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We investigate how the anchoring effect—a well-established cognitive bias—influences the full distribution of subjective beliefs. While prior research extensively examines the impact of anchoring and other biases on point estimates, their effect on higher moments of the distribution remains unexplored. Through a pre-registered online experiment (N=732), we find that anchoring impacts the mean, variance, and skewness of belief distributions. Notably, the anchoring effect diminishes when eliciting distributions rather than means. Furthermore, presenting anchors prior to eliciting beliefs reduces the variance in belief distributions compared to when elicited without anchors. Our study shows that cognitive biases may have important impacts beyond point estimates.

Keywords: Anchoring, Belief Elicitation, Heuristics and Biases

JEL Classification*:* D73, C91, K42

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1. Introduction

Beliefs about numerical variables, such as prices, costs, or investment outcomes, are fundamental in shaping economic decisions. Our decisions are influenced by both average beliefs (e.g., expected future prices) as well as by other moments such as the variance (e.g., with risky decisions) or maxima and minima (e.g., for bidding behaviour in auctions). Despite their important role, beliefs may often be formed in suboptimal ways through various cognitive biases (e.g., Kahneman & Tversky, 1979; Benjamin, 2019). Yet, while extensive research has documented how these biases affect point estimates of subjective beliefs, their impact on higher moments of the distribution remains unexplored. This paper seeks to address this oversight by investigating how one of the most well-established biases—the anchoring effect—affects the *full distribution* of subjective beliefs.

The anchoring effect refers to people's tendency to rely too heavily on initial (possibly irrelevant) pieces of information ("anchors") when they make their estimates. For example, Tversky and Kahneman (1974) show that an irrelevant piece of initial information—a random number drawn from a wheel of fortune—strongly impacted a subsequent estimate of the number of African countries. We focus on the anchoring effect because it is generally considered as one of the most important and most robust cognitive biases (Schley & Weingarten, 2023; Jung et al., 2016; Li et al., 2021; Furnham & Boo, 2011; Jacowitz & Kahneman, 1995; Tversky & Kahneman, 1974). Although the literature on anchoring is voluminous, no previous study has examined the impact of anchoring on higher moments of subjective belief distributions.

We fill this gap by studying how anchoring affects the higher moments of a subjective belief distribution using a pre-registered online experiment (N=732). We ask participants in our experiment to estimate historical hotel prices in Rome, using either a point estimate (the mean) or a subjective belief distribution. Prior to either belief elicitation, subjects are given either a low or a high anchor. This allows us to test whether the anchoring effect (the difference between the low-anchor and high-anchor treatments) is also present when subjective beliefs are elicited using distributions instead of point estimates. We then assess how anchoring influences beliefs about the range and distribution of prices by studying the variance and skewness of the distributions. We also include a control group, whose beliefs are elicited using a distribution but receives no anchor, to serve as a baseline for a belief distribution in the absence of anchoring.

Our first key result is that the size of the anchoring effect decreases substantially when eliciting distributions rather than means. In particular, the difference between the estimated average in the low-anchor and high-anchor treatment is 2.4 times larger when the standard elicitation of a mean is applied compared to when distributions are elicited. Secondly, we also find that both the low anchor and the high anchor decrease the variance of the elicited belief distributions relative to the control group with no anchor. Thirdly, we also report that the estimated distributions tend to "lean" towards the anchor, which generates a higher positive skewness for low anchors compared to high anchors. Finally, participants who score high in cognitive reflection and financial literacy have more concentrated and accurate belief distributions.

Our results provide important context to previous work on anchoring which has relied on point estimates. Providing such context is important because higher moments also play a role in many key applications. This is most notable in decision making under risk and uncertainty, where variance and skewness play key roles for risk averse and prudent agents, and maxima and minima are important for the ambiguity averse. The relevance of higher moments extends beyond situations directly related to risk and uncertainty considerations. For example, consumers deciding when to buy may care more about the minimum (i.e., the highest discount) than about the average future price. Similarly, buyers bidding on real estate will likely care more about the highest valuation of other buyers in determining their bids. These observations underscore the importance of extending our knowledge of the anchoring effect to higher moments and to investigate the extent to which anchoring impacts these moments. To our knowledge, ours is the first study to do so.

Knowledge of how anchors affect the higher moments of subjective belief distributions may also provide important practical insights. To give an example, many stores routinely post discounted prices that are below the advertised reference prices. In such cases, reference prices are often interpreted as anchors that increase buyers' valuation of the good and thus their willingness to pay (Chandrashekaran & Grewal, 2006; Li et al., 2021; Simonson & Drolet, 2004). However, whether an anchor-exposed customer will buy the good in a store with a high reference price and lower sales price will also depend on how the anchor affects the prices she expects to be available in other stores. In such cases, the higher moments of expected price distributions in alternative stores will likely play a key role. For example, a lower variance in this distribution would decrease the likelihood that an exceptionally good deal would be observed in another store, reducing the expected value of visiting other stores. Thus, knowing how the reference price (i.e., the anchor) impacts the variance of the customer's price distribution is relevant not just academically, but also for practical retail strategies. Studies that only consider the anchor's impact on the mean or median fail to take this effect into account.

Our results are also important for other research and policy work that elicits beliefs using subjective belief distributions. In particular, our results suggest that such elicited distributions may fall victim to the anchoring bias too, and that the effects of such anchors may be non-trivial in that they affect not just the mean but also other moments of the distribution. More generally, our results suggest that it is important to consider traditional belief biases also when moving beyond the point estimate paradigm that these biases have usually been studied in.

The structure of the paper is as follows. We start, in section 2, by presenting earlier research in anchoring and the elicitation of subjects' belief distributions. In section 3 we provide our hypotheses and the questions we aim to explore. We then describe the design of our study in section 4, followed by our results in section 5. In section 6 we present our conclusion.

2. Earlier research

This paper relates and contributes to two strands of literature, the research on anchoring and the research on subjective belief distributions. We will give a short account of these research areas and how they are related to our study.

2.1 The Anchoring Effect

In a now classic paper, Tversky and Kahneman (1974) showed that subjects' estimations of the percentage of African countries in the United Nations were starkly influenced by a random number generated by a wheel of fortune. This paper generated a stream of empirical studies on the anchoring effect using a variety of anchors and estimation tasks (e.g., Maniadis et al., 2014; Ariely et al. 2003; Schley & Weingarten, 2023; Epley & Gilovich, 2001; Jacowitz & Kahneman, 1995; Mussweiler & Strack, 1999). The general finding is that anchoring is a robust effect, also after performing publication-bias corrections (Schley & Weingarten, 2023). In a recent meta-study on anchoring effects in economics on willingness-to-pay, Li et al. (2021) found more moderate effects of anchoring and that the early anchoring studies had larger effect sizes than the more recent ones. The same article reports that studies using explicitly random anchors, laboratory experiments, and anchors incompatible with the evaluated item typically had lower effects.

In connection with the empirical research, several theories have been proposed to provide a theoretical foundation for the anchoring effect. Tversky and Kahneman (1974) propose that people form their beliefs using an "anchoring-and-adjustment" heuristic that implies adjusting away from an initial estimate (the "anchor"). Adjustments are typically insufficient, biasing the estimate towards the anchor. A second theory—selective accessibility—proposes that the anchor makes memories consistent with its value more accessible and salient, which in turn makes values closer to the anchor appear more probable than values further away from it (Strack and Mussweiler, 1997). A third theory based on scale distortion argues that a subject who receives a low (high) anchor feels that large (small) values are seen as even larger by comparison, thus biasing estimates toward the anchor (Frederick & Mochon, 2012). Intuitively, just like a room appears warmer when entering it on a cold winter day, a small numerical anchor makes a given number seem relatively large. A fourth theory assumes that the anchor is seen as a "conversational hint" from the experimenter, which "subjects clutching at straws quite reasonably use" (Jacowitz & Kahneman, 1995). This mechanism should be of less relevance when the anchor is explicitly random than when it is less clear how the anchor value is generated.

To our knowledge, no previous study elicits beliefs about the distribution of a variable after being exposed to an anchor. There are, however, two studies that elicit estimates of the range of the variable, that is its maximum and minimum value (Epley & Gilovich, 2006; Lee & Morewedge, 2022). These studies are not primarily focused on distributional properties, but on the range, to understand the adjustment heuristics (Epley & Gilovich, 2006) and the role of noise in the mental representation of the target (Lee & Morewedge, 2022).

2.2 Elicitation of subjective belief distributions

In an influential paper, Manski (2004) argues that economists' traditionally exclusive focus on observed choice behavior has forced them to make empirically unfounded assumptions about expectations. This problem can be mitigated by directly eliciting individuals' subjective expectations. In this paper, we elicit subjects' beliefs about the distribution of a specific variable, namely hotel room prices, and refer to these as subjective belief distributions (henceforth SBD). To make it more accessible, we ask about the distribution of this variable without explicitly using probabilities, which can be abstract for some people. The elicitation of individuals' SBDs is well-established and has attracted increased attention (Delavande, 2014; Di Girolamo et al., 2015; Haaland et al., 2023; Hurd, 2009).

The elicitation of SBDs is now conducted regularly by many organizations. For instance, the New York Federal Reserve collects consumer expectations in terms of SBDs on a monthly basis (Armantier et al., 2017). One task in the NY Fed survey asks subjects to estimate the probability that the inflation rate over the next twelve months is equal to a number in a given interval (e.g., between 2% and 4%). To elicit the whole SBD of the subject's inflationary expectations the subject estimates probabilities for all conceivable intervals. SBDs are also elicited frequently in recent research, often in terms of choice probabilities (Blass et al., 2010; Wiswall & Zafar, 2018, 2021).

Despite its growing popularity, eliciting SBDs is not without problems, see, e.g. Comerford (2023). Whenever SBDs are to be interpreted as probabilities, some people may have difficulties understanding them (Bar-Hillel, 1973; Tversky & Kahneman, 1974). Ways to mitigate this problem might be to elicit SBDs as distributions of frequencies instead of referring to probabilities (Gigerenzer, 1991) and to use visualizations when presenting probabilities (Delavande, 2014). A related but more technical problem is that people tend to assign higher probabilities to events that are divided into two or more subevents, that is, how outcomes are categorized (Ahn & Ergin, 2010; Sonnemann et al., 2013; Tversky & Koehler, 1994). This and other technical problems pose challenges for the eliciting of SBDs. While these issues have informed how we have chosen our methodology for eliciting SBD (Crosetto and de Haan, 2023), they are separate from the problem studied here, namely how anchors affect SBDs.

3. Hypotheses

In this section, we will describe our main hypotheses and continue thereafter with questions that are more exploratory and of secondary importance. All our main and secondary hypotheses are pre-registered.[1] Following the convention in the literature, we will refer to the variable being estimated by subjects—hotel room price in our study—as the "target". The anchor in our study refers to either a low or high dollar number in the following question: "Do you think that the average price for such a [hotel] room is lower or higher than $[134/546]?" This "anchoring question" was given before the subjects estimated the target (see Section 4).

3.1 Main hypotheses

Our first hypothesis is that the anchoring effect is observed both when the target is elicited as a point estimate (the traditional anchoring effect) and when it is elicited as an SBD. This conjecture is based on the documented robustness of the anchoring effect (Schley & Weingarten, 2023; Furnham & Boo, 2011; Jacowitz & Kahneman, 1995; Tversky & Kahneman, 1974). Keeping in mind that the traditional anchoring effect is defined as the mean in the high-anchor treatment minus the mean in the low anchor treatment, we obtain:

[1] Available at https://www.socialscienceregistry.org/trials/11396 and also included in the Appendix.

H1A (means): The target mean elicited with a low anchor is lower than that elicited with a high anchor.

H1B (SBDs): The mean of the target SBD elicited with a low anchor is lower than that elicited with a high anchor.

Our second hypothesis is that the traditional anchoring effect is smaller when eliciting SBDs. Our rationale for this conjecture is twofold. First, it seems plausible that elicitation of the SBD requires more cognitive effort than the elicitation of the mean. If the anchoring effect is driven by heuristics such as the anchoring-and-adjustment process, which require cognitive effort (Epley & Gilovich, 2006; Simmons et al., 2010), this may leave fewer cognitive resources and hence a lower influence for the anchoring-and-adjustment heuristic. Second, if anchoring is driven by selective accessibility, scale distortion or conversational hints, anchoring may be smaller for SBDs because of a reduced similarity between the target (an SBD) and the anchor (a number). This is consistent with prior research showing that the similarity or compatibility between the anchor and the target may matter for the size of the anchoring effect (Li et al., 2021; Strack & Mussweiler, 1997). Thus,

H2: The anchoring effect is smaller when the target mean is elicited using SBD than when it is elicited as a point estimate.

