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Speculating in zero-value assets: The greater fool game experiment

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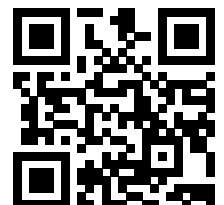
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Speculating in zero-value assets: The greater fool game experiment

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Abstract: In a pre-registered laboratory asset market study, we investigate dynamics of asset markets with zero (or close to zero) fundamental values. We introduce the “greater fool asset market game” with a zero-value token, whose price doubles in each period. We design several treatments, which differ in terms of whether the fundamental value is zero for sure, and whether the rather low probability of non-zero fundamentals is known (*RISK*) or not (*AMBIGUITY*). We find that prices in markets with zero fundamental value are clearly above zero. Furthermore, we report that prices in treatment *AMBIGUITY* are substantially higher than those in the baseline and in treatment *RISK*. Finally, we show that beliefs regarding the asset’s value and others’ participation explain individual market participation.

JEL: C91, C92, G12, G41

Keywords: speculative bubbles, greater fool, behavioral economics, experimental finance

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1 Introduction

Assume we offer you an opportunity to buy an asset that can quickly double in price. Under what conditions will you be willing to buy it? Does it depend on your belief regarding the fundamental value of the asset or rather on your belief about others being willing to buy from you at a higher price? Do you fear missing out when prices skyrocket? In other words, how much does your investment decision rely on narratives regarding underlying value or your beliefs regarding others?¹

These questions confer two basic approaches of financial market valuation: (1) the intrinsic-value theory and (2) the beauty contest aka greater fool theory (Malkiel, 1999).

(1): The intrinsic-value theory is the standard of textbook finance according to which the value of every asset is equal to the sum of its expected discounted cash flows. For example, the value of a stock is the discounted sum of expected dividends, and the value of fixed income assets as bonds is the sum of discounted annuity and principal payments. Investors are interested in the long-term cash-flows of assets, and markets have the ability to collect and equilibrate the long-term expectations regarding the intrinsic value of assets and the preferences of investors in this regard. Almost the entire financial asset pricing literature applies the intrinsic-value theory, only allowing for behavioral biases to explain anomalies relative to this theory. With real-world data, the intrinsic value theory is difficult to test directly, as the fundamental value cannot always be unambiguously determined. In laboratory research in which fundamental values can be directly observed and tested, prices have not always been shown to confirm the intrinsic value, as the formation of price bubbles were reported, thereby suggesting that intrinsic value is not the only aspect of importance for asset valuation (Palan, 2013).

(2): The greater fool theory suggests that an asset is worth what someone else will pay for it, independently of its intrinsic value. This theory assumes that market participants speculate on future prices, and markets collect individuals' (short-term) expectations on asset demand. Asset holders value the option to resell the asset at a higher price. We provide theoretical considerations in Section 4, which builds on the beauty contest theory and levels of reasoning (Nagel, 1995; Biais and Bossaerts, 1998; Crawford and Iriberri, 2007). In his essay on the state of long-term expectations, Keynes (1936) (chapter 12, V.4) famously suggested that asset pricing in the short-term is like a beauty contest:

“[Most persons] are concerned, not with what an investment is really worth to a man who buys it ‘for keeps,’ but with what the market will value it at, under

¹In our context, a narrative is an investment story or pitch aimed at persuading people to invest their money, particularly by emphasizing the potential for high returns.

the influence of mass psychology, three months or a year hence. [...] For it is not sensible to pay 25 for an investment of which you believe the prospective yield to justify a value of 30, if you also believe that the market will value it at 20 three months hence.”

According to the greater fool theory, market participants speculate on reselling the asset at a higher price in the future to someone else, who is commonly referred to be the “greater fool” (Malkiel, 1999; Aliber et al., 2015). Future price expectations have indeed been revealed to be a relevant factor in individual investment decisions (Carlé et al., 2019) and might be of particular importance in market environments with lottery-like assets with close-to-zero fundamentals and associated variability in traders’ beliefs regarding assets. In lottery-like assets, the very unlikely high payout of the asset (i.e., that the asset will skyrocket) can either be in an environment with known (decision under risk) or unknown (decision under ambiguity) probabilities (e.g., Ellsberg, 1961; Huber et al., 2014). Recent examples of such markets include cryptocurrencies² or collectibles.³ Furthermore, it is not uncommon for such markets to generate large amounts of trading volume but to potentially disappear due to scams or shutdowns, thereby leaving investors who failed to find a greater fool and, thus, wasting millions or even billions of dollars.⁴

At the time of writing this paper, we are not aware of a direct test of the greater fool theory. In this project, we propose such a test in a market experiment with zero-value assets—that is, assets for which the intrinsic value is zero or very close to zero. In this environment, we are able to eliminate the implications of the intrinsic-value theory. The reservation value is derived exclusively from the potential ability to resell the asset at a higher price in the future—that is, building on the expectations of the market participants.

²For example, cryptocurrencies have been suggested to derive their fundamental value from consumption and beliefs regarding its future value (Biais et al., 2023). However, cryptocurrencies have barely been used for consumption in the regular economy (Athey et al., 2016). First, for sellers, it is risky to accept cryptocurrencies as payment because there is no sovereign guarantee, the lack of which renders any currency easily replaceable. The high mortality rate of new cryptocurrencies emphasizes the instability and riskiness, as, for example, every third cryptocurrency coin issued between 2014 and 2021 vanished (Ammann et al., 2022). Second, purchasing goods with cryptocurrencies triggers a capital gains tax event, thereby rendering consumption significantly costlier in terms of transaction fees compared to fiat money. Cheah and Fry (2015) conclude that the fundamental value of cryptocurrency is zero and its market price is prone to speculative bubbles.

³Collectibles usually have no intrinsic financial value. Examples of collectibles include art, stamps and rare coins, antiques, game cards, crypto non-fungible tokens, and others. Beauty lies indeed in the eye of the beholder and such objects could potentially provide pleasures to the eye. However, most collectibles are not consumed by looks but are stored, preserved and maintained in safe places where they rarely entertain viewers’ eyes. See Pénasse and Renneboog (2022) for a study on mispricing in the art market.

⁴For a chronological listing of so called “rug-pulls” in markets for cryptocurrencies and NFTs, see <https://web3isgoinggreat.com/>.

Additionally, by introducing positively skewed assets, we aim to obtain an additional understanding of whether highly unlikely—but potentially high—payments drive participation in speculation. Finally, we are also interested in potential correlations with individual skills (e.g., level-k reasoning and CRT) and socioeconomic characteristics. We detail our research questions below in Section 5.

Our experimental design can be explained in the following manner: Five investor subjects simultaneously decide whether to buy a non-divisible, zero-value token at a fixed price. After each buying decision, we elicit the investors’ beliefs regarding market demand (greater fool beliefs), and assess their false belief in the token that has a value higher than zero. The token is randomly assigned to one of those who are willing to buy. The market repeats this in the next period with the price doubling and the token being put up for resale. The market game ends when there is no demand for the token in the market or when the maximum price is reached. The last buyer liquidates the token. In the *BASELINE* treatment, the token value is zero for sure, which is known to the subjects. We induce narratives by suggesting a potential but unlikely high positive payoff of the token, and vary subjects’ uncertainty regarding the potential payoff in *RISK* (knowing the probability) and *AMBIGUITY* (not knowing the probability) treatments. Overall, we ran the experiment with 94 independent groups, 47 of which participated in three *RISK* and one *BASELINE* market, while the other 47 were part of three *AMBIGUITY* and one *BASELINE* market, yielding a total of 376 markets included in our analysis.

Our results can be explained in the following manner: First, in the *BASELINE* treatment where the fundamental value is known to be zero, prices are usually positive and bidding does not stop in the first period, as suggested by intrinsic value theory. On average, *BASELINE* markets reach period 5 (average period of 5.18) out of a maximum of 11 periods. Second, we report that prices in markets with uncertainty regarding the fundamental value are substantially higher compared to markets in the *BASELINE* condition. Markets in the *RISK* treatment reach, on average, period 9 (average period of 9.49), while markets in the *AMBIGUITY* treatment are even higher and reach, on average, period 10 (average period of 10.34). This difference between *RISK* and *AMBIGUITY* markets is also significant. Furthermore, we show that incorrect subjective beliefs regarding the token’s value and, particularly, greater fool beliefs regarding the others’ future demand are determinants of individual market participation. This is evidence for greater fool trading motives, as traders, on average, believe that they will be able to resell the asset at inflated prices. Finally, we find suggestive evidence that level-k reasoning is negatively associated with participation, while both male gender and risk tolerance are positively correlated.

