4468
Income_0_5000	5.4833	10.8206	86.0000	0.5068	0.6136
Income_30001_45000	0.0796	8.2908	86.0000	0.0096	0.9924
Income_45001_60000	5.7899	10.1830	86.0000	0.5686	0.5711
Income_Above_60000	0.6055	16.3308	86.0000	0.0371	0.9705
Age	-0.2307	0.6197	86.0000	-0.3723	0.7106
Confidence_Percentage:Group_Dummy	0.3819	0.2965	86.0000	1.2880	0.2012

Underestimation case (few examples with different reference dummies):

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	48.3922	16.0279	102.6413	3.0192	0.0032
M_100_SD_50	-4.0549	4.8383	148.6134	-0.8381	0.4033
M_80_SD_5	-12.5078	4.9570	150.3491	-2.5233	0.0127
M_300_SD_60	23.7023	5.5331	156.2017	4.2838	0.0000
Confidence_Percentage	-0.2906	0.1068	108.5150	-2.7200	0.0076
Group_Dummy	-16.1973	8.9628	116.1029	-1.8072	0.0733
Gender_Male	3.5860	4.3237	83.5081	0.8294	0.4092
Education_High_School_or_below	-14.7072	6.5339	67.9850	-2.2509	0.0276
Education_Masters	-2.9245	4.2995	76.4094	-0.6802	0.4984
Education_PhD_or_equivalent	-0.4009	11.9206	107.1882	-0.0336	0.9732
Income_0_5000	-8.8194	8.8834	90.5791	-0.9928	0.3235
Income_30001_45000	-1.6672	8.0774	107.6015	-0.2064	0.8369
Income_45001_60000	-5.7026	8.2522	96.0689	-0.6910	0.4912
Income_Above_60000	-14.2066	11.3023	87.4247	-1.2570	0.2121
Age	-0.2405	0.5075	120.7171	-0.4740	0.6364
Confidence_Percentage:Group_Dummy	0.2950	0.1585	128.2669	1.8607	0.0651

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	35.8844	15.6459	96.0868	2.2935	0.0240
M_100_SD_50	8.4529	4.6480	148.1217	1.8186	0.0710
M_400_SD_10	12.5078	4.9570	150.3491	2.5233	0.0127
M_300_SD_60	36.2101	5.3077	154.3176	6.8222	0.0000
Confidence_Percentage	-0.2906	0.1068	108.5150	-2.7200	0.0076
Group_Dummy	-16.1973	8.9628	116.1029	-1.8072	0.0733
Gender_Male	3.5860	4.3237	83.5081	0.8294	0.4092
Education_High_School_or_below	-14.7072	6.5339	67.9850	-2.2509	0.0276
Education_Masters	-2.9245	4.2995	76.4094	-0.6802	0.4984
Education_PhD_or_equivalent	-0.4009	11.9206	107.1882	-0.0336	0.9732
Income_0_5000	-8.8194	8.8834	90.5791	-0.9928	0.3235
Income_30001_45000	-1.6672	8.0774	107.6015	-0.2064	0.8369
Income_45001_60000	-5.7026	8.2522	96.0689	-0.6910	0.4912
Income_Above_60000	-14.2066	11.3023	87.4247	-1.2570	0.2121
Age	-0.2405	0.5075	120.7171	-0.4740	0.6364
Confidence_Percentage:Group_Dummy	0.2950	0.1585	128.2669	1.8607	0.0651

Random intercept for model 1.

Groups	Name	Variance	St Deviation
Number	(intercept)	81.5	9.027
Residual		741.3	27.22