In addition to testing the extent to which the traditional anchoring effect in means generalizes to elicitations of SBDs, we also examine how anchoring affects other moments of the distribution. We start with the variance, which may play an important role in decision making under risk and many consumer choice problems, as discussed above. Extending the anchoring-and-adjustment heuristic to the case of the variance, the variance of the final estimate will then also be formed as a combination between the anchor and the variance of the prior SBD (that is, the target SBD a participant would give without an anchor). Unlike the case for means, however, this heuristic does not reduce the estimated variance to a simple linear combination of the variance of the prior and the variance of the anchor. Intuitively, an anchor that falls far outside the prior SBD may stretch the SBD towards the anchor, increasing its variance. On the other hand, an anchor close to the mean of the prior SBD may have the opposite effect. As a result, we do not have an a priori directional hypothesis for the variance.

To avoid that potential differences in the variations of the SBDs are merely effects of scale (Frederick & Mochon, 2012) we will frame our hypothesis in terms of coefficients of variations (CVs), that is, the standard deviation of the SBD normalized by dividing by its mean. This leads to the following hypothesis.

H3A: A low anchor does not change the coefficient of variation of the elicited SBD relative to the control treatment.

H3B: A high anchor does not change the coefficient of variation of the elicited SBD relative to the control treatment.

3.2 Secondary hypotheses

In addition to our main hypotheses, we also pre-registered several secondary hypotheses and exploratory research questions. These relate to higher moments (skewness), factors affecting the variance (CV) of the SBD and factors affecting the accuracy of the estimate respectively.

Skewness: There is convincing evidence from finance and betting behavior that people have a preference for positively skewed distributions of monetary outcomes (Garrett & Sobel, 1999; Golec & Tamarkin, 1998; Harvey & Siddique, 2000; Trautmann and van de Kuilen, 2018). Hence, how anchors affect the skewness of SBDs may matter for decision-making and therefore also for anyone considering exploiting an anchor (e.g., a seller considering a reference price). We have no strong a priori expectation about how anchors impact skewness, and we therefore hypothesize that there is no significant difference in the average skewness of subjects' SBDs in each of the no anchor, low anchor, and high anchor treatments.

Factors affecting the CV of the SBD: We also investigate potential factors that may explain the size of the coefficient of variation (CV) of the elicited SBD. First, we expect that the individual degree of cognitive uncertainty regarding the mean price (Enke & Graeber, 2023) is positively correlated with her CV, since an individual who is more cognitively certain about the mean of a variable should have a more concentrated SBD than an individual who is cognitively uncertain and therefore finds it difficult to exclude many values as plausible. We also study other factors that may be related to the individual's knowledge of the SBD of prices, namely financial literacy (Lusardi & Mitchell, 2014), and cognitive reflection (Frederick, 2005). It is reasonable to conjecture that a high cognitive reflection and financial literacy will make the subjectable to narrow down the set of the possible values of the target, which would negatively affect the CV of her SBD. We also expect the subject's willingness to take risks to be negatively correlated with CV since a high variation in the SBD can be seen as "insurance" or "hedge" against getting everything wrong and thereby not receiving any payment at all in the elicitation (as we explain further in the design section below).

Factors affecting the ability to estimate the true distribution: Finally, we also study how various factors affect how good subjects are at estimating the true distribution (i.e., how close their SBD is to the true SBD). We expect that education, cognitive reflection, and financial literacy are all positive predictors of accuracy. In addition, we expect that cognitive uncertainty and the presence of an anchor will negatively affect the subject's accuracy.

4. Design

We test our hypotheses in an online experiment on Prolific, a common platform to conduct online experiments. The main task in the experiment was to estimate the price of a hotel room, both as a point estimate and as an SBD. We compared responses across several treatment conditions that varied whether the estimates were first elicited as point estimates or first elicited using SBDs, and whether both elicitations were preceded by a high, low or no anchor. After the two belief elicitations, all subjects answered survey questions about their individual characteristics. We will now describe the different parts of the experiment in greater detail. The instructions of the experiment can be found in the Appendix.

4.1 Information, control questions, and exercises

We started our experiment by presenting subjects with information about key concepts in the experiment such as “average”, “distribution,” and “histogram.” This information was followed by a set of control questions that were designed to check that they understood these concepts. Subjects could not proceed until they had answered the control questions correctly.

In addition to familiarizing our subjects with relevant concepts, we also gave them the opportunity to familiarize themselves with the interface we used to elicit the SBDs. For this purpose, we used the “click-and-drag” application developed and tested by Crosetto and De Haan (2023), shown in Figure 1. This technique lets participants click on the blank histogram area to create one or more support points which are then connected linearly to create a histogram. Participants can easily adjust the relative size of the bins by clicking and dragging up or down a specific bin and the final histogram is automatically normalized so that all the bars sum up to 100%. Crosetto and De Haan (2023) show that this method is considered to be more intuitive and less frustrating than other elicitation methods, and outperforms other techniques in terms of accuracy and speed. Part of the learning process required subjects to replicate a given histogram using this interface. Subjects are informed that they would receive a score based on how close their replication is to the original histogram, calculated using the following method: for each of the histogram bins, we calculate the absolute difference in percentage points between the percentage of prices allocated to that bin by the participant and the correct value. Then we sum these differences, subtract this sum from 100, and take the greater of this and zero. The maximum score was 100 (when the replication was perfect) and the median score was 99, suggesting that subjects understood and mastered the elicitation technique.[2]

Figure 1. Click-and-Drag interface used to elicit beliefs

[2] All results are robust to dropping the bottom 10% of respondents (whose score was 40 or lower), see Table A 2 in the Appendix.

4.2 The estimation task

Participants then moved on to the main estimation task, for which they were asked to estimate the mean and the full distribution of prices of a one-night stay at a hotel room in Rome. The information given to the subjects was as follows:

> "In the question below we will ask you to give your best guess of the prices of a one-night stay in a 4-star hotel double room in the central parts of Rome, the capital city of Italy. On an internet platform for hotel reservations, we obtained prices (including all taxes) for available double rooms for a one-night stay for two persons with check-in on Saturday, February 18^{th}, 2023, and check-out the day after. The prices were downloaded on February 8th, that is, ten days before the stay."

The reason we used this task was three-fold. First, we wanted the target to be intuitive to participants, which is why we used hotel prices. Second, we wanted the target to be not too easy to guess, which is why we used US-based participants and a European city. Third, we wanted the answer not to be easy to google, which is why we used historical prices from a specific weekend.

Participants did the estimation task twice, using both the mean and the full SBD respectively. When eliciting means, participants were simply asked to report their expected hotel room price, restricting their guesses to be between $0 and $799. They were paid according to how close they are to the true value, see Table 1. When eliciting SBDs, they were instead asked to draw a histogram capturing the distribution of prices using the click-and-drag method. Based on a small pilot, we decided to split the histogram into 16 intervals between $0 and $799, each with a width of $50. In this case, their payment would be based on their score as calculated using the method described above, and increases the higher the score (see Table 1).[3]

Table 1. Incentives in Elicitation Tasks

Payment in USD	**Means treatment** |Guess – true value|	**SBD treatment** Score
5	0-5	95-100
3	6-25	55-94
2	26-50	30-54
1	51-100	5-29
0	>100	0-4

4.3 Anchors

Before doing their first elicitation task, but after participants were given information about the hotel rooms, those in the anchor treatments were asked if they thought that the average price for such a room is lower or higher than $[134/546]. Participants then proceeded to the elicitation tasks and were asked to give their own estimate, either using a mean or using the SBD. The process of asking directly about the anchor prior to the main elicitation comes from Tversky and Kahneman (1974), and is thought to increase the salience of the anchor. The reason we chose $134 and $546 as the low and high anchor respectively is that they correspond to the minimum and maximum values of real hotel prices on the specified date (i.e., the 18th of February 2023). Participants were not aware of this; they were instead simply presented with the anchors without any explanation. This way of presenting anchors is common in the literature and has typically led to anchoring biases that are representative for the literature at large (Li et al., 2021).

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[3] To test that the experiment runs smoothly, we conducted a pilot a few weeks before the main study with 145 participants. The results confirmed our initial hypotheses.

4.4 Treatments

We randomly allocated our participants across five treatments, as summarized in Table 2. All five treatments contain two belief elicitations, one based on the SBD and one based on the mean. In accordance with our pre-analysis plan, we will focus our main analysis on the first elicitation. This allows for a clean between-subject comparison between low and high anchors and elicitation techniques. We included the second elicitation task to ensure that participants went through the same set of tasks in all treatments prior to the questionnaire (e.g., to prevent participants' self-evaluation of financial literacy from being biased by their experience in the experiment). All our results are robust to using the second elicitation task instead, see Table A 8 in the Appendix.

The treatments differed in the anchor (either high or low) and which of the two tasks served as the primary elicitation task. In the LowMean treatment, participants encountered a low anchor and were asked for the mean in the first elicitation. In the HighSBD treatment, they instead encountered a high anchor and were asked for the SBD in the first elicitation. The LowSBD and HighMean treatments are defined similarly. Finally, we also included a control treatment that omitted the anchoring question and used the SBD as the first elicitation task. We use this treatment primarily as a reference treatment when studying variance and skewness in the two SBD treatments.

Table 2. Experimental Treatments

Control	LowMean	LowSBD	HighMean	HighSBD
General information Control questions SBD exercise				
No anchor	Low anchor	Low anchor	High anchor	High anchor
1st elicitation SBD	Mean	SBD	Mean	SBD
2nd elicitation Mean	SBD	Mean	SBD	Mean
Cognitive uncertainty (CU) Demographics Cognitive reflection test (CRT) Risk-taking and investment behavior (IF, IS) Financial literacy (FL)				
N=145	N=147	N=148	N=147	N=145

4.5 Questionnaire

After the two main elicitations, we proceeded to ask participants how certain they are about their estimations by eliciting their cognitive uncertainty (CU). For those asked about the mean in the second elicitation, we asked: "How certain are you that your average price lies somewhere between +/-5% of the true average price?" and for those receiving the SBD as their second elicitation we asked "How certain are you that your distribution matches 90% of the true distribution (that is that your score is 90 or more)?" Following Enke and Graeber (2023) subjects then indicated on a 5% interval scale how certain they are, from "very uncertain" (0%) to "completely certain" (100%). Similar to Enke and Graeber (2023), we did not incentivize this task. We reverse code this response by subtracting the value from 1 to generate a measure of cognitive *un*certainty.

After eliciting cognitive uncertainty, all subjects indicated their age, gender, and education level. We also asked them about their risk preferences, investment behavior, and financial literacy and let them complete a cognitive reflection test. To elicit subjects' cognitive reflection (CRT), we modified the original three-question test by Frederick (2005) and used five questions instead. This is due to concerns that the original test has been used so much that the Prolific sample, who often participate in experiments and surveys, know the answers to these questions by heart (Brañas-Garza et al., 2019). The question eliciting risk attitude is taken from the German Socio-Economic Panel (Dohmen et al., 2011). Additionally, we asked two questions on investment behavior (if subjects invest in equity fund and/or individual stocks), and three financial literacy questions taken from Lusardi and Mitchell (2014).

5. Results

We will first present some general descriptive statistics and then continue with presenting results linked to our main hypotheses, followed by our secondary hypotheses and more exploratory analysis.

5.1 Descriptive statistics

The online experiment was conducted on Prolific on May 17, 2023. We aimed at a gender-balanced sample of 750 subjects (150 in each treatment) from the Prolific population in the USA with the restriction that the respondents should be at least 18 years old. We obtained 732 responses that met our criteria after attrition.[4]

In Table 3 we present some descriptive statistics.[5] Half of the subjects are males, and the majority have at least a bachelor's degree. The average age of subjects is 41, and they generally consider themselves to be moderately risk-taking. About one-half own individual stocks and

[4] Prolific sent out more invitations than the requested 750 to allow for attrition. 891 participants started the task, but only 732 completed (82% completion rate) with the rest leaving the study at various points.

[5] The descriptive statistics split by treatment are presented in Table A 1 in the Appendix.

one-third own stocks in equity funds. The median subject had three correct answers out of five on the CRT test, which indicates that the test was not trivial for most subjects. The questions on financial literacy were less difficult since the majority of subjects answered all three questions correctly.

Table 3. Descriptive Statistics of Independent Variables

	N	Mean	SD	Min	Max
Male	732	0.50	0.50	0	1
Age	732	41.07	13.03	18	79
Education	732	4.39	1.36	1	7
Risk	732	5.08	2.55	0	10
Invest fund	732	0.36	0.48	0	1
Invest stock	732	0.51	0.50	0	1
CRT	732	2.85	1.61	0	5
Financial literacy	732	2.52	0.78	0	3

Notes: Education is a categorical variable from 1 to 7 (Elementary school, High school graduate, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). Risk attitude ranges from 0 (completely unwilling to take risks) to 10 (very willing to take risks).

5.2 Main hypotheses

We will now present results relating to our main hypotheses. We follow our pre-analysis plan throughout; any deviations are noted clearly in the text. In line with the pre-analysis plan, all results presented in this section use only the data from the first elicitation.