The most important finding of the study is that the resale option and narratives enter-

tain beliefs and impact trading behavior in asset markets. Thus, we contribute to literature on the beauty contest, the greater fool, and on mispricing in financial markets.

The remainder of the paper is organized in the following manner: Following the discussion of the related literature in section 2, we detail the experimental design in section 3. In section 4, we provide theoretical considerations, and section 5, we lay out the research questions and testable hypotheses. In section 6, we report the experimental results, followed by a brief discussion in section 7. In section 8, we present the concluding remarks.

2 Related literature

Most of the experimental literature on speculative bubbles builds on the paradigm established by [Smith et al. \(1988\)](#). In [Smith et al.’s \(1988\)](#) setup, a long-lived asset that pays a positive dividend at the end of each period is traded in a continuous double auction market. Because the number of periods is finite, the fundamental value of the asset decreases over time. Experimental evidence has revealed that in the early periods, the price typically moves from below to above the fundamental value and remains elevated for several periods, thus leading to over- and mispricing, subsequently crashing shortly before the final period. The following relevant results were reported: [Kirchler et al. \(2012\)](#) identified confusion as a driver of speculative bubbles, mainly resulting from the declining fundamental value. [Akiyama et al. \(2017\)](#) found that uncertainty regarding the behavior of others also contributes to mispricing. [Carlé et al. \(2019\)](#) revealed that individual beliefs regarding future prices guide the trading decisions of subjects. [Razen et al. \(2017\)](#) reported on the effects of novice traders on bubbles, and numerous studies have shown that experience, market liquidity, and trader characteristics impact mispricing ([Palan, 2013](#)). However, none of these studies directly addressed the greater fool theory.

The greater fool theory concerns heterogeneous expectations, mispricing, and speculation. [Keynes \(1936\)](#) introduced this idea through his “beauty contest” analogy, thereby suggesting that speculation is the primary driver of short-term investment. His theory emphasizes that what matters most in the short term is anticipating what the average opinion believes the average opinion will be. This concept has been tested in laboratory settings, such as the guessing game ([Nagel, 1995](#)), which reveals both heterogeneity and bounded rationality in decision-making. This observation inspired a broader literature on level-k thinking, which is a model of non-equilibrium behavior ([Crawford and Iriberri, 2007](#)). The impact of heterogeneous expectations on stock market prices was studied in a multi-period context with risk-neutral investors by [Harrison and Kreps \(1978\)](#). They revealed that

heterogeneous expectations can lead to asset prices exceeding the intrinsic asset value in certain periods in equilibrium. Following up on Harrison and Kreps’ suggestions that assets have speculative resale value, [Biais and Bossaerts \(1998\)](#) modeled investors’ heterogeneous expectations regarding both fundamentals and resale values. They reported that when investors agree to disagree about resale values, the investor with the maximum private appreciation of the fundamental value need not necessarily be a holder of the asset in all periods, but that investors with a lower appreciation of the fundamental value may hold the asset in certain periods if they highly value the resale option. [Scheinkman and Xiong \(2003\)](#) built on [Harrison and Kreps \(1978\)](#) proposed a theory of heterogeneous expectations. They propose that overconfidence leads to disagreements among agents regarding asset fundamentals, potentially resulting in mispricing. Similarly, [Pénasse and Renneboog \(2022\)](#) acknowledged the role of heterogeneous expectations and the greater fool theory in their empirical analysis of mispricing in the art market.

Closely related to our study is the paper of [Moinas and Pouget \(2013\)](#), which introduced a game to study speculative bubbles. This so-called *bubble game* shares a few similarities to the centipede game,⁵ in which the joint payoff sum can increase if players play “buy.” [Moinas and Pouget \(2013\)](#) applied behavioral game theory to show that irrational bubbles and (assuming unbounded signals also) rational bubbles can form in the bubble game, which implies that that bounded rational players choose “buy.” If players expect the following players to select “buy” due to irrationality, the player can earn a higher expected payoff by selecting “buy” than in the rational strategy equilibrium.⁶ Irrationality—which may lead to deviation from rational equilibrium play in the bubble game—can be of any kind, including the beliefs regarding others, confusion, or altruism. Since the experimental design of [Moinas and Pouget \(2013\)](#) involved no elicitation of individual beliefs, the rationale underlying selecting “buy” cannot be clearly identified and, in contrast to our design, the greater fool theory cannot be tested.

⁵Like in the centipede game, in the unique equilibrium, all players select “take” when it is their turn, and no player selects “pass”. The action “pass” in the bubble game is called “buy”, the action “take” is called “not buy”. Unlike the centipede game, it is a three-player game and each player makes just one decision. Players have incomplete information regarding their type; a private noisy signal indicates the player’s likely turn in the game, and players frequently make their decisions without knowing when it is their turn.

⁶In line with the theory, the data reveal that subjects are more likely to choose “buy” when their probability of not being last increases. In particular, subjects always select “buy” if they are certain about not being last. At odds with the theory, a few subjects even buy when they know they are last, which indicates that they are either confused or acting altruistically.

3 Experimental procedure

In our experiment, five participants were grouped according to their arrival time in the session and participated in four incentivized experimental tasks—that is, (i) the beauty contest (Nagel, 1995), (ii) our greater fool game as group tasks with fixed groups, (iii) the game of NIM (Dufwenberg et al., 2010), and (iv) a modified cognitive reflection test (Fredderick, 2005)—as individual tasks. At the end of the experiment, participants filled out a questionnaire (see Appendix A for details on the questions). In order to avoid any house money effects across tasks, participants learned about their total payoff and their performance in each task only at the end of the experiment. The experiment was programmed using oTree Chen et al. (2016). We ran the experiment between December 2023 and March 2024 at the EconLab of the University of Innsbruck. In total, 470 subjects participated in the experiment. The target sample size was derived by ex-ante power calculations (see Section B in the Appendix for details). The average payout for participants in the experiment was €14.50, and the average duration of a session was 35 minutes. Screenshots of the software and instructions in English are provided in Appendix A. The lab experiment was conducted in German.

Beauty Contest: Based on Nagel (1995), each participant selected an integer number between 0 and 100 and the winner of the contest was the one whose number is closest to two-thirds of the average number selected within the group. For illustration purposes, an example was provided, while the time was limited to 5 minutes. Our variable of interest is the type of level- k of a player, which we calculate in a similar manner that in Nagel (1995): A person is of type level- k if $50p^{k+1} < guess \leq 50p^k$, where $guess$ is the selected integer number and $p = \frac{2}{3}$.⁷ The type of level- k serves as a control variable in one of our main analyses. As this task served as an initial task that gave participants an endowment for the subsequent auctions in the greater fool game, every participant received €12 for providing a guess (to ensure that everybody has the same endowment for the greater fool Game), and the winner of the contest (only announced at the end of the experiment) received a bonus payment of €5.

The Greater Fool Game: This is the main task of the experiment. Within the same group, subjects participated in four independent sequential markets consisting of up to 11 periods each. In the end, one market was randomly determined to be payout-relevant.

⁷Because participants can only type in positive integer numbers, we define an integer number range around $50p^k$; thus for example a participant is of type level-1 when the guess is 33 or 34, and so on. For guesses higher than 34, we set level- k to be 0, assuming that the subject made a random guess. Additionally, we set the maximum level- k a participant can be classified as at 8, in which participants were categorized according to whether they guessed the numbers 0 or 1.