Hypothesis 1: The Anchoring Effect in Means

Figure 2 displays the distribution of mean hotel prices by treatment group. Our first hypothesis was that the traditional anchoring effect in means would emerge in both elicitation techniques. As shown in the figure, we find support for this hypothesis. The mean estimates of hotel room prices in the *LowMean* and *HighMean* treatments were \$292 and \$481 respectively, leading to a significant anchoring effect of \$189, which is approximately 1.05 standard deviations (t(292)

=-10.73, one-sided t-test p<0.0001). For SBDs, the averages of the means inferred from the elicited distributions were \$339 and \$418 respectively, resulting in a statistically significant anchoring effect of \$80 or approximately 0.75 standard deviations (t(287) =-6.92, one-sided t-test p<0.0001).[6] The OLS regression estimates in Columns 1 and 2 of Table 4 show that these results are robust to controlling for education, age and gender.[7]

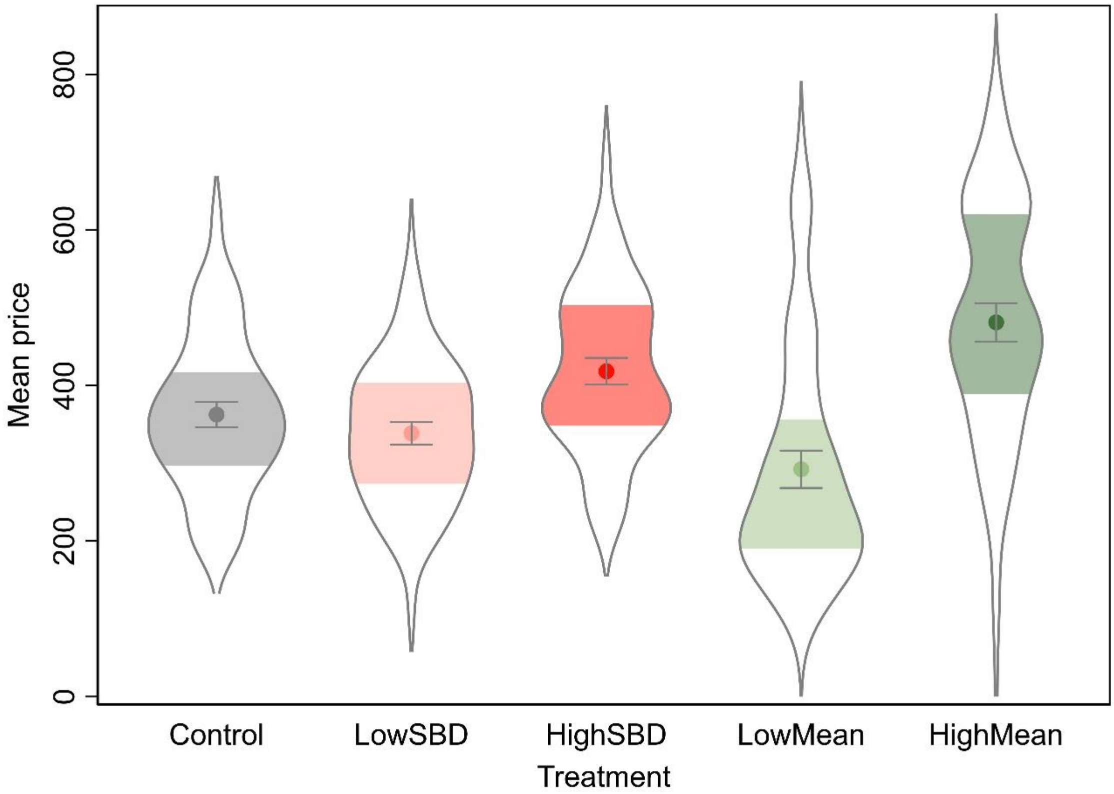

Figure 2. Distributions of Estimated Mean Hotel Prices by Treatment Group. *Notes:* In the LowMean and HighMean treatments, beliefs of the mean hotel price are directly stated by participants and in Control, LowSBD and HighSBD means are inferred from participants' SBDs. The central marker within each shaded area indicates the mean estimate, with bars representing the corresponding 95% confidence intervals. The shaded/coloured areas depict the interquartile ranges.

[6] An alternative measure of the effect size is the Anchoring Index, which is defined by Jacowitz and Kahneman (1995) as: (median in high anchor – median in low anchor)/(high anchor – low anchor) and ranges from 0 to 0.93 in their studies. Our results imply an AI of 0.53 from the Mean treatments and 0.16 from the SBD treatments.

[7] All our main results are robust to dropping subjects' probability weights in the top and bottom bins, indicating that the results are not driven by the fact that our SBDs are restricted to a limited interval. See Table A 3 in the Appendix.

Table 4. Regression Analysis for Main Hypotheses

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Mean	Mean	Mean	CV	CV
High anchor	183.48***	79.07***	188.83***	186.29***	-0.09***	
	(17.86)	(11.62)	(17.59)	(17.63)	(0.02)	
SBD treatment			46.22***	42.97***		
			(14.37)	(14.46)		
High anchor x SBD			-109.15***	-104.65***		
			(21.05)	(21.01)		
Low anchor						-0.00
						(0.02)
Constant	308.11***	362.45***	292.34***	310.79***	0.40***	0.42***
	(33.20)	(20.84)	(12.31)	(22.44)	(0.03)	(0.02)
Controls	X	X		X	X	X
Treatments	*Mean	*SBD	*Mean & *SBD	*Mean & *SBD	Control & HighSBD	Control & LowSBD
N	294	289	583	583	283	288

Notes: OLS regressions of mean hotel price (columns 1-4) and coefficient of variation of SBD (columns 5-6). Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Hypothesis 2: Smaller Anchoring Effect in Means for SBDs

Hypothesis 2 postulates that the anchoring effect in means is smaller when eliciting SBDs. Visual inspection of Figure 2 offers support for this hypothesis. We can test this formally by comparing the size of the anchoring effect (the difference between the Low and High treatments) across the two elicitation methods. We do this using a one-sided difference-in-difference test, that is, an OLS regression regressing the mean estimate on a dummy for being in either of the two high-anchor treatments, a dummy for being in either of the two SBD treatments, and their interaction, which is the main variable of interest. The results are shown in columns 3 and 4 of Table 4, with and without demographic controls, respectively. The coefficient for the interaction variable is -109 without and -105 with controls and highly significant either way ($p<0.0001$). In dollar terms, this means that the anchoring effect is $105-109 less in the SBD treatments compared to the Mean treatments, or a 58% decrease. In other words, we find strong evidence in favor of hypothesis 2: the anchoring effect in means is smaller when eliciting SBDs.

Hypothesis 3: Anchoring and Coefficients of Variation

We now turn our attention to how the low and high anchor affect the higher moments of the SBDs. Our primary interest is in the coefficient of variation, that is, the standard deviation normalized by dividing by the mean, which serves as our measure of variance. For this purpose, we calculate the coefficient of variation (CV) for each participant, and then compare the average CV across treatments. Figure 3 plots the distributions of the average coefficient of variation (CV) for the control, HighSBD and LowSBD treatments. While the mean CV does not differ significantly between the LowSBD and control treatments, it is substantially lower in the HighSBD treatment ($t(281) = 5.82$, $p<0.0001$). These results are very similar when we control for demographics, as per columns 5 and 6 in Table 4. In other words, anchoring reduced the CV for the high anchor and did not change it for the low anchor.

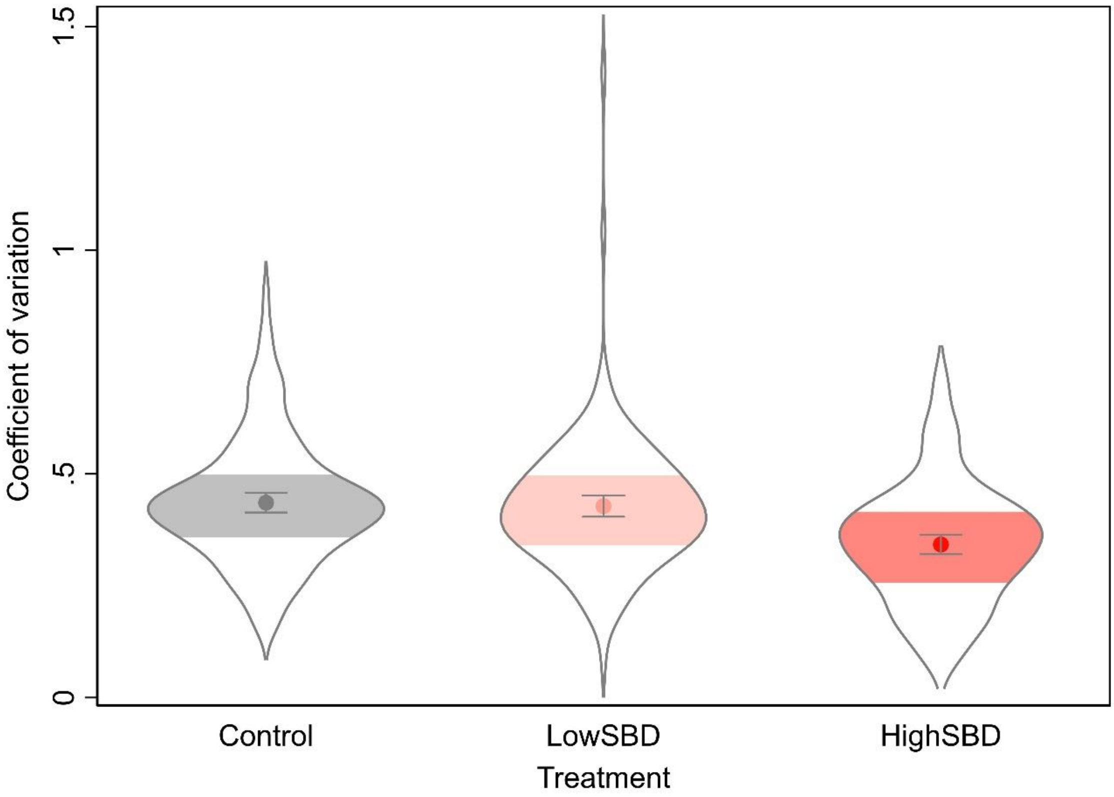

Figure 3. Average coefficient of variation in SBD treatments. *Notes*: The central marker within each shaded area indicates the mean estimate, with bars representing the corresponding 95% confidence intervals. The shaded/coloured areas depict the interquartile ranges.

While not pre-registered, we can also examine the standard deviation directly, that is, without normalizing it by dividing by the mean. When doing so, it turns out that the average standard deviations in the LowSBD and HighSBD treatments are 141 and 134, respectively, both of which are significantly lower than the standard deviation in the control treatment at 151 ($p = 0.03$ and $p<0.0001$ respectively), see Figure 4.[8] In other words, when looking at the standard deviation directly, we find evidence that both the high and the low anchor significantly reduce the estimated variation in the SBD. Hence, the reason that the CV was similar in the

[8] Note that the average standard deviation discussed here is distinct from the standard deviation of the mean of the distribution as implied by Figure 3. The standard deviation of the mean in the Control, LowSBD and HighSBD are 99.5, 89.9 and 105.6 respectively.

LowSBD and Control treatments was that the decrease in standard deviation was offset by a decrease in the mean (from 363 to 339, p = 0.03), leading to a net-zero effect on the CV.

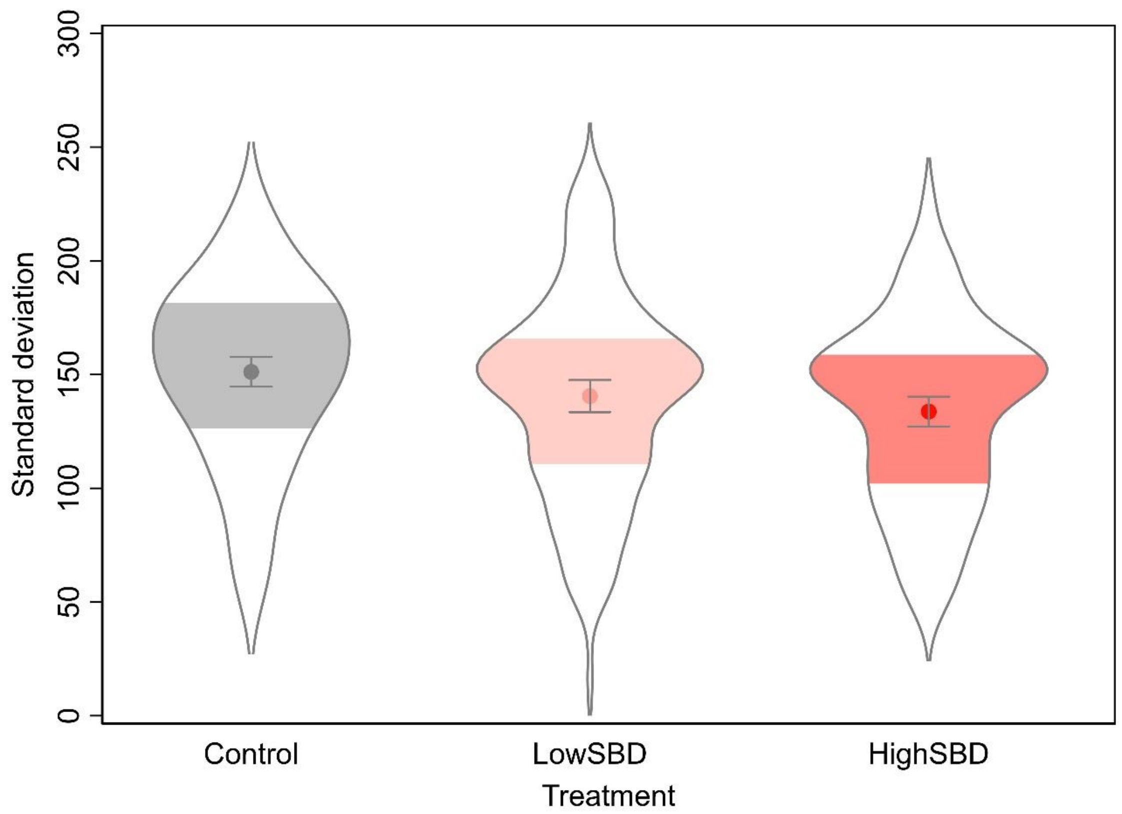

Figure 4. Average mean and standard deviation in SBD treatments. *Notes*: The central marker within each shaded area indicates the mean estimate, with bars representing the corresponding 95% confidence intervals. The shaded/coloured areas depict the interquartile ranges.

5.3 Secondary hypotheses and exploratory analysis

We will now present and analyze results from the more explorative part of our study.[9]

[9] We also preregistered heterogeneity analyses of treatment effects in Hypotheses 1-3 above, but none of the interaction coefficients is significant at the 5% level. Results are available upon request.

Skewness

We investigate how the presence of anchors affects skewness by calculating Fisher's moment coefficient of skewness for each individual SBD elicited in the HighSBD, LowSBD and Control treatments. Whereas the average coefficient of skewness is similar in the Control (0.36) and LowSBD (0.48) treatments (t(286) = 1.54, p = 0.125), it is significantly smaller in the HighSBD treatment (0.05; t(281) = 3.34, p = 0.0009). In other words, the presence of the high anchor significantly reduces the positive skewness of the distribution. This reduction in skewness is depicted in Figure 5, which shows the average stated frequencies for each price bin in the SBD elicitation.[10] The lower level of skewness in the HighSBD treatment is further confirmed in OLS regressions shown in Table A 4 in the Appendix.

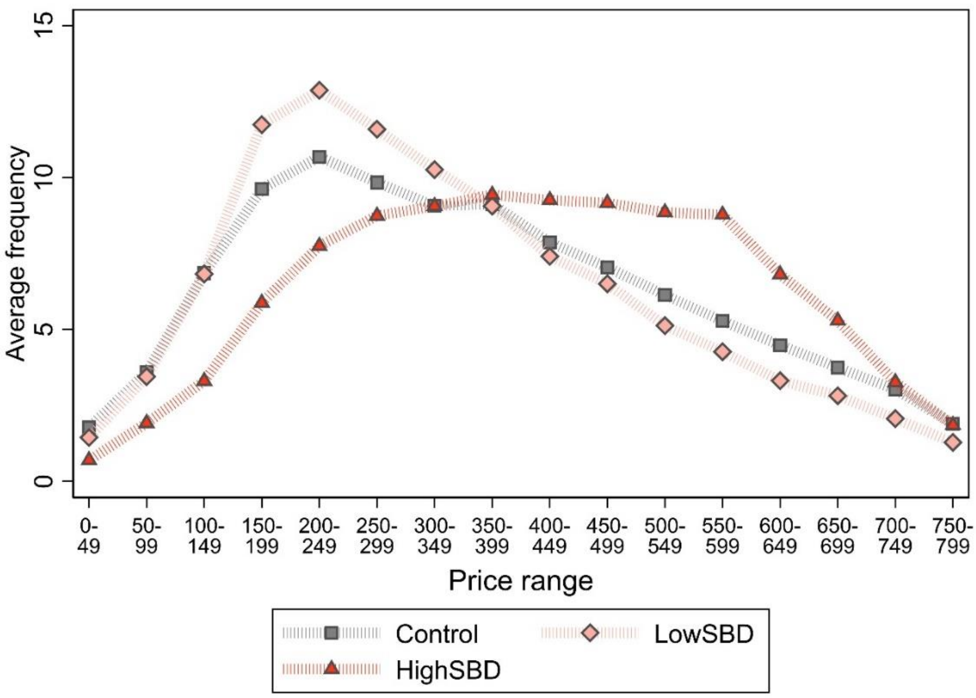

Figure 5. Average stated frequencies for each price interval in the SBD elicitation by treatment.

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[10] Figure A 1 displays the distributions of the individual stated frequences for each price interval.

Drivers of SBD variation

We next examine which factors predict the variation of the SBD by regressing the CV on cognitive uncertainty, risk attitude, investment behavior, CRT and financial literacy, while controlling for treatment dummies and demographic variables. As in our previous analysis, we only use the data from the LowSBD, HighSBD and Control treatments, where the SBD was the first elicitation. Results are shown in Table A 5 in the Appendix. While not pre-registered, we also show the effects for the mean and standard deviation for completeness.

Cognitive uncertainty is not significantly correlated with CV or the SBD standard deviation. However, cognitive uncertainty is negatively correlated with the mean, though this relationship is not significant at the 5% level after controlling for treatment dummies and demographics.

A priori, we expected that *risk attitude and investment behavior* to be negatively correlated with CV since a high variation in the SBD can be seen as insurance against not receiving any payment at all in the elicitation. However, a higher willingness to take risk is instead associated with higher SD and CV in our data.

CRT and financial literacy: If subjects have no knowledge at all about the variable to be estimated or no cognitive resources to reflect on it, it is reasonable to apply the principle of insufficient reason, which means that all prices are equally probable, and the estimated SBDs would then be uniform distributions with a high standard deviation. Reflection and/or knowledge would make it more concentrated. Hence, our a priori conjecture is that CRT and financial literacy may negatively affect CV. We find a significant negative correlation between CRT and the SBD standard deviation, and between financial literacy and the SBD standard deviation (columns 5-6). However, only CRT significantly correlates with CV (columns 1-2).

Drivers of SBD accuracy

As the final part of our pre-registered analysis, we look at how various factors affect the accuracy of the elicited SBD, as proxied by the SBD score. A priori we expected that education, cognitive reflection, and financial literacy are all positively correlated with the subject's score. In addition, we expect that cognitive uncertainty and treatments including anchors will negatively affect score. We present regression results in Table A 6 in the Appendix. Column 1 shows that CRT and financial literacy are indeed positively correlated with SBD score. The low anchor treatment (T3) also improves performance, while no correlation is observed for cognitive uncertainty and education. We do not find consistent heterogeneous treatment effects on any of the above independent variables (columns 2-5).[11]

The second elicitation

Thus far we have followed our pre-analysis plan by only analyzing the first elicitation encountered by each participant. In Table A 8, we deviate from the pre-analysis plan and instead use the second elicitation, as a robustness check. The results are fully consistent with the first elicitation. In particular, the anchoring effect in means is significant in both elicitation methods (H1), is significantly smaller in SBDs (H2) and high anchors increase the CV but low anchors do not (H3). The point estimates are also very similar.

[11] While not pre-registered, we can also explore how the elicitation method affects subjects' accuracy in terms of predicting the mean price. For each subject, we calculate the absolute deviation of their mean hotel price (either elicited as a point estimate or using the SBD) from the true mean of \$279.50 and regress this deviation on the high anchor dummy, the SBD dummy, and their interaction. Results are shown in Table A 7 in the Appendix. Deviations are much higher in the high anchor treatment: this is due to the fact that even without anchors (in the control treatment), subjects guessed that the mean price was \$341, somewhat higher than the true value. Hence the low anchor pulled subjects closer to the true value while the high anchor pulled them away from it. Nevertheless, the SBD elicitation reduces deviation even in the low anchor treatment by \$32, and in the high anchor treatment by \$37.

The one exception is that the anchoring effect in means appears to be smaller in the second elicitation (145) than in the first (193) when means are elicited directly. In Table A 9, we show that this difference is significant at the 10% level (column 1). There is no significant difference when the mean is elicited as part of a distribution (column 2). We then investigate whether the anchoring effect in means in the second elicitation can be fully explained by the anchoring effect in the first elicitation. This turns out to be the case when the mean is elicited first and the SBD second: in this case all differences in the second elicitation (SBD) are fully explained by differences in means observed in the first elicitation. When the SBD is elicited first, however, the initial anchoring effect (in means of SBDs) only explains some of the differences in means observed in the second elicitation; the high anchor dummy is still significant as well. One interpretation of these results is that the mean elicitation is more closely connected to the anchor than the SBD elicitation. When the first elicitation is the mean, all of the anchoring effect has already occurred, leaving no scope for further anchoring in the second elicitation. By contrast, when the first elicitation is the SBD, only part of the anchoring effect in means has been captured by the SBD, leaving additional scope for the anchor to have an effect on the second elicitation.

6. Discussion and concluding remarks

We generalize the study of the anchoring effect by testing whether an anchoring effect also emerges when eliciting an entire subjective distribution instead of just eliciting the mean. We replicate the traditional anchoring effect in means when eliciting the entire subjective distribution: participants facing a high anchor report distributions with a significantly higher mean than those facing a low anchor. However, this effect is 60% smaller relative to treatments where participants are asked directly about the mean. In addition, we find that anchoring also affects higher moments of the distribution: anchoring pulls the distribution towards the anchor, changing the skewness and lowering the variance relative to an environment without anchors.

Our results add important context to a literature that has looked almost exclusively at anchoring effects in point estimates (typically means). Not only do we show that anchoring also systematically affects the means of entire elicited distributions, it also consistently impacts the higher moments. This is important because the higher moments play a key role in many types of decision problems, including decision making under risk and uncertainty. We are the first to demonstrate these effects, and in so doing also demonstrate the robustness of the anchoring effect to these alternative types of elicitation techniques.

At the same time, it is also important to note that moving from the elicitation of means to the elicitation of entire distributions reduced the size of the anchoring effect in means by 60%. These results occurred despite our design restricting the range of responses to be similar across elicitation methods. The reduced strength of the anchoring effect in means is consistent with previous results showing that anchoring effects tend to be smaller when the estimation task and the anchor are dissimilar (Li et al., 2021). It also suggests that framing belief questions more broadly (instead of specifically the mean) may help reduce the prevalence of anchoring and other cognitive biases in the real world, which may help e.g., employers to reduce such biases among their employees.

We also document that anchoring affects the higher moments of the belief distribution, by pulling probability mass towards the anchor. These results have potentially important implications in that they suggest that exposing agents to anchors might lead to lower subjective probabilities of extreme events or (in our case) extreme prices. This may also be true outside the traditional context of anchoring. For example, financial analysts repeatedly exposed to past rates of return may reduce their subjective probability that an extreme event (a black swan) arises and tilt their distribution towards positive returns.

Our results also have implications for the broader literature on belief elicitation and cognitive biases. Notably, to our knowledge we are the first to demonstrate that traditional biases such as the anchoring effect also impact elicitations of entire elicited distributions, in part by affecting the higher moments of these distributions. This has importance also for situations without explicit anchors, as participants may be influenced by other sources of information, including previous parts of the experiment as well as the media they recently consumed. Finally, future research can explore how other cognitive biases affect distribution elicitations, potentially shedding light on the underlying mechanisms behind the findings reported in this paper.

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Appendix

A. Additional results

This section presents several additional results. Figure A 1 displays the stated frequences of all participants for each price interval by treatment. Table A 1 presents descriptive statistics; the results are similar across treatments. Table A 2 replicates the analysis from Table 4 while omitting participants who performed poorly on the practice task for the SBD (score lower than 40). The results are essentially unchanged. Table A 3 replicates the main analysis dropping subjects' probability weights in the top and bottom bins, indicating that the results are not driven by the fact that our SBDs are restricted to a limited interval. Table A 4 shows the anchoring effect on the skewness of the SBD, in particular that high anchor reduces skewness. Table A 5 presents results from regressions of SBD variation on individual characteristics; a higher risk tolerance, lower cognitive reflection and financial literacy are associated with higher SBD variation. Table A 6 presents results from regressions of SBD score on individual characteristics. While CRT and financial literacy are positively correlated with SBD score, none of the coefficients interacted with treatment is found to be significant. Table A 7 shows how the accuracy of the elicited mean differed across the four anchor treatments. Highest accuracy was observed in the low anchor and SBD treatments. Table A 8 shows the robustness of our main results using the second elicitation. Consistent with the first elicitation, the anchoring effect is significant for both mean and SBD, significantly smaller in the latter, and high anchor increases the CV. Table A 9 compares the first and second elicitation, showing that the anchoring effect in means is smaller in the second elicitation than the first.