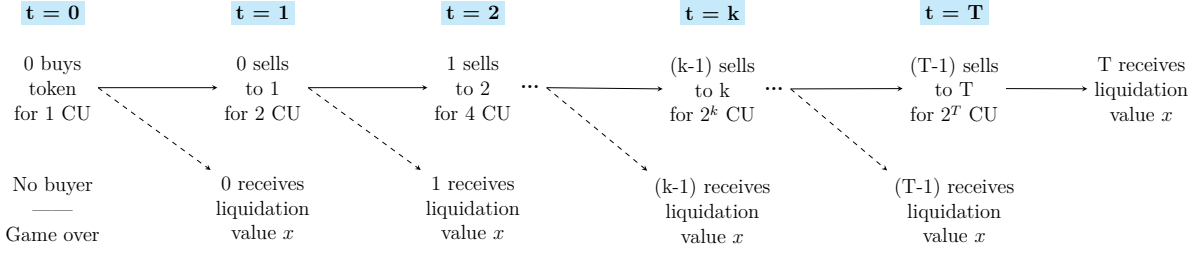


Figure 1: Timeline. This figure illustrates the timeline of the greater fool game. Investor $i = \{0, 1, \dots, T\}$ indicates a buyer in a particular market period. The solid horizontal arrows indicate the consequence when there is a buyer for the token, while the dashed diagonal arrows illustrate the consequence if there is no other buyer except the current token holder. i can be a buyer in multiple periods and even buy from herself if there are other bidders in the market period (i.e., if he/she is again the randomly selected bidder across all bidders in the current period). In our baseline experiment, we set the parameter to $T = 10$, $x = 0$. CU denotes Eurocents.

Each of the four markets proceeded in the following manner: In the first period, one non-divisible token was put up for sale with the possibility of resale in subsequent periods for a higher price. Subjects had an endowment of €12 and were aware from the beginning that the price of the token doubled from period to period. The price in the first period was €0.01; hence, the price in period 11 was €10.24. In each period, every subject made a decision to bid or not to bid for the token at the announced price. The market ended after period 11 or in the period in which no subject (other than the current token holder) decided to bid for the token—that is, as soon as all subjects (other than the current token holder) exited the market.

In the first period, the first token holder was randomly selected from among the bidders and paid €0.01 for the purchase (to the experimenter). In each subsequent period, the buyer was also randomly selected from among the bidders. The buyer then paid the price to the old token holder and became the new token holder. The new token holder could be the old token holder, if he/she was the randomly selected bidder in that period. If the old token holder was the only bidder, the market would end after that period. When a market ended, irrespective of whether it reached period 11 or ended in an earlier period, the current token holder received the liquidation value of the token (usually zero) to his account. Figure 1 illustrates the timeline of a market.

The token’s liquidation value, which always resulted in being zero in the experiment, was private information to its final holder and remains ambiguous information to the others (except in the baseline condition, in which the value was zero with certainty). In addition to their bidding behavior, participants in each round had to make predictions regarding the value of the token (estimated probability that the value of the token is anything other than €0), and the number of other bidders in both the current and the following period (integer

between 0 and 4, respectively). At the end of the experiment, one period of the payout-relevant market was randomly drawn. If the participant’s predictions for that period were accurate⁸, a bonus payment of €1 was added to their total payoff.

We introduced treatment variations along two dimensions—that is, within-subjects and between-subjects.

First, to investigate the effect of narratives in the form of higher prospective gains in such markets, we varied the fundamental value the token holder received at the end of a market within-subjects. In our *BASELINE* condition, the value of the token was €0 with certainty, while in other markets the value of the token was either €0 with a probability of $\frac{46655}{46656}$ or €H with a probability of $\frac{1}{46656}$. This is the probability that six sequentially rolled fair dice all show six simultaneously. This is also how the probability was explained to participants in treatment *RISK*. We set $H = 10, 30, 100$, which implies that the fundamental value of the token in expectation was always below €0.01. In particular, the expected values ranged from €0.00021 to €0.0021, thus making it irrational to place any bids according to the intrinsic-value theory. Groups participated in a total of four markets, the baseline condition (i.e., the token value is €0 with certainty) and three treatment variations (i.e., the token value is either €0 or a higher liquidation value €H, which was either €10, €30, or €100). The sequence of markets is determined by a random draw without replacement at the beginning of the experiment for each group, respectively.

Second, we varied the degree of uncertainty between subjects. We distinguished between two treatment conditions, i.e., *RISK* and *AMBIGUITY*. In the *RISK* treatment, the groups were aware of the probability of the token having the higher liquidation value as we commonly informed them about the $\frac{1}{46656}$ probability. In contrast, in the *AMBIGUITY* treatment, the groups did not receive information regarding this probability. Table 1 summarizes our treatments.

In order to ensure that participants understood the game, we introduced several comprehension checks in which we also elicited whether market participants got these questions right or wrong.⁹ After reading the instructions, participants were required to answer two

⁸We defined the predictions to be accurate when (i) the rounded probability of the token having a value other than €0 was correct (i.e., smaller than 50% when the value of the token is €0, and greater than or equal to 50% when the value was €H), (ii) the guessed number of bidders was correct, and (iii) the guessed number of bidders in the following period was correct. In case period 11 or a period in which the market ended early is randomly selected, only (i) and (ii) applied.

⁹We recorded participants’ initial answer. If they got it wrong, they saw a clarification box and had to adjust their answers. In case they answered the question correctly, they saw a confirmation message along with a detailed description on why the answer is correct.

Table 1: Treatment design. Groups were assigned either the *RISK* or the *AMBIGUITY* treatments (i.e., between-subject variation), where they participated in a total of four markets (i.e., one of two within-subject variations, separated by the vertical line). In each market the fundamental value of the token was altered. In the baseline condition, the fundamental value of the token was €0 with certainty, while in the other markets it could also be worth either €10, €30, €100 with a probability of $\frac{1}{46656}$ —that is, when six independent dice throws showed the number six each.

Treatment	Token value	Information about other value
<i>BASELINE: RISK 0</i>	€0 certain	
<i>RISK 10</i>	€0 or €10	“six dice show the number 6 each”
<i>RISK 30</i>	€0 or €30	“six dice show the number 6 each”
<i>RISK 100</i>	€0 or €100	“six dice show the number 6 each”
<i>BASELINE: AMBIGUITY 0</i>	€0 certain	
<i>AMBIGUITY 10</i>	€0 or €10	no information
<i>AMBIGUITY 30</i>	€0 or €30	no information
<i>AMBIGUITY 100</i>	€0 or €100	no information

questions regarding the outcome of two hypothetical market periods¹⁰ and two questions regarding the general mechanics of the game.¹¹ Additionally, we asked one treatment-specific question immediately before the corresponding market started.¹² All questions are provided in the instructions in Appendix A.

Finally, to enable a smooth flow of the experiment, we included several time limits for responses. Note that each group progressed at its own pace, independently of the other groups. If no one in the group was willing to bid on the token, the experiment for that group would end quickly. As groups were able to finish early and thereby earn a higher hourly wage, we believe this approach minimized any potential “experimenter demand effect” (Zizzo, 2010) and boredom. For the instructions and the initial battery of comprehension checks, participants could take five minutes. For the treatment-specific checks, the time was limited to one minute. For the first decision in their first market, participants got three minutes for familiarizing themselves with the market environment or to read the instructions again, if necessary. Similarly, they had three minutes of time

¹⁰For example, “Given that the participant is the current holder of the token and the market ends in that period, what is the minimum and maximum amount that the participant gets given a current price of the token and the potential value(s) of the token (depending on whether the token value is €0 with certainty, or either €0 or €H)?”

¹¹For example, “Given that the participant is the current token holder and sells it to someone else, does he or she then get the price or the value of the token?”

¹²For example, “Given the participant is in the treatment where the token value can be either €0 or €H, with H being 30, what is the minimum and maximum amount the participant gets being the current token holder if the market ends in a period in which the price is €1.28 and the value of the token is €0 or €30?”

for their first prediction. Thereafter, every bidding decision and prediction elicitation was restricted to a maximum of 20 seconds. In any case, if there was a timeout, the computer made a decision for the participants; the default was not to bid; if they made a bidding decision in a previous period, this decision was repeated. We told subjects that for timeouts the computer will decide for them. For the beliefs in the case of a timeout, the inputs that were already made were recorded. We additionally recorded the number of timeouts per individual, which then served as a potential metric for the exclusion criteria for the analysis for the individual participant data.¹³

Game of NIM: After our greater fool game, participants played a game of NIM against a computer player, which closely followed the two-player *Game of 21* given in [Dufwenberg et al. \(2010\)](#). In our version of the game, the computer and the participant alternately selected an integer number between one and three, where the computer was the first mover and generally made random selection.¹⁴ The first player who reached the number of 20 won the game. The participants got a bonus payment of €1 if he/she won the game. Our variable of interest is the number of backward induction steps. We assigned a player to level 1 if 16 was one of his/her observed choices; to level 2 if he/she selected 16 and 12; to level 3 if he/she selected 16, 12, and 8; and to level 4 if he/she selected 16, 12, 8, and 4. In all other cases, the player was assigned to level 0.¹⁵ However, this variable only served as control variable in one of our analyses.