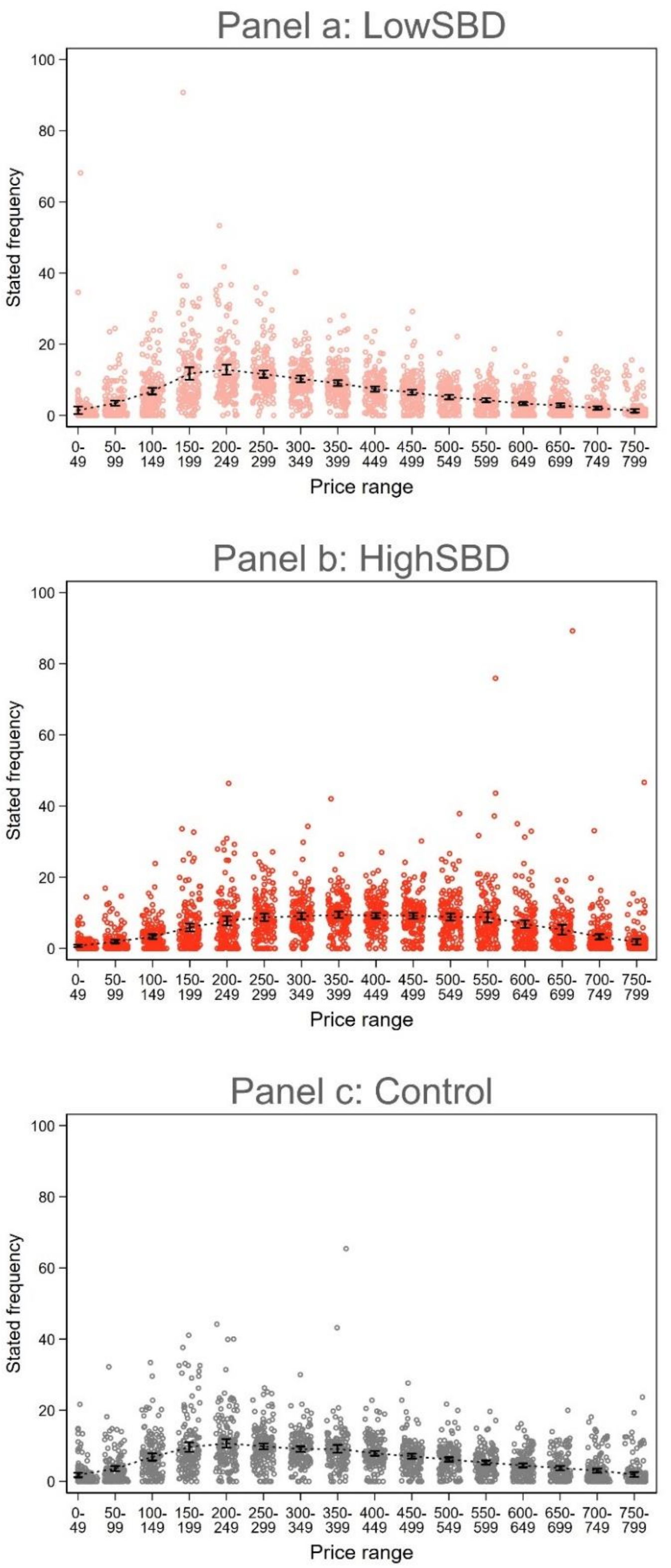
Panel a: LowSBD
Panel b: HighSBD
Panel c: Control
Stated frequency
Price range
0
20
40
60
80
100
0-49
50-99
100-149
150-199
200-249
250-299
300-349
350-399
400-449
450-499
500-549
550-599
600-649
650-699
700-749
750-799

Figure A 1 Distributions of individual SBDs. Panels a-c display the stated frequences of all participants for each price interval by treatment. Dotted lines represent the average frequencies with corresponding confidence intervals.

Table A 1 Summary statistics by treatment

	Control	HighMean	HighSBD	LowMean	LowSBD	All
Male	0.552	0.476	0.490	0.435	0.534	0.497
	(0.499)	(0.501)	(0.502)	(0.498)	(0.501)	(0.500)
Age	41.59	41.10	41.45	40.27	40.96	41.07
	(12.12)	(13.16)	(13.41)	(13.02)	(13.49)	(13.03)
Education	4.469	4.327	4.428	4.354	4.358	4.387
	(1.349)	(1.346)	(1.408)	(1.384)	(1.335)	(1.362)
Risk	4.903	5.122	5.283	5.048	5.047	5.081
	(2.734)	(2.421)	(2.471)	(2.660)	(2.461)	(2.548)
Invest fund	0.400	0.327	0.414	0.388	0.257	0.357
	(0.492)	(0.471)	(0.494)	(0.489)	(0.438)	(0.479)
Invest stock	0.559	0.476	0.538	0.469	0.500	0.508
	(0.498)	(0.501)	(0.500)	(0.501)	(0.502)	(0.500)
CRT	2.966	2.667	2.945	2.830	2.858	2.852
	(1.647)	(1.685)	(1.571)	(1.537)	(1.595)	(1.607)
Financial literacy	2.600	2.469	2.497	2.510	2.514	2.518
	(0.740)	(0.822)	(0.826)	(0.762)	(0.751)	(0.780)
N	145	147	148	147	145	732

Notes: Standard deviation in parentheses. Education is a categorical variable from 1 to 7 (Elementary school, High school graduate, Some college, Associate degree, Bachelor’s degree, Master’s degree or Doctorate). Risk attitude ranges from 0 (completely unwilling to take risks) to 10 (very willing to take risks).

Table A 2 Main results dropping subjects scoring 40 or less in SBD exercise

	(1) Mean	(2) Mean	(3) Mean	(4) Mean	(5) CV	(6) CV
High anchor	188.20***	86.20***	192.40***	190.50***	-0.09***	
	(18.71)	(12.07)	(18.51)	(18.49)	(0.02)	
SBD treatment			46.44***	43.40***		
			(14.40)	(14.57)		
High anchor x SBD			-105.69***	-102.47***		
			(22.09)	(21.99)		
Low anchor						-0.00
						(0.02)
Constant	287.47***	359.54***	287.50***	298.85***	0.39***	0.43***
	(34.72)	(21.59)	(12.32)	(22.69)	(0.03)	(0.02)
Controls	X	X		X	X	X
Treatments	*Mean	*SBD	*Mean & *SBD	*Mean & *SBD	Control & HighSBD	Control & LowSBD
N	263	265	528	528	256	261

Notes: OLS regressions of mean hotel price (columns 1-4) and coefficient of variation of SBD (columns 5-6). Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor’s degree, Master’s degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 3 Main results dropping subjects' probability weights in the bottom (0-49) and top (750-799) bins

	(1) Mean	(2) Mean	(3) Mean	(4) Mean	(5) CV	(6) CV
High anchor	183.48***	76.71***	188.83***	186.24***	-0.09***	
	(17.86)	(10.92)	(17.59)	(17.63)	(0.02)	
SBD treatment			45.79***	42.59***		
			(14.08)	(14.15)		
High anchor x SBD			-111.42***	-106.93***		
			(20.68)	(20.65)		
Low anchor						-0.01
						(0.01)
Constant	308.11***	357.46***	292.34***	308.76***	0.39***	0.41***
	(33.20)	(19.47)	(12.31)	(22.20)	(0.02)	(0.02)
Controls	X	X		X	X	X
Treatments	*Mean	*SBD	*Mean & *SBD	*Mean & *SBD	Control & HighSBD	Control & LowSBD
N	294	289	583	583	283	288

Notes: OLS regressions of mean hotel price (columns 1-4) and coefficient of variation of SBD (columns 5-6). Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 4 Anchoring effect on skewness of SBD

	(1) Skew	(2) Skew
Low anchor	0.12	0.11
	(0.08)	(0.08)
High anchor	-0.31***	-0.31***
	(0.09)	(0.10)
Constant	0.36***	0.12
	(0.06)	(0.18)
Controls		X
N	430	430

Notes: OLS regressions of SBD. Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 5 Factors affecting SBD variation

	(1) CV	(2) CV	(3) Mean	(4) Mean	(5) SD	(6) SD
Cog. uncertainty	0.01	0.00	-44.26**	-32.94*	-11.73	-11.06
	(0.03)	(0.03)	(19.96)	(18.88)	(8.57)	(8.40)
Risk	0.01**	0.01**	-0.91	-2.08	1.71*	1.57*
	(0.00)	(0.00)	(2.11)	(2.07)	(0.91)	(0.89)
Invest fund	0.02	0.02	3.37	-9.72	1.58	-0.56
	(0.02)	(0.02)	(11.91)	(11.51)	(4.61)	(4.82)
Invest stock	-0.01	-0.02	-8.81	-3.89	-1.95	-2.82
	(0.02)	(0.02)	(11.60)	(11.59)	(4.64)	(4.71)
CRT	-0.01***	-0.01***	-3.98	-4.41	-5.66***	-5.63***
	(0.01)	(0.01)	(3.43)	(3.40)	(1.30)	(1.33)
Financial literacy	-0.01	-0.01	-4.52	-6.35	-6.46**	-8.49***
	(0.01)	(0.01)	(6.71)	(6.86)	(2.76)	(2.78)
Constant	0.43***	0.45***	431.17***	434.30***	173.80***	186.86***
	(0.03)	(0.04)	(24.20)	(27.90)	(10.69)	(11.76)
Treatment DV		X		X		X
Controls		X		X		X
N	430	430	430	430	430	430

Notes: OLS regressions of SBD CV (columns 1-2), mean (columns 3-4) and standard deviation (columns 5-6). Cognitive uncertainty is 1 minus subject's level of certainty in their SBD score. Risk attitude ranges from 0 (completely unwilling to take risks) to 10 (very willing to take risks). Invest fund and Invest stock are dummy variables which equal 1 if the subject invests in the corresponding asset type. CRT is cognitive reflection test score between 0 and 5. Financial literacy score ranges between 0 and 3. Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 6 Factors affecting SBD score

	(1) Score	(2) Score	(3) Score	(4) Score	(5) Score
Low anchor	7.07***	5.70	3.78	9.34	0.39
	(2.34)	(5.87)	(4.13)	(6.51)	(6.95)
High anchor	-2.37	-2.62	-0.55	3.82	-8.17
	(2.19)	(5.00)	(4.09)	(4.97)	(6.65)
Cog. Uncertainty (CU)	6.42*	5.62	6.63*	6.60*	6.60*
	(3.56)	(5.57)	(3.55)	(3.60)	(3.54)
CRT	2.27***	2.27***	2.05**	2.26***	2.33***
	(0.61)	(0.60)	(0.92)	(0.61)	(0.62)
Financial Literacy (FL)	3.24***	3.21***	3.30***	4.44***	3.21***
	(1.11)	(1.11)	(1.12)	(1.52)	(1.11)
Education	-0.87	-0.86	-0.78	-0.87	-2.12
	(0.76)	(0.76)	(0.77)	(0.76)	(1.40)
Low anchor x CU		2.21			
		(8.73)			
High anchor x CU		0.36			
		(8.10)			
Low anchor x CRT			1.14		
			(1.35)		
High anchor x CRT			-0.62		
			(1.32)		
Low anchor x FL				-0.86	
				(2.60)	
High anchor x FL				-2.43	
				(2.06)	
Low anchor x Edu					1.95
					(1.89)
High anchor x Edu					1.67
					(1.76)
Controls	X	X	X	X	X
N	438	438	438	438	438

Notes: OLS regressions of SBD score. Cognitive uncertainty (CU) is 1 minus subject's level of certainty in their SBD score. CRT is cognitive reflection test score between 0 and 5. FL is financial literacy score between 0 and 3. For simplicity, education is included as a continuous variable, where 1 is high school graduate or less, 2 is some college, 3 is Associate degree, 4 is Bachelor's degree, 5 is Master's degree, and 6 is Doctorate. Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), and dummies for Male and non-binary and education as a continuous variable. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 7 Elicitation method and deviation from correct value

	(1) Deviation	(2) Deviation
High anchor	101.68***	99.40***
	(13.25)	(13.24)
SBD treatment	-29.49***	-32.10***
	(9.48)	(9.67)
High anchor x SBD	-41.01**	-36.50**
	(16.33)	(16.34)
Constant	115.32***	124.50***
	(7.84)	(17.11)
Controls		X
Treatments	*Mean & *SBD	*Mean & *SBD
N	583	583

Notes: OLS regressions of absolute deviation of mean hotel price from true value ($279.50). Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 8 Main results using second elicitation

	(1) Mean	(2) Mean	(3) Mean	(4) Mean	(5) CV	(6) CV
High anchor	144.85***	83.71***	144.98***	145.20***	-0.09***	
	(15.81)	(12.57)	(15.26)	(15.37)	(0.02)	
SBD treatment			57.15***	59.19***		
			(13.52)	(13.75)		
High anchor x SBD			-57.93***	-60.40***		
			(19.60)	(19.79)		
Low anchor						-0.02
						(0.02)
Constant	315.04***	362.05***	294.22***	307.14***	0.42***	0.42***
	(30.53)	(22.27)	(10.57)	(21.04)	(0.03)	(0.02)
Controls	X	X		X	X	X
Treatments	*Mean	*SBD	*Mean & *SBD	*Mean & *SBD	Control & HighSBD	Control & LowSBD
N	293	290	583	583	285	287

Notes: OLS regressions of mean hotel price (columns 1-4) and coefficient of variation of SBD (columns 5-6). Controls include categorical age dummies (18-24, 25-34 omitted, 35-44, 45-54, 55-64, 65 and above), dummies for Male and non-binary, and categorical dummies for each of the education levels (Elementary school and High school graduate omitted, Some college, Associate degree, Bachelor's degree, Master's degree or Doctorate). We pre-registered Elementary school as the omitted category but decided to combine it with High school graduate since only two subjects reported Elementary school as their education level. Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

Table A 9 Comparing first and second elicitation

	(1) Mean	(2) Mean (SBD)	(3) Mean	(4) Mean (SBD)
High anchor	188.83***	79.68***	71.52***	-0.59
	(17.59)	(11.55)	(13.33)	(9.18)
Second Elicitation	1.88	12.82		
	(16.22)	(11.22)		
High anchor x Second Elicitation	-43.85*	7.37		
	(23.29)	(16.88)		
First elicitation mean			0.93***	0.47***
			(0.06)	(0.03)
Constant	292.34***	338.56***	-22.02	214.90***
	(12.30)	(8.42)	(17.98)	(12.54)
Elicitation	both	both	second	second
N	587	579	289	290

Notes: OLS regressions of mean hotel price based elicited through means (column 1 and 3) or distributions (column 2 and 4). Robust standard errors in parentheses, ***p<0.01, **p<0.05, *p<0.1.

B. Pre-Analysis Plan

In this section we reprint our original pre-analysis plan (also available from https://www.socialscienceregistry.org/trials/11396). We include several authors' notes in italics in the analysis section (section 3) to indicate where the relevant tests can be found in the paper.

Pre-analysis plan:
Anchoring and Subjective Belief Distributions

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1) Purpose and Motivation

The purpose of this project is to study how anchors affect estimations of subjective belief distributions (SBDs). Anchoring is a well-known judgment bias in decisions. Although the impact of anchors has been studied extensively on estimations of single-number summary statistics, its impact on higher moments of SBDs is to a large extent unexplored. This makes it valuable to study since SBDs play an important role in economic theory.

Our overall aim is to investigate how anchoring affects SBDs. More specifically, we will study: 1) if elicitations of averages through SBDs are less affected by anchors than direct elicitations of means and 2) how anchors affect the 2nd (and, of secondary importance, 3rd) moment of SBDs. In addition, we will investigate how individual characteristics can explain heterogeneities in the properties of SBDs and how these impact the anchoring of SBDs.

In the presentation of our pre-analysis plan, we have followed the suggestion of moderation in Duflo et al. (2020) when it comes to detail. While we have tried to give sufficient detail to the planned study for it to generate testable hypotheses, some details of the parts of secondary importance have not been specified and may be left as an exploratory analysis.

2) Design

We conduct an online experimental survey on Prolific. In the online survey, we randomly allocate participants to five treatment conditions where we elicit beliefs in various ways to be described in more detail below. After the belief elicitations, all subjects answer survey questions about their individual characteristics.

2.1) *Online Survey/Experiment*

We start by giving all subjects information about central concepts in the survey such as the average and the frequency distribution of a set of values. We also let subjects answer a few control questions that are designed to check that the subjects understand the concepts.

The next step is to inform subjects that we have collected information about a given price distribution. It will be a distribution of historical prices for a one-night hotel room in the city of Rome. This distribution was selected since we want the subject to have some idea about the price distribution but not too much information about it.

Subjects are then randomly allocated to one of the following five treatments, where subjects' beliefs are elicited with monetary incentives.

- *Control elicitation of Distribution (CD).* We elicit the SBDs of the hotel room prices using the procedure suggested by Crosetto and de Haan (2022). There is no anchoring in this treatment.

- *Low anchor elicitation of Mean (LM).* The subjects are first asked if they believe that the average price is lower or higher than the value of a low anchor. After that subjects are asked to guess the average price of the hotel room.

- *Low anchor elicitation of Distribution (LD).* The subjects are first asked if they believe that the average price is lower or higher than the value of a low anchor. After that, we elicit the SBDs of the hotel room prices by the same technique as in *CD*.

- *High anchor elicitation of Mean (HM).* The subjects are first asked if they believe that the average price is lower or higher than the value of a high anchor. After that subjects are asked to guess the average price of the hotel room.

- *High anchor elicitation of Distribution (HD).* The subjects are first asked if they believe that the average price is lower or higher than the value of a high anchor. After that, we elicit the SBDs of the hotel room prices by the same technique as in *CD*.

We then run a 2nd elicitation so that subjects who received the *LM* and *HM* will receive *CD* and subjects who received *CD*, *LD*, and *HD* will be asked to guess the average hotel prices. (Hence, they receive the same treatment as in *LM* and *HM* but without any anchor, which will be denoted as *M*.) In connection with the 2nd elicitation, we will ask how certain the subjects are about their estimations following the elicitation of cognitive uncertainty (CU) by Enke and Graeber (2022). The 2nd round elicitations are of secondary importance and will only be used in the exploratory analysis.

After the treatment, all subjects answer questions about demographics, cognitive reflection, investment behavior, and financial literacy.

Demographic questions:
1) How old are you? ___________ (years)
2) What is your gender: ______(man/woman/non-binary/other(please specify))
3) What is the highest education level you have reached?
1. Elementary School
2. High school graduate
3. Some College
4. Associate Degree
5. Bachelor's Degree
6. Master's Degree
7. Doctorate Degree
Questions designed to measure cognitive reflection inspired by Frederick (2005)
4) A house contains a living room and a kitchen that are perfectly square. The living room has four times the area of the kitchen. If the walls of the kitchen are four meters long, how long are the walls of the living room?
5) Yesterday a store owner reduced the price of a pair of $100 shoes by 10 percent. This morning he reduced the price further by 10 percent. How much does the pair of shoes cost now?
6) If it takes 4 machines 4 minutes to make 4 forks, how many minutes would it take 80 machines to produce 80 forks?
7) In a lake there is a patch of lily pads. Every day it doubles in size. If it takes 100 days for the lily pads to cover the entire lake. How long (in days) does it take for the lily pads to cover half the lake?
8) A meal and a drink cost $11 in total. The meal costs $10 more than the drink. How much does the meal cost?

Questions concerning risk-taking, investment behavior, and financial literacy (risk question is taken from the German Socio-Economic Panel, and the financial literacy questions are taken from Lusardi and Mitchell, 2014)
8) How willing are you to take risks, in general?
[Respondents rate their willingness on a scale from 0 to 10.]
9) Do you own stocks in any form: a) in equity funds? ______(yes/no) b) individual stocks in specific companies? _____ (yes/no)
10) Suppose you had $100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:
Alternatives: [more than $102; exactly $102; less than $102; do not know]

11) Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy:
Alternatives: [more than, exactly the same as, or less than today with the money in this account; do not know.]
12) Do you think that the following statement is true or false? “Buying a single company stock usually provides a safer return than a stock mutual fund.”
Alternatives : [true; false; do not know]

The overall design is summarized in the table below:

Table of Design

Tasks / Number of Subjects	*150*	*150*	*150*	*150*	*150*
General information	X	X	X	X	X
Information about means/distributions and control questions	X	X	X	X	X
1st Elicitation	CD	LM	LD	HM	HD
2nd Elicitation	M	CD	M	CD	M
Cognitive uncertainty question	X	X	X	X	X
Questionnaire on demographics, Cognitive reflection, Risk-taking, Financial literacy	X	X	X	X	X

X- subjects will be doing the task. 150- number of subjects in each treatment (motivated by power calculations specified in section 4.2 below).

3) Analysis

To explain our analysis we start by defining some variables. All variables refer to the first elicitation round if not otherwise explicitly stated:

Type of anchor: *L-Low, H-High, C-Control (no anchor)*
Elicitation of: *M-Mean; D-SBD*
Treatment $X \in \{CD, LM, LD, HM, HD\}$
N = number of subjects in Treatment *X*
TrueMean = objective mean of the elicited variable’s true distribution.
$Match_i(X)$ = The score indicating how close *i*’s SBD is to the true distribution in treatment *X*. The maximum and minimum score is 100 and 0, respectively.
$Mean_i(X)$ = Elicited mean for individual *i* (directly in M-treatments and indirectly in D-treatments) in Treatment *X*
$\overline{Mean}(X) = \frac{\sum_i^N Mean_i(X)}{N}$ = group mean
$\sigma_i(X)$ = standard deviation of individual SBD in Treatment *X*
$CV_i(X) = \frac{\sigma_i(X)}{Mean_i(X)}$ = Coefficient of variation of *i*’s SBD
$\overline{CV}(X) = \frac{\sum_i^N CV_i(X)}{N}$ = group mean of $CV_i(X)$
$Skew_i(X)$ = the Fisher’s moment coefficient of skewness of *i*’s SBD

$\overline{Skew}(X) = \frac{\sum_i^N Skew_i(X)}{N}$ = mean skewness of group receiving treatment *X*.
$CU_i(X) \in \{0, 5, 10, \dots, 100\}$ = Cognitive uncertainty in Treatment *X* of individual *i*.
$\overline{CU}(X) \frac{\sum_i^N CU_i(X)}{N}$ = group mean of cognitive uncertainty
Age – age of respondent
Gender – gender of the respondent
Education – highest educational level of respondent
CRT – number of correct answers on questions 4-7.
Risk – willingness to take risks
IF – investment in funds (dummy)
IS – Investment in individual stocks (dummy)
FL – score on financial literacy questions 10-12

Our main hypotheses are as follows:

H1A: $\overline{Mean}(LM) < \overline{Mean}(HM)$, and H1B: $\overline{Mean}(LD) < \overline{Mean}(HD)$
Hypothesis 1 is about the anchoring effect per se. H1A will seek to confirm that the standard anchoring effect on means also exists in our data. In H1B, based on the documented robustness of the anchoring effect (e.g., Furnham and Boo, 2011), we conjecture that anchors affect elicitations of SBD in a directionally similar way. To test these claims statistically we use a one-sided two-sample t-test in each case. We then run an OLS regression with $Mean_i(X)$ as the dependent variable with a dummy for the high-anchor treatment (HD or HM) and controlling for Age, Gender, and Education.[12] For this regression and all other regressions we will use robust standard errors unless otherwise specified.
Authors' notes: the t-tests can be found in the text of section 5.2, the regression analysis is in Table 4.

H2: $\overline{Mean}(HM) - \overline{Mean}(LM) > \overline{Mean}(HD)$- $\overline{Mean}(LD)$
Hypothesis 2 postulates that the anchoring effect is smaller when eliciting SBDs. This is based on previous research suggesting that the anchoring effect may be driven by heuristics such as the anchoring-and-adjustment process, which require cognitive effort (see e.g., Epley and Gilovich,2006; Simmons et al, 2010). If the elicitation of the SBD requires more cognitive effort than the mean, as seems likely, this may leave fewer cognitive resources for the anchoring-and-adjustment heuristic and hence less scope for an anchoring effect. In addition, compared to the mean, the SBD is less compatible with the anchor, which is thought to lower the scope for the anchoring effect (e.g., Strack and Mussweiler, 1997; Li et al., 2021). We test Hypothesis 2 using a one-sided difference-in-difference test, that is, an OLS regression of $Mean_i(X)$ on a dummy for the two high-anchor treatments (HD, HM), a dummy for the two D-treatments (HD,

[12] We will control for age using the following categorical dummies: 18-24, 25-34, 35-44, 45-54, 55-64, 65 and above. For gender, we will include a dummy for men and a dummy capturing other/non-binary individuals, provided these are present in our data. For education, we will include dummy variables for each of the 7 categories, using elementary school as the reference category.

LD), and their interaction (the main variable of interest). We also run a second regression controlling for Age, Gender, and Education.
Authors' notes: the difference-in-difference tests can be found in Table 4 both with controls (column 3) and without (column 4).

H3A: $\overline{CV}(CD) = \overline{CV}(LD)$, and H3B $\overline{CV}(CD) = \overline{CV}(HD)$
Hypothesis 3 is about the coefficient of variation of the elicited distribution. A popular explanation for the anchoring effect in means is the anchoring-and-adjustment heuristic (Tversky and Kahneman, 1974). This heuristic implies that the final estimate will be a linear combination between the anchor (*a*) and the prior belief (*x*) (that is, the estimate the participant would give without an anchor). There exist several potential ways of extending this heuristic to the case of SBDs. Assume that the subjects have a prior SBD and that they form a distribution of beliefs over the potential anchors (of which they observe one realization). We can then model the final estimates as a linear combination of two random variables (*a* and *x*). Alternatively, the final distribution may be viewed as a weighted mixture distribution of the two distributions.