Cognitive reflection test (CRT): In the last task, participants answered three modified questions of a CRT, following [Frederick \(2005\)](#). Here, our variable of interest is the number of correct answers in the CRT, which also served as a control variable. In the end, one question was randomly drawn and if participants answered that question correctly, a bonus payment of €1 was added to their payoff. As in the prior tasks, a timeout of 90 seconds was included for all three questions.

Questionnaire: Finally, subjects filled out a questionnaire that elicited data on the fear of missing out (FOMO) using nine items, which are inspired by [Przybylski et al. \(2013\)](#) and were set in a finance context, financial literacy using the sum of correct answers in the “Big Three” (see [Lusardi and Mitchell, 2011](#)), self-assessed financial literacy, proficiency in

¹³A timeout occurred only in 0.8% of bidding decisions and 2.81% of belief elicitations a timeout happened.

¹⁴The exception here was when the computer had the possibility of winning the game (i.e. the counter > 16). If this was the case, the computer was coded in such a manner that it won the game.

¹⁵[Dufwenberg et al. \(2010\)](#) calls the first round in which the player hits the sequence of numbers of the dominant strategy *the moment of epiphany*. For ease of interpretation in the analysis, our measure is the direct inverse of that number, thereby implying that higher numbers indicate a more sophisticated level of rationality.

math, whether they are a number cruncher or a storyteller from [Damodaran \(2017\)](#), and self-stated risk preferences when doing investments adjusted from [Dohmen et al. \(2011\)](#). All these items were asked using a 11-point likert scale.¹⁶ Additionally, we also asked for subjects' age (integer number) and gender (female, male and diverse). All the variables serve as control variables in our analysis for individual data.

The experiment ended with a summary where participants saw their performance and payoffs in the different tasks. After completing the experiment, they received their payoff privately.

4 Theoretical considerations

To illustrate how the intrinsic value and greater fool theory differently impact the investing decision of participants in our experiment, we drew on models from the literature, particularly those proposed by [Biais and Bossaerts \(1998\)](#), [Nagel \(1995\)](#), and [Crawford and Iriberri \(2007\)](#).

Each investor i has a reservation value, r_t^i , that represents her maximum willingness to pay. This reservation value combines both the private intrinsic value, μ_t^i , and the optional value assigned to the possibility of reselling the asset, w_t^i .

$$r_t^i = \mu_t^i + w_t^i, \quad (1)$$

In our experiment, since the fundamental was a constant common value, F , we have $\mu_t^i = F \forall i, t$. Investors derive their reservation values through backward induction. Rationality dictates that in the final trading period, no reservation price could exceed F , as that value must be consumed in $T < \infty$. Hence, $w_T^i = 0$ and $r_T^i = F$. Assuming mutual knowledge of rationality (at least up to level $T-t+1$), the expected maximum resale value is calculated in the period $t \leq T-1$ in the following manner:

$$w_t^i = \lambda_t^i(\max\{r_{t+1}^1, r_{t+1}^2, \dots, r_{t+1}^n\} > p_{t+1}) \cdot \max\{(p_{t+1} - \mu_t^i); 0\}, \quad (2)$$

where $\lambda_t^i(.)$ denotes investor i 's belief regarding the market reservation value and p_t denotes

¹⁶The items in the FOMO questionnaire were designed in such a manner that stronger agreement translates into a stronger fear of missing out. However, two items are related to the concepts of temptations and self-discipline ([Razen et al., 2021](#)). For these variables, we reversed the order, which implies that lower values indicate a stronger fear of missing out. For proficiency in math and finance, the scale ranges from 0 (very weak/low) to 10 (very strong/high); for questions from [Damodaran \(2017\)](#) it ranges from 0 (number cruncher) to 10 (storyteller); and for self-stated risk preferences it ranges from 0 (not willing to take any risks) to 10 (fully prepared to take risks).

the market price in the period. Note that the resale value depends on the expectation of being able to sell the asset at a higher price to someone else.

In period $T-1$, no rational buyer will offer more than the fundamental value for the asset, since any potential buyer in the final period will pay at most that amount, $\max\{r_T^j\} = F$. If investor i buys the asset at a price that exceeds the fundamental value, he/she will either consume the fundamental value in the final period, or receive at most the fundamental value in the resale. Consequently, he/she would make a loss when agreeing to purchase at a price that exceeds the fundamental value in period $T-1$. Since each investor recognizes this, given the mutual knowledge of rationality, the maximum price cannot exceed the fundamental value in any of the $T-t+1$ remaining periods by the same reasoning. Therefore, the maximum price in any period cannot exceed the fundamental value. According to the rational intrinsic value theory, the market price is determined by the fundamental value,¹⁷—that is.,

$$p_t \leq F. \quad (3)$$

In contrast, the greater fool theory suggests that some level of irrationality exists among investors, along with heterogeneous expectations. This irrationality can manifest as confusion regarding an asset's fundamental value (e.g., [Kirchler et al., 2012](#)), thereby leading an investor to assign a higher private value to the asset, $\mu_t^i > F$, despite the common information. Due to the potential of false beliefs, the possibility that the market price in the final period may exceed the fundamental value cannot be eliminated.

However, more critical than individual irrational behavior is the cascading effect of mutual beliefs regarding others' irrationality on market behavior. The belief that the asset can potentially be sold in all periods for a price above its fundamental value alters the belief hierarchy, thereby impacting the perceived value of the resale option and the reservation price. The resale value is a function of these cascading mutual beliefs; it depends on the belief regarding the belief regarding the belief etc. that the possibility of a confused investor who buys at all price levels does exist. Consequently, the reservation value changes by backward induction. The following equations illustrate the process of recursive reasoning:¹⁸

$$r_T^i = \mu_T^i \quad (4)$$

¹⁷In case of continuity of price and fundamental value, the two numbers coincide; price equals fundamental value.

¹⁸We use the following notation here—first-order belief: $\lambda_1^i(r_t) \equiv \lambda_1^i(r_t^1, \dots, r_t^n)$; second-order belief: $\lambda_2^i(\lambda_1(r_t)) \equiv \lambda_2^i(\lambda_1^1(r_t), \dots, \lambda_1^n(r_t))$; etc.

$$r_{T-1}^i = \mu_{T-1}^i + w_{T-1}^i(\lambda_{T-1}^i(r_T)) \quad (5)$$

$$r_{T-2}^i = \mu_{T-2}^i + w_{T-2}^i(\lambda_{T-2}^i(\lambda_{T-1}^i(r_T))) \quad (6)$$

$$r_{T-k}^i = \mu_{T-k}^i + w_{T-k}^i(\lambda_{T-k}^i(\lambda_{T-k+1}^i(\dots(\lambda_{T-1}^i(r_T))\dots))), \quad (7)$$

To keep things simple in terms of clarifying the greater fool concept in our experimental setting, we referred to the level-k model (i.e., [Nagel, 1995](#); [Crawford and Iriberri, 2007](#)). [Crawford and Iriberri \(2007\)](#) applied this non-equilibrium concept to the winner’s curse problem. Level-0 players represent confused investors who would be willing to buy the asset above fundamental value in the last period if and only if their private value exceeds the fundamental value, $\mu_T^i > F$. Assuming the existence of such level-0 players, level-1 players playing best response to level-0 would be willing to buy at every lower price than level-0 is willing to pay. Level-2 players best respond to level-1 players by bidding to buy the asset at least until period $T - 2$. This recursion extends to level-k players, who will bid to buy the asset at least until period $T - k$. Each investor of level-k, $k > 0$, assumes that he/she can sell to a greater fool at a higher price in the future.

5 Research questions and hypotheses

In this section, we translate the outlined theoretical considerations into testable hypotheses to address our research questions (RQs). Both the hypotheses and research questions follow our pre-analysis plan.

RQ 1: Do markets with zero fundamental value reach prices above zero?

RQ 2: Does uncertainty regarding the fundamental value of the asset lead to higher prices compared to the markets with known zero fundamental value?

RQ 3: Do prices differ in a situation with ambiguity (no probabilities of a potentially high outcome known) or in a situation with risk (known probabilities)?

RQ 4: Which role do beliefs play for participation in such markets?

RQ 5: Which personal characteristics can explain participation in such markets?

RQ 1 is an attempt to bring asset markets with zero fundamental value from the field into the lab. **RQ 2** mirrors the effect of possible high future gains potentially driving these markets, which is, as outlined above, their common feature. **RQ 3** identifies the effect of knowing or believing to know about the probability of high payouts. Therefore, **RQ 1** and **RQ 2** touch upon the literature strands on “greater fool” ([Miller, 1977](#); [Malkiel,](#)

1999; Aliber et al., 2015) and on probability misweighting (i.e., one important feature of Prospect Theory of Kahneman and Tversky, 1979). **RQ 4** and **RQ 5** focus on the role of beliefs and personal characteristics on the participation in such markets.

In line with the intrinsic value theory, and as suggested in equation (3), our first testable hypothesis, *H1*, which mainly concerns the baseline treatment, addresses **RQ1**.

H1: Markets with a certain fundamental value of zero do not reach positive prices.

This hypothesis of market pricing at intrinsic value is straightforward when the fundamental value is known with certainty, but it also applies to all risk treatments. In the risk treatments, the fundamental value is known to be below the smallest possible positive price. Therefore, according to the intrinsic value theory, no positive market price of the token can be expected. Hypothesis *H1* builds on rational expectations.

For **RQ2**, we anticipate that altering the potential payoff of the token will affect its price—due to the cascading of (false) beliefs—even if the fundamental value remains largely unchanged due to the low probability of the occurrence of the high payout. In line with the greater fool theory, subjects may believe that the maximum reservation price in the market exceeds zero, either because someone else holds false beliefs on fundamentals and/or because others believe that someone else holds false beliefs, etc. If there exist such false beliefs in the market, it appears reasonable to expect that the possibility of obtaining a high potential token value reinforces them. As the potential payoff increases, this possibility is likely to impact the perceived resale value and thus accelerate mispricing.

H2a: Prices are higher when the prospective high value is positive than when it is zero.

H2b: Prices increase with the prospective high value.

For **RQ3**, we explore the secondary treatment variation of uncertainty. For example, Maafi (2011), shows preference reversals under ambiguity, indicating that ambiguous lotteries (where probabilities are unknown) tend to be overvalued compared to risky lotteries with known probabilities. In addition, the cancellation of extremely small probabilities would imply that when subjects in the risk treatment are informed of the low probability of winning, ($\frac{1}{46656}$), they may treat it as zero (Kahneman and Tversky, 1979; Neugebauer, 2010). Thus, given the extremely low probability of winning in our setting, leaving the winning probability ambiguous could lead to higher prices, as people assume a higher winning probability. In contrast, ambiguity aversion (Ellsberg, 1961) provides a rationale for a di-

minished willingness to pay when the probability of winning is unknown. Since preferences for ambiguity are reported in lotteries with low probability outcomes (e.g., [Maafi, 2011](#)), we anticipate that cancellation of probabilities can play a role for many participants in the *RISK* treatment, thereby impacting the perceived resale values and ultimately leading to higher prices in *AMBIGUITY* than in *RISK*:

H3: Prices in a situation with *AMBIGUITY* (no probabilities known) are higher than in a situation with *RISK* (known probabilities), given the extremely low probability of the prospective high value.

With regard to **RQ4**, we expect that beliefs determine an individual’s market participation ([Carlé et al., 2019](#)). In line with the greater fool theory discussed in the previous section, false beliefs regarding fundamentals, along with expectations regarding others’ future participation, are likely to shape individual reservation values and, consequently, bidding behavior. Hence, we test the following hypotheses:

H4a: The probability to bid increases with the subjective stated probability of observing a positive token value.

H4b: The probability to bid increases with the expected number of bidders in the following period.

Note that we did not formulate a clear hypothesis for **RQ5**, as this research question is of exploratory nature. However, as suggested in the previous section, level-k reasoning should influence bidding behavior, with bids decreasing as the level (k) of reasoning increases. The individual level-k was assessed during the guessing game stage of our experiment. We decided to run a multiverse analysis (see [Simonsohn et al., 2020](#)) to account for the exploratory nature of **RQ5**.

6 Results

Descriptive statistics regarding the sample and the outcome variables of the side tasks are shown in Table 2. Additionally, Figure 2 illustrates the relative frequencies of final transaction prices, which are separated across treatments. In brief, this figure depicts that the mass of final transaction prices shifts to higher amounts in markets in which the payoff of the token is higher than €0. In the upcoming section, we present the main findings based on the hypotheses first and then the exploratory results related to individual outcomes. If not stated otherwise, all figures and regression models mentioned there are pre-registered. Finally, note that we follow significance thresholds of Benjamin et al. (2018), where a p -value < 0.05 is considered “suggestive evidence,” while a p -value < 0.005 defines “statistical significance.”

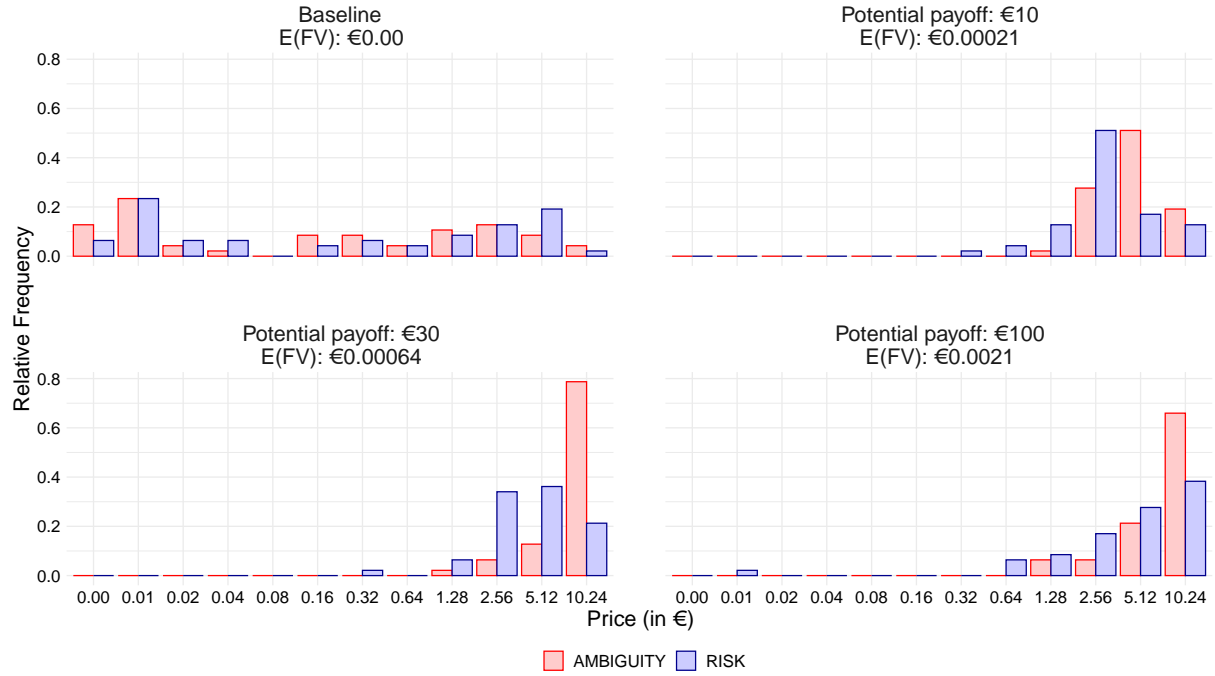


Figure 2: Final prices. This figure illustrates the relative frequency of final trading prices across treatments. In *BASELINE*, the token value was €0 with certainty, while in all other treatments the token could have a value of €10, or €30, €100 with a probability of $\frac{1}{46656}$, respectively. In *RISK*, participants were informed about this probability (i.e., “when six dice show six at the same time”), while in *AMBIGUITY* this information was not made known to participants.

Table 2: Sample descriptions. This table presents descriptive statistics of the sample characteristics as well as the outcome variables of the the side tasks, separated by our between-subject design. “Age” is participants’ age in years. “Math” denotes participants’ self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong). “Guess” is the number participants guessed in the beauty contest, with lower numbers translating into higher levels of rationality. “Nim” is the number of times participants consecutively hit a multiple of four, with higher numbers implying that the participant figured out the backward-inducing dominant strategy earlier. “CRT” is the number of correct answers in the three-item cognitive reflection test. “Self-assessed” knowledge denotes participant’s self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while “financial literacy” is the number of correct answers in the Big Three financial literacy quiz. “Storyteller/Number cruncher” is participant’ self-assessed positioning of themselves of whether they are more of a story teller or more of a number cruncher kind of person on a 11-point scale (0 = Story teller; 10 = Number cruncher), and “self-assessed risk” is participants’ self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks). “FOMO” denotes our 9-item questionnaire eliciting participants’ self-assessed susceptibility to the fear of missing out, including their resistance to temptations (“Temptations”), level of self-discipline (“Self-disciplined”), fear of others make more money in the experiment (“Fear”), being bothered by missing an opportunity to make money (“Missed opportunity”), agreement that investing early in a project is most beneficial (“Early investment”), susceptibility to making an investment based on a friend’s recommendation (“Exciting investment”) or celebrities making an investment (“Celebrities”), and their susceptibility to investing when they see asset prices skyrocketing (“Skyrocketing”) or plummeting (“Plummeting”). All these items are elicited using an 11-point likert scale (0 = strongly disagree; 10 = strongly agree). Gender denotes participants’ gender.

	RISK (N = 47)					AMBIGUITY (N = 47)				
	N	Mean	SD	Min.	Max.	N	Mean	SD	Min.	Max.
Age	235	23.32	5.12	18	82	235	22.68	3.32	18	44
Math	235	5.84	2.10	1	10	235	6.00	2.04	0	10
Guess	235	30.01	21.26	0	100	235	30.65	20.52	1	100
Nim	235	0.73	0.95	0	4	235	0.76	1.02	0	4
CRT	235	1.78	1.08	0	3	235	1.90	1.02	0	3
Self-assessed knowledge	235	4.10	2.30	0	10	235	4.24	2.34	0	10
Financial literacy	235	2.61	0.72	0	3	235	2.62	0.62	0	3
Number cruncher/Storyteller	235	4.51	2.60	0	10	235	4.61	2.59	0	10
Self-assessed risk	235	3.60	2.43	0	10	235	4.09	2.39	0	10
FOMO										
Temptations	235	5.50	2.33	0	10	235	5.37	2.35	0	10
Self-disciplined	235	5.83	2.45	0	10	235	5.76	2.44	0	10
Fear	235	5.23	3.15	0	10	235	6.13	2.85	0	10
Missed opportunity	235	5.69	2.69	0	10	235	6.17	2.74	0	10
Early investment	235	6.03	2.50	0	10	235	6.51	2.18	0	10
Exciting investment	235	3.26	2.41	0	10	235	3.29	2.44	0	10
Celebrities	235	1.19	1.53	0	8	235	1.28	1.85	0	10
Skyrocketing	235	2.82	2.14	0	8	235	2.80	2.18	0	8
Plummeting	235	3.26	2.45	0	10	235	3.59	2.66	0	10
Gender										
Female	144	0.61				139	0.59			
Male	90	0.38				95	0.40			
Diverse	1	0.00				1	0.01			

6.1 Market outcomes

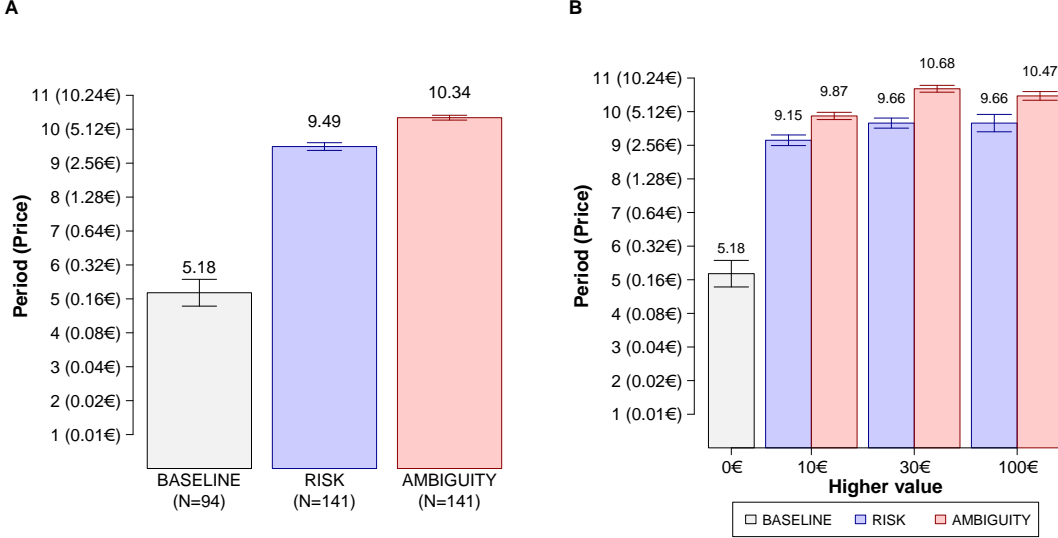


Figure 3: Last trading prices. This figure illustrates the average last trading price across A) uncertainty treatments (pooled in higher prospective values), and B) uncertainty treatments and higher prospective values, respectively. Note that the expected fundamental values in markets in *RISK* range between €0.00021 (higher value = €10) and €0.0021 (higher value = €100).

Result 1 (H1): Markets with a certain fundamental value of zero do regularly reach positive prices.

Support: Panels A and B in Figure 3 provide an overview of the mean last period prices (and numbers of periods traded) across *BASELINE*, *RISK*, and *AMBIGUITY* (Panel A) and across the higher token values (Panel B). Furthermore, Figure C.2 in the Appendix depicts the average number of bidders over time (periods) across treatments. As indicated by these figures, we find strong evidence against *H1*, as, on average, markets in *BASELINE* end after period five (5.18) and, thus, reach price levels of more than €0.16. Hence, participants in our experiment clearly engaged in some form of speculation, hoping not only that they can sell a token with zero liquidation value to someone else at a higher price, but also that other participants in their group have similar reasoning.

Result 2: Prices in markets with uncertainty are higher than in markets with a certain fundamental value of zero (*H2a*), and increase with the prospective high value (*H2b*).

Support: As indicated in Figure 3, market settings other than *BASELINE* tend to end in subsequent periods and reach higher transaction prices. On average, prices in the *RISK* treatment reach levels of over €2.56, while prices in *AMBIGUITY* reach levels of over €5.12

(see Panel A of Figure 3). Additionally, as outlined in column (1) of Table 3, the coefficient for being in a market other than in the baseline (i.e., *UNCERTAIN*) is positive and highly significant.¹⁹ We find strong support for *H2a*, thereby indicating that as soon as there is the slightest likelihood of fundamentals climbing above zero—in our case the probability of the token value exceeding zero is $\frac{1}{46656}$ and this yields expected fundamental values in ranging between €0.00021 and €0.0021—prices become significantly higher than in zero fundamental value environments. Moreover, we observe support for significantly increasing market prices with increasing high outcomes of the token value (i.e., €0, €10, €30, or €100)—see column 2 in Table 3. The increase in prices is significant for differences from 0 to 10 and from 10 to 30, but not from 30 to 100 (tests for significant differences between treatments are outlined at the bottom of the table). This finding provides partial evidence that high outcome values with low probabilities (or ambiguous ones) are attractive and trigger traders to overvalue token values even more. Discussing hypotheses *H2a* and *H2b* jointly, we observe a strong overvaluation of markets with non-zero fundamentals. As compared with the the expected fundamental values of €0.00021 and €0.0021, in markets with higher prospective token values of 10 and 100, respectively, average market prices of over €2.56 (predominantly in *RISK*) and more than €5.12 (mainly in *AMBIGUITY*) indicate massive overvaluation of these positively skewed assets.

Result 3 (H3): Prices in *AMBIGUITY* are higher than those in *RISK*.

Support: We find support for *H3* in column 3 of Table 3. Here, we regress the final trading period on treatment dummies for all *RISK* and *AMBIGUITY* treatments again. We tested the latter coefficients for significant differences, with the results presented at the bottom of the table.²⁰ We find a clear pattern of significantly higher prices (more trading periods) under ambiguity than under risk. The only exception is the difference between both treatments with a prospective high outcome value of 100, as the difference is only at the level of suggestive evidence (i.e., the 5% level). This finding is in line with the literature on preference reversals under ambiguity and supports the findings of Maafi (2011), thereby

¹⁹We pre-registered using H1 robust standard errors in our models. However, due to the grouping nature of the data imposed by the experimental design, cluster robust standard errors are more appropriate.

²⁰For the model in column (3) of Table 3, we pre-registered a regression with a dummy indicator for *AMBIGUITY* markets and dummy indicators for the higher value the token can possibly take on, including interaction terms among all of them. However, running such a model causes co-linearity issues—that is, a dummy variable trap. Hence, we include dummy variables of each of our between-subject designs (see Table 1), respectively, and run post-hoc tests for significant differences between *RISK* and *AMBIGUITY* markets. An alternative but similar analysis as the one that is pre-registered and also includes interaction terms is a subsample analysis, where only markets other than *BASELINE* are included in the sample. This is presented in Appendix C in Table C.1. The results are qualitatively the same.

revealing preference reversals under ambiguity. Here, ambiguous lotteries (probabilities are unknown) with positive skewness (i.e., high potential gain with low probability) are overvalued with respect to risky lotteries where probabilities are given.

6.2 Individual beliefs and behavior

Result 4: The probability of bidding increases with the subjective belief that the token’s value is not zero ($H4a$) as well as the belief regarding the number of bidders in the current (non pre-registered) and next round ($H4b$). Furthermore, individuals with the token in their possession are more likely to sell it immediately (non pre-registered).

Support: We turn to individual bidding behavior and the role of beliefs and personal characteristics across various market settings. Figure 4 and Table 4 present the results.²¹ Note that we exclude observations from period 11 since we did not elicit individuals’ belief for the number of upcoming bidders in the last period. Additionally, we exclude all observations in which there was a timeout (695 of 16,700 full observations between periods 1 and 10).

In line with $H4a$ and $H4b$, we find that an individual’s likelihood to bid increases significantly with his/her subjective belief regarding (i) the higher value of the token and (ii) the expected number of bidders in the following period—that is, greater fool expectations. Moreover, by expanding the set of explanatory variables in an additional, non pre-registered analysis (see Table C.3 in Appendix C), we find that (iii) holding the token during a period significantly reduces the likelihood of bidding, thereby increasing the propensity to sell the token. Moreover, we find that (iv) beliefs regarding the number of bidders in the current round are also significantly related to bidding behavior. While the findings related to beliefs are in line with consistent bidding behavior—that is, higher beliefs regarding the token value trigger a higher propensity to bid—the latter finding on immediately reselling the token further corroborates the greater fool motives being a potential explanation for trading in our markets. Finally, the results remain robust when controlling

²¹We pre-registered a mixed effect logit regression since we assumed a nested structure (i.e., multiple observations of the same individual being part of the same group over the course of the experiment). When running the nested model with the battery of covariates presented in column 3 of Table C.2, the output suggests that no variance stems from the group structure. We did not expect that, but as the level of interaction between group members is kept at a bare minimum (i.e., participants did not receive any information regarding the number of bidders in the current period; the only feedback they saw was whether their order was successful, and they knew when the market continued that at least one bidder in addition to the token holder is in the market), it is reasonable. Hence, we decided to reduce to a model that only includes individual random effects. The output of the analysis suggested in the pre-analysis plan is presented in Appendix C in Table C.2. The results remain quantitatively and qualitatively the same.

Table 3: Ordered logistic regressions. This table presents the regression results of the last period of trading on various sets of dummy variables, where the reference category is the *BASELINE* treatment in all models. In column 1, *UNCERTAIN* is a dummy indicator for a market being in any other treatment than in the baseline—that is, all *RISK* and *AMBIGUITY* markets. In column 2, the set consists of dummy indicators for the potential higher values the token could possibly take on and irrespective of the kind of uncertainty—that is, in *HIGHER VALUE = 10*, the token value was either zero or €10; in *HIGHER VALUE = 30*, the token value was either zero or €30, and in *HIGHER VALUE = 100*, the token value was either zero or €100. In column 3, the set of covariates include binary indicators for each between-subject treatment separately (see Table 1), where the first term refers to being in a market in which the probability of the higher token value is either known (*RISK*) or not known (*AMBIGUITY*), and the second term refers to the height of the high possible value (either €10, €30, or €100). All models include controls for the market number to also account for learning effects. Coefficients are presented in terms of log-odds. Standard errors are given in parenthesis and clustered on group ID. *p < 0.05; ** p < 0.005

	Dep. var: Last period of trading		
	(1)	(2)	(3)
<i>UNCERTAIN</i>	3.226** (0.284)		
<i>HIGHER VALUE = 10</i>		2.591** (0.273)	
<i>HIGHER VALUE = 30</i>		3.778** (0.352)	
<i>HIGHER VALUE = 100</i>		3.763** (0.363)	
<i>RISK 10</i>			2.211** (0.282)
<i>AMBIGUITY 10</i>			3.227** (0.325)
<i>RISK 30</i>			2.941** (0.337)
<i>AMBIGUITY 30</i>			5.563** (0.502)
<i>RISK 100</i>			3.355** (0.449)
<i>AMBIGUITY 100</i>			4.687** (0.466)
# of Market	Yes	Yes	Yes
Pseudo R2	0.368	0.413	0.498
Observations	376	376	376
<i>Hv 30 - Hv 10 = 0</i>		1.187 (0.195)**	
<i>Hv 100 - Hv 30 = 0</i>		-0.015 (0.233)	
<i>AMBIGUITY 10 - RISK 10 = 0</i>			1.016 (0.276)**
<i>AMBIGUITY 30 - RISK 30 = 0</i>			2.622 (0.464)**
<i>AMBIGUITY 100 - RISK 100 = 0</i>			1.331 (0.505)*

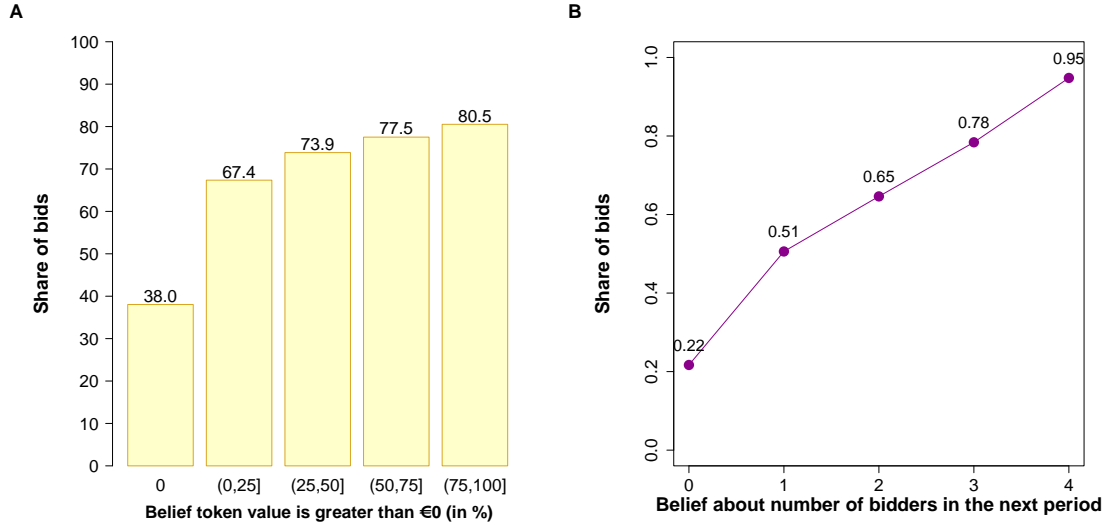


Figure 4: Bids and beliefs. This figure illustrates the share of bids (i.e., willingness to buy the token) across belief measures, elicited after each bidding decision, respectively. Panel (A) depicts the share of bids across buckets of beliefs regarding the token value being greater than €0. Panel (B) depicts the share of bids across beliefs regarding the number of bidders in the next period are depicted.

for a battery of individual skills and sociodemographic variable (see columns 3 of Tables 4 and C.3, respectively). In the upcoming result, we focus on these variables in more detail.

Result 5: There is suggestive evidence that higher levels of rationality measured in the beauty contest are negatively correlated with the likelihood to bid. Additionally, there is suggestive evidence that the male gender and higher levels of risk tolerance are positively correlated with bidding.

As depicted in models 2 and 3 in Table 4, we find suggestive evidence for the impact of level-k reasoning, gender, and risk tolerance on bidding behavior. In particular, we find that—in line with theoretical considerations presented in section 4—subjects with lower level-k reasoning skills in the beauty contest game and subjects with higher self-assessed risk tolerance are more likely to bid in the markets. Furthermore, we report suggestive evidence that male subjects are more likely to bid. Given that no other control variables show significant results and the correlations we find are only significant at the 5% level, we emphasize not to overinterpret the role of demographics, cognitive skills, and socioeconomic variables for bidding behavior.

Table 4: Random effects logit regressions. This table presents the results of random effects logit regressions of individual's decisions to bid for the token in a given round (bid = 1; no bid = 0) on (1) belief estimates, (2) personal characteristics, and (3) belief estimates and personal characteristics. The sample includes periods 1 – 10 and excludes timed-out observations. *HIGHER VALUE* is an individual's own belief that the token value is higher than €0 in percentage value. *BIDDERS NEXT PERIOD* is and individual's belief of how many bidders there are in the next period (integer between 0 and 4, respectively). *AGE* is individual's age. *NON-MALE* is a binary indicator for being of female or diverse gender, with the reference category being male. *FOMO* is individual's mean score across all nine-items in the fear of missing out questionnaire in which the items related to *TEMPTATION* and *SELF-DISCIPLINED* are reverse coded (continuous between 0 and 10). *NIM* is the number of times an individual consecutively hit a multiple of four, with higher numbers indicating that the participant figured out the backward-inducing dominant strategy earlier (integer between 0 and 4). *CRT* is the number of correct answers the participant provided in the three-item cognitive reflection test (integer between 0 and 3). *LEVEL K* is the participant's level of rationality in the beauty contest, with higher numbers indicating higher levels of rationality (integer between 0 and 8). *STORYTELLER/NUMBER CRUNCHER* is participants' self-assessed positioning of themselves of whether they are more of a storyteller or more of a number cruncher kind of person on a 11-point scale (0 = Story teller; 10 = Number cruncher). *SELF-ASSESSED KNOWLEDGE* denotes participants' self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while *FINANCIAL LITERACY* is the number of correct answers in the Big Three financial literacy quiz. *SELF-ASSESSED RISK* is subjects' self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks), and *MATH PROFICIENCY* denotes subjects' self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong). All models include controls for treatments, the market number and period (price) fixed effects. Coefficients are shown in terms of log-odds. Standard errors are given in parenthesis. Random effects on subject ID are included. *p < 0.05; **p < 0.005

	Dep. variable: Bid		
	(1)	(2)	(3)
<i>BELIEFS:</i>			
<i>HIGHER VALUE</i>	0.023** (0.001)		0.023** (0.001)
<i>BIDDERS NEXT PERIOD</i>	0.856** (0.023)		0.856** (0.023)
<i>PERSONAL CHARACTERISTICS:</i>			
<i>AGE</i>		−0.004 (0.014)	−0.002 (0.014)
<i>NON-MALE</i>		−0.351* (0.140)	−0.327* (0.138)
<i>FOMO</i>		−0.005 (0.058)	0.013 (0.057)
<i>NIM</i>		0.002 (0.063)	0.004 (0.063)
<i>CRT</i>		−0.026 (0.064)	0.025 (0.063)
<i>LEVEL K</i>		−0.082* (0.030)	−0.075* (0.030)
<i>STORYTELLER/NUMBER CRUNCHER</i>		−0.003 (0.028)	−0.001 (0.027)
<i>SELF-ASSESSED KNOWLEDGE</i>		−0.039 (0.032)	−0.017 (0.032)
<i>FINANCIAL LITERACY</i>		−0.085 (0.095)	−0.003 (0.093)
<i>SELF-ASSESSED RISK</i>		0.080* (0.029)	0.068* (0.029)
<i>MATH PROFICIENCY</i>		0.014 (0.036)	−0.023 (0.036)
<i>CONSTANT</i>	−2.293** (0.120)	0.342 (0.547)	−1.999** (0.541)
Controls	Yes	Yes	Yes
Conditional/Marginal R squared	0.594/0.412	0.479/0.242	0.596/0.426
Observations	16,005	16,005	16,005

6.3 Multiverse analysis (exploratory)

To eliminate p-hacking and promote transparent and open science, we utilize the specification curve analysis suggested by [Simonsohn et al. \(2020\)](#) as an “extensive robustness check” for the analysis on individual data (Results 4 and 5).²² Generally speaking, in this approach, researchers define so-called “decision nodes” from which different forks of analysis specifications can emerge, considering plausible distinct specifications in each node. The specification curve considers every possible combination of specifications and reports which of them yield significant results and which not. Our universal regression framework, which is applied across all specifications, is model 1 given in Table 4 without random effects, as we will account for the non-independence of observations in a distinct decision node.

Table 5 present the data analytical decisions along with specifications we consider for this study.²³ Our first decision node centers around the kind of regression model we run. As we model the probability of bidding, one might consider a linear probability model (i.e., OLS) or a logit and a probit model as reasonable alternatives. Second, it is also common practice in the economics literature to “clean” the data by excluding major “outliers”. Potential criteria upon which researchers may decide to include or not include observations are comprehension checks, time-outs, or overall time spent in the experiment. Furthermore, the thresholds for the criteria might also be arbitrary and, thus, we include multiple thresholds, respectively. Third, our data comprise multiple observations for every individual who is part of a group, thereby providing the opportunity for a variety of panel-data models, i.e., fixed effect or random effect estimation, increasingly accounting for potential sources of correlation on multiple levels. In this sense, one could merely cluster the standard errors on an individual (group) level to account for correlation within individuals (groups) or one could include group fixed effects and cluster standard errors on subject level.²⁴ The fourth decision node is regarding the inclusion or exclusion of control variables. In order to not artificially increase the multiverse we investigate, we thematically summarize the control variables. Finally, the remaining decision node deals

²²Additionally, we added another robustness check for Result 5 by regressing the number of bids per individual over all markets on personal characteristics and an indicator for our between-subject variation (i.e., being in *AMBIGUITY* markets). The results remain qualitatively the same.

²³Note that we do not claim this list of nodes and specifications to be final and all-encompassing. Rather, our aim is to utilize this tool for conducting a large robustness check in order to account for the most common forking paths in the field.

²⁴We do not include subject fixed effects as we are also interested in the correlation with time-invariant subject characteristics (i.e., skills and sociodemographics). Note also that we do not include nested models since the output in column 3 of Table C.2 suggests that no variance stems from the group random effect (see footnote 22).

Table 5: Multiverse specifications. This table presents data analytical decisions with specifications for the regression of the individual binary decision to bid on a number of covariates. Bold specifications indicate the specification of our main analysis. SE denotes “standard errors”.

Decision	Specification
(1) Type of regression model	OLS, Logit , and Probit
(2) Dropping individual observation	None (i.e., exclude timed-out observations) , based on correct comprehension checks (minimum five out of eight are correct), based on timeouts (individuals with at least 90% no timeouts), based on general time needed in the market experiment (top and bottom cut-off of 1%, 2.5%, and 10%)
(3) Accounting for non-independence of observations	Clustering SEs on individual level, clustering SEs on group level, fixed effects on groups and clustering SEs on individual level, random effects on individual level
(4) Sets of control variables (game-related [i.e., got-token indicator and beliefs regarding bidder in current period], demographics [i.e., age, gender], field behavior [i.e., fomo-index, numbercruncher, risk aversion], skill [i.e., level-k, financial literacy, math, Nim, CRT])	Include all sets, cross-combinations of sets (e.g., demographics and field behavior, but not skill), or none.
(5) FOMO modelling	Mean over all items , product over all items, every questions by itself, principal component analysis (1 st component)

with the modelling of the fomo index. Here, multiple approaches might be suitable. Overall, we investigate 3456 meaningful specification combinations.

As shown in Figure 5, we report supporting evidence for findings depicted in Result 5. Histograms that depict the p-values of coefficients