If we consider the first approach and study the distribution of a linear combination of two (independent) random variables, the variance of the final estimate will depend on the variances of the anchor distribution and the prior SBD, as well as the weighting parameter. If the variance of the anchor is equal to or smaller than the variance of the initial belief, the variance of the final estimate will be lower than the variance of the prior belief distribution. Correspondingly, the coefficient of variation of the final belief distribution will be lower than the prior SBD, at least for the situation in which the mean of the anchor distribution is greater than the mean of the prior SBD. However, it is possible to imagine that the effect goes in the other direction. For example, if the variance of the anchor is much larger than the variance of the initial beliefs, and the adjustment towards the anchor is strong.

If we instead consider the second approach and model the final distribution as a weighted mixture distribution of the distributions of prior beliefs and anchors, the effect is again ambiguous. The coefficient of variation of the final estimate will depend on the variances and means of the anchor and the initial belief, as well as the degree of adjustment towards the anchor.

As a result, the overall prediction is ambiguous: the coefficient of variation may both decrease or increase if the converse holds. We will test this hypothesis using two two-sided two-sample t-tests and then run two OLS regressions for subjects receiving the relevant treatment (either HD or LD, with CD as the control group) with $CV_i(X)$ as the dependent variable, and with a dummy for the relevant treatments (HD or LD) and controlling for Age, Gender, and Education.
Authors' notes: these tests are included in section 5.2 and Table 4 (columns 5 and 6).

Hypotheses of secondary importance and secondary analysis:
H4A: $\overline{Skew}(LD) = \overline{Skew}(CD)$. H4B: $\overline{Skew}(CD) = \overline{Skew}(HD)$.

It could be interesting to look at higher moments as well. Lacking an a-priori hypothesis, we will use two two-sample two-sided t-tests to test whether the skewness in the respective anchor treatments differs from the skewness in the control treatment. We will also run an OLS regression for subjects with the skewness coefficient as the dependent variable and with the dummy variables D_{HD} and D_{CD} for treatments HD and LD while controlling for Age, Gender, and Education.
Authors' notes: the tests are included in section 5.3; the regressions are in Table A 4.

Analysis of factors affecting $CV_i(X)$
We will study how various factors correlate with the individual coefficient of variation. We expect that $CV_i(X)$ is positively correlated with $CU_i(X)$ for all *X.* The intuition for this is that an individual who is certain about a variable should have a more concentrated SBD than an individual who is uncertain and therefore finds it difficult to exclude many values as plausible. We expect *Risk* (taking) (and IF, IS) to be negatively correlated with $CV_i(X)$ since a high variation in the SBD can be seen as "insurance" against getting everything wrong and thereby not receiving any payment at all in the elicitation. We also conjecture that cognitive reflection (*CRT*) and financial literacy (*FL*) may negatively affect $CV_i(X)$ (see e.g., Bergman et al., 2010).
We study this by an OLS where $CV_i(X)$ is the dependent variable and $CU_i(X)$, *Risk*, *CRT*, *IF*, *IS*, and *FL* as independent variables. We control for treatment dummies in addition to the standard demographic controls (Age, Gender, Education).
Authors' notes: the results are discussed in section 5.3; the regressions are in Table A 5.

Heterogeneous treatment effects for H1-H3
We will also explore heterogeneous treatment effects for H1-H3 using Age, Gender, Education, Risk, CRT, FL, CU, IF and IS. For H1, we will regress $Mean_i(X)$ on a dummy for the high anchor treatment (HM or HD), the relevant heterogeneous effect variable, and the interaction of the two. For H2, we regress $Mean_i(X)$ on a dummy for the two high-anchor treatments (HD, HM), a dummy for the two D-treatments (HD, LD), and their interaction, as well as the heterogeneous treatment effect variable and its interaction with all three previously listed variables. For H3, we use two OLS regressions on $CV_i(X)$ relevant treatment (either HD or LD, with CD as the control group) with $CV_i(X)$ as the dependent variable, and the dummy for the anchor treatment (either HD or LD), the heterogeneous effect variable and their interaction as independent variables.
Authors' notes: as we explain in footnote 9, we found no evidence of significant heterogeneous treatment effects; the results are available upon request.

Analysis of factors affecting $Match_i(X)$
We will study how various factors affect how good subjects are in estimating the true distribution. We expect that Education, cognitive reflection (CRT), and financial literacy (FL) are all positively correlated with $Match_i(X)$. In addition, we expect that $CU_i(X)$ and treatments including anchors will negatively affect $Match_i(X)$.
We study this by an OLS using subjects in CD, LD, and HD where $Match_i(X)$ is the dependent variable and *Education, CRT, FL,* $CU_i(X)$, and a treatment dummy for anchor treatments (LD, HD) are independent variables. We also include Age and Gender as controls.

In a second specification, we explore heterogeneous interaction effects between the treatment dummies with the independent variables mentioned above. For instance, it is plausible that anchors impact high-CRT subjects less than low-CRT subjects.
Authors' notes: we discuss this analysis in section 5.3 and report the regression results in Table A 6.

4) Data collection and sample size

4.1) Data collection

The experimental and survey data are collected on the online platform Prolific. We aim for a sample as close as possible to a representative one of the population in the USA that Prolific can provide in the age group over 18. We aim to collect data from 750 subjects with 150 in each of the five treatment groups (based on the 1st elicitation), based on the power calculations presented in section 4.2.

We will conduct our analysis using the following samples:
i) Full sample of all participants who finished the full survey.
ii) The full sample from (i) minus participants who completed the study in 5 minutes or less.
iii) The sample from (ii) minus outlier responses: those who state a mean price of 50 USD or less (in the elicitation of the mean) or those who state a mass of 5% or more for the lowest or highest bin (that is, the 0-49 USD and 750-799 USD intervals in the elicitation of SBD).

4.2) Power Calculation

Our power calculation is based on a study by Lee and Morewedge (2022) that used a relatively similar design as we do in terms of domain and anchors. They asked subjects in different treatment groups to estimate their willingness to pay in USD for 4-star hotel rooms, not in Rome (as we will do) but in Miami providing them with either no anchor, a low anchor, or a high anchor. The mean prices and standard deviations (in parentheses) were 197 (100), 147 (81), and 330 (176) for the no anchor, low anchor, and high anchor treatments, respectively. The low anchor in this study was \$44 and the high anchor was \$610. Our low and high anchors are \$134 and \$546, which are based on the low and high boundaries of the true underlying distribution of hotel prices. Our anchors are slightly less dispersed, which may lead to less extreme results in both anchor treatments. For the purposes of our power calculation, we therefore assume mean prices (standard deviations) of 180 (100) and 300 (160) in the low-anchor and high-anchor treatments, where the standard deviations are adjusted in proportion to the change in means. We further assume that the anchoring effect will be 50% smaller in the SBD treatments. In our pilot (N=143 across all treatments) we found somewhat larger effects, but we stick with these initial estimates to keep our power estimates conservative.

We compute power for hypothesis 1 using "power twomeans" in Stata for a one-sided two-sample t-test, one for (LM,HM) and one for (LD,HD), for a power of 0.80. For hypothesis 2, we simulate normally distributed data and look for the minimum sample size required to have a significant difference-in-difference coefficient in 80% of simulated samples. We perform these power calculations both for an uncorrected significance threshold of $p<0.05$ and for the Benjamini-Hochberg correction for multiple testing.[13] Since we do not have a directional hypothesis for H3, we do not include this hypothesis in

[13] This correction ranks all *n* hypothesis from the lowest p-value to highest and then multiplies the significance threshold for the lowest p-value by (1/*n*), the second-lowest p-value by (2/*n*), etc. In our case, this implies

our analysis, but do take it into account in our adjustment for multiple testing.

The Table below presents the results, which show that a sample size of 150 participants per treatment would be sufficient to have a power of 0.80 to observe a significant difference-in-difference result even after applying the multiple testing correction (and a higher power for the other tests). As a result, we aim for a sample size of 150 participants per treatment.

	Standard	Benjamini-Hochberg correction
H1a: $\overline{Mean}(LM) < \overline{Mean}(HM)$	17	27
H1b: $\overline{Mean}(LD) < \overline{Mean}(HD)$	62	85
H2: difference-in-difference	130	150

multiplying the thresholds for H1a, H1b and H2 by 1/5, 2/5 and 3/5 respectively, given a total of five hypotheses including H3a and H3b.

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EXPERIMENTAL INSTRUCTIONS

WELCOME!

This study is conducted by researchers from University College Dublin and Lund University. You have been invited to take part since you meet the research requirements: you are an adult aged over 18 years living in the US. If you choose to participate, you will fill out a 20-minute survey through Prolific using your computer. Your participation will help the researchers better understand the determinants of decision-making and earn you a participation fee through Prolific. You also have the chance to earn an additional bonus depending on how you answer the survey questions. You will be reminded about this before you start to answer the main survey.

It helps us a great deal if you respond as carefully as possible. Therefore, please consider all your answers carefully. There are no foreseeable risks to taking part in the study. However, if you have any concern and wish to withdraw at any point, simply close the survey window.

All your responses are anonymous. Your data will be analysed and aggregate results will be reported in a future research paper. The data will be stored indefinitely. As per the publication policy of most economics journals, upon publication data will need to be made available for viewing or use by future researchers.

Contact details for further information: margaret.samahita@ucd.ie

If you consent to the above information sheet, please select Yes below.

I have read and understood the above and want to participate in this study.

- ○ Yes
- ○ No

What is your Prolific ID? Please note that this response should auto-fill with the correct ID

____

INFORMATION

Before the main survey starts, we ask you to read about some concepts that are important in this survey. You will also be asked some test questions that you need to answer correctly before you can take the main survey.

Important concept: "Average"

The first concept you need to know is the average of a sequence of numbers. This is calculated as the sum of all the numbers divided by the amount of numbers. Hence, if the five values are 4, 3, 2, 8, and 3, the average is (4+3+2+8+3)/5=20/5=4. We will now check that you are able to calculate the average. (If you want you can use a calculator.)

The values are: 2, 3, 2, and 5. What is the average?

____

The values are: 400, 300, and 800. What is the average?

____

Later in this study, you will have the opportunity to make additional money by guessing the average. We will pay you according to how close your guess is to the true average value.

We pay you:

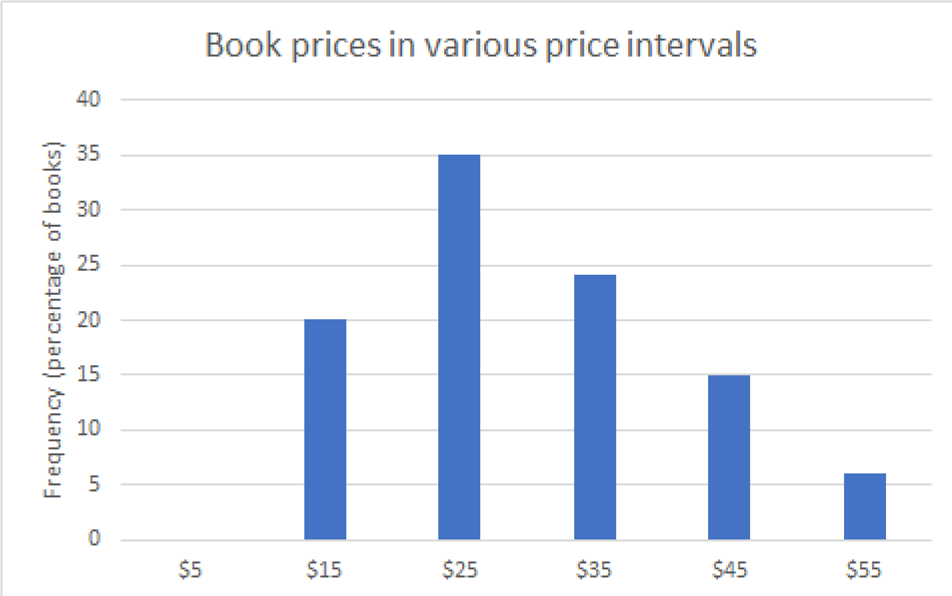
- $5 if your guess of the average and the true average value differ by 5 or less.
- $3 if your guess of the average and the true average value differ by 6-25.
- $2 if your guess of the average and the true average value differ by 26-50.
- $1 if your guess of the average and the true average value differ by 51-100.

Important concepts: "Distribution" and "Histogram"

We also want you to learn about a distribution for a number. The distribution for a number tells us how often we might expect possible values of that number to arise. Consider the following distribution for a collection of book prices in a book store.

Price interval:	$0-9.99	$10-19.99	$20-29.99	$30-39.99	$40-49.99	$50-59.99	Sum
Midpoint:	$5	$15	$25	$35	$45	$55	
Frequency: (the percentage of books in the interval)	0%	20%	35%	24%	15%	6%	100%

For example, this distribution tells us that 35% of all the books in the store will be between $20 and $29.99. A distribution can also be portrayed by a *histogram*, which for the bookshop prices is given below:



Note that, for simplicity, we show the midpoint of each price interval on the histogram. For example, the label for the first price interval is shown as $5, representing the midpoint of the true interval $0-9.99.

Comprehension check

Consider now a new distribution over bread prices (from a bakery shop) in various price intervals.

Price interval:	$0-0.99	$1-1.99	$2-2.99	$3-3.99	$4-4.99	$5-5.99	$6-6.99	$7-7.99	$8-8.99
Midpoint:	$0.50	$1.50	$2.50	$3.50	$4.50	$5.50	$6.50	$7.50	$8.50

We portray the distribution using the histogram below:

We will now ask you a few test questions about the distribution of bread prices in the histogram above that you can answer with a "yes" or "no".

Please answer the questions below. You will only be able to proceed if you answer all four questions correctly.

	Yes	No
Are less than 15 percent of the pieces of bread priced below $2?	○	○
Are more than 30 percent of all pieces of bread priced above $5?	○	○
Is there any bread with a price less than $2?	○	○
Are more than 15 percent of all pieces of bread priced in the interval between $4 and $4.99?	○	○

Click-and-Drag interface

In the main survey, you may be asked to use a click-and-drag interface to describe a histogram of prices. You will now familiarize yourself with such an interface by a "match the graph task".

You will see an example histogram at the top of the page. Your task is to recreate the same histogram below it, using the click-and-drag interface.

You can adjust the histogram by adding, moving, or removing points: You can add points by clicking anywhere on the graph. You can move points around by dragging them. You can remove points by clicking on them.

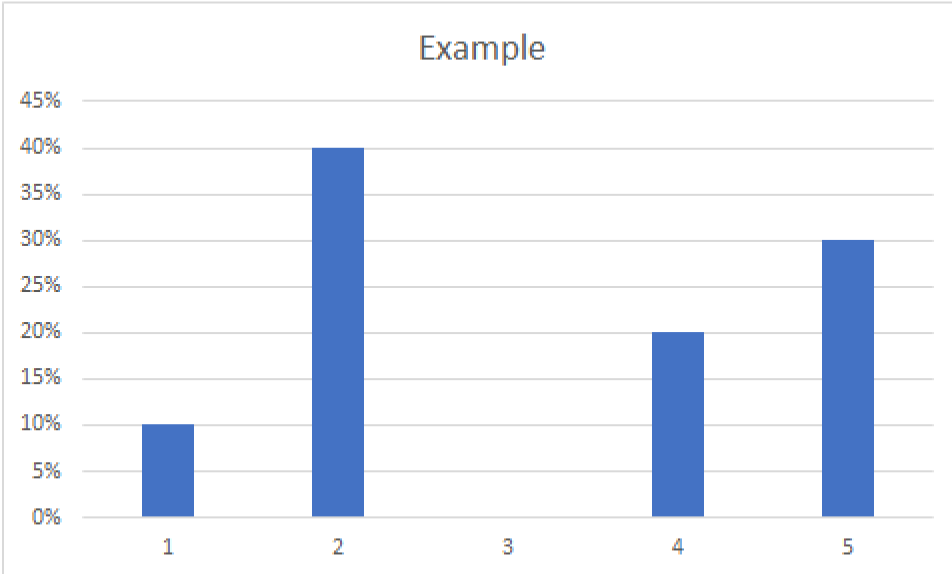
You can test the interface as you wish and your score depends on how closely your recreated histogram matches the original one. If you perfectly match the original histogram, you get the maximum score, which is 100. If you fail to match any part of the original histogram, you get the minimum score, which is 0.

The exact calculation of your score is as follows:

- For each of the histogram bars, we calculate the absolute difference between your response and the correct value.
- Then we calculate the sum of these differences.
- Then we subtract this sum from 100, and take the greater of this and zero.

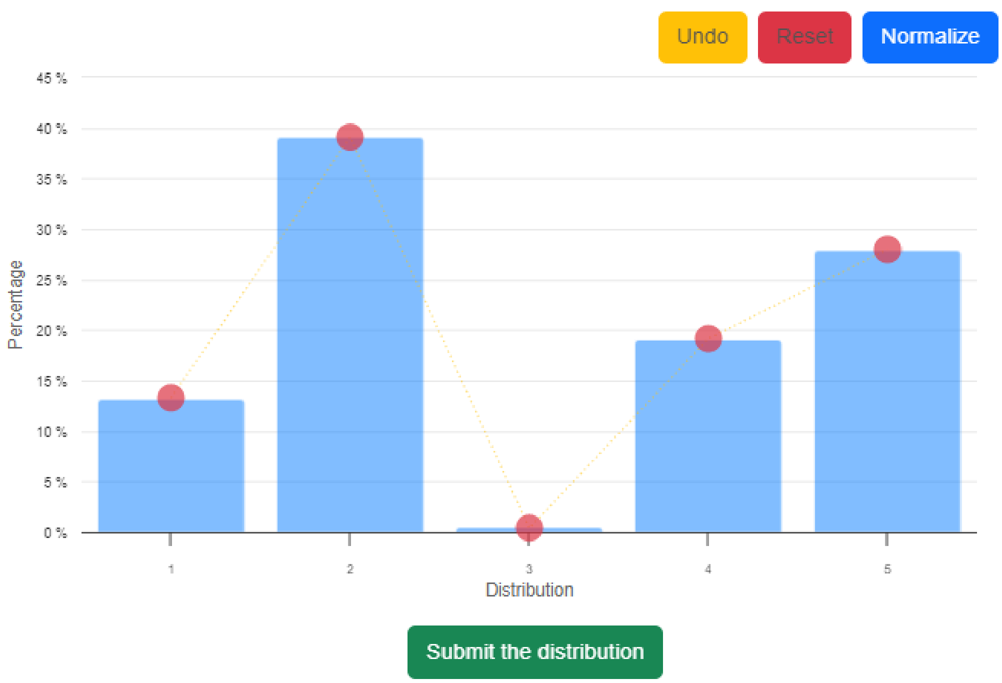
After you complete the example task, you will be given feedback about your score.

Please recreate the following example histogram.



If you like, you can click "Normalize" which simply adjusts your histogram bars proportionally to sum up to 100% (otherwise, we will automatically do this for you).

[EXAMPLE INPUT TO CLICK-AND-DRAG INTERFACE]



Your Score

Your score will be calculated as follows:

- For each of the 5 values above, we calculate the absolute difference between your response and the correct value.
- Then we calculate the sum of these 5 differences
- Then we subtract this sum from 100, and take the greater of this and zero.

- **Bar 1:** Your response of **13** was incorrect! The correct answer was **10**. You were off by **3**.
- **Bar 2:** Your response of **39** was incorrect! The correct answer was **40**. You were off by **1**.
- **Bar 3:** Your response of **1** was incorrect! The correct answer was **0**. You were off by **1**.
- **Bar 4:** Your response of **19** was incorrect! The correct answer was **20**. You were off by **1**.
- **Bar 5:** Your response of **28** was incorrect! The correct answer was **30**. You were off by **2**.

Your total error is **8**.
Therefore your score is **92**.

Your Payment

Later in this study, you will have the opportunity to make additional money by making a good guess of the distribution. We will pay you according to how close your created histogram is to the true one.

We pay you:

- $5 if your histogram perfectly matches the true histogram. This corresponds to a score of 95 or more.
- $3 if your histogram closely matches the true histogram but not perfectly so. This corresponds to a score of 55-94.
- $2 if your histogram matches the true histogram reasonably well. This corresponds to a score of 30-54.
- $1 if your histogram matches only a few parts of the true histogram reasonably well. This corresponds to a score of 5-29.

In the study, you will make guesses in different situations. One of the situations you will encounter will be selected at random as a “money-earning situation” and you will be paid according to your guess in this situation. The money-earning situation will be determined at the end of this session.

The possibility to earn real money is important in economic experiments and there are strict rules against deceiving persons who participate. Hence, all information given here about money and other aspects is true and will be carried out according to the information given. Your answers will only be used for research purposes and will be kept strictly confidential. Read the instructions for each task carefully.

General information about the price data

In the question below we will ask you to give your best guess of the prices of a one-night stay in a 4-star hotel double room in the central parts of Rome, the capital city of Italy. On an internet platform for hotel reservations, we obtained prices (including all taxes) for available double rooms for a one-night stay for two persons with check-in on Saturday, February 18th, 2023, and check-out the day after. The prices were downloaded on February 8th, that is, ten days before the stay.

[presented only in treatments 2-3 (low anchor) and 4-5 (high anchor)]
Do you think that the average price for such a room is lower or higher than $[134/546]? Answer by pressing one of the buttons below.

○ Higher

○ Lower

[In treatments 1, 3, 5, order is: SBD elicitation, Mean elicitation, CU for Mean]
[In treatments 2, 4, order is: Mean elicitation, SBD elicitation, CU for SBD]

[SBD elicitation]
Please start using the click-and-drag histogram to describe how you believe the prices of such a room are distributed. Recall that each price label represents the midpoint of the corresponding interval, as shown below. Remember that the closer your guess is to the real price distribution, the greater the bonus you receive.

Price interval:	$0-49	$50-99	$100-149	$150-199	$200-249	$250-299	$300-349	$350-399	$400-449	$450-499	$500-549	$550-599	$600-649	$650-699	$700-749	$750-799
Midpoint:	$25	$75	$125	$175	$225	$275	$325	$375	$425	$475	$525	$575	$625	$675	$725	$775

[CLICK-AND-DRAG INTERFACE]

If you like, you can click "Normalize" which simply adjusts your histogram bars proportionally to sum up to 100% (otherwise, we will automatically do this for you).

[Mean elicitation]
Now please guess what the average price of such a room is. If this task is chosen for payment, payment will be between $0 and $5. Remember that you will earn more the closer your answer is to the true average price. Your answer should be somewhere between 0 and 799 USD.

I guess that the average price of such a room is (in USD):

____

[CU for Mean]

We are now interested to learn how certain you are about your suggested average price. Suppose that we compare your guessed average price with the true average price. How certain are you that your average price lies somewhere between +/-5% of the true average price?

[Very uncertain 0% - completely certain 100%, in 5% interval]

[CU for SBD]
We are now interested to learn how certain you are about your suggested distribution. Suppose that we compare the distribution of prices that you have guessed with the true distribution of the prices that we have collected. How certain are you that your distribution matches 90% of the true distribution (that is that your score is 90 or more)?

[Very uncertain 0% - completely certain 100%, in 5% interval]

How old are you (in years)?

____

What is your gender?

- ◯ Man
- ◯ Woman
- ◯ Non-binary
- ◯ Other, please specify: ____

What is the highest education level you have reached?

- ◯ Elementary school
- ◯ High school graduate
- ◯ Some college
- ◯ Associate degree
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ Doctorate

A house contains a living room and a kitchen that are perfectly square. The living room has four times the area of the kitchen. If the walls of the kitchen are four meters long, how long are the walls of the living room?

____

Yesterday a store owner reduced the price of a pair of $100 shoes by 10 percent. This morning he reduced the price further by 10 percent. How much does the pair of shoes cost now?

____

If it takes 4 machines 4 minutes to make 4 forks, how many minutes would it take 80 machines to produce 80 forks?

____

In a lake there is a patch of lily pads. Every day it doubles in size. If it takes 100 days for the lily pads to cover the entire lake. How long (in days) does it take for the lily pads to cover half the lake?

____

A meal and a drink cost $11 in total. The meal costs $10 more than the drink. How much does the meal cost?

____

Please tell us, in general, how willing or unwilling you are to take risks.

[Completely unwilling to take risks 0 – very willing to take risks 10, in intervals of 1]

Do you own stocks in any form:

	Yes	No
Equity funds	○	○
Individual stocks in specific companies	○	○

Suppose you had $100 in a savings account and the interest rate was 2 percent per year. After 5 years, how much do you think you would have in the account if you left the money to grow:

○ More than $102

○ Exactly $102

○ Less than $102

○ Do not know

Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, with the money in this account, would you be able to buy:

- ○ More than today
- ○ Exactly the same as today
- ○ Less than today
- ○ Do not know

Do you think that the following statement is true or false? “Buying a single company stock usually provides a safer return than a stock mutual fund.”

- ○ True
- ○ False
- ○ Do not know

Thank you for participating in our study.

If you wish to remove your data from the study, please contact us through your Prolific account.

If you earn any bonus payment, it will be paid through Prolific in the next few weeks.

If you have any questions about the study, please feel free to contact Margaret Samahita (margaret.samahita@ucd.ie).

Please click the button below to be redirected back to Prolific and register your submission. In case needed, the completion code is C1E7BO2J.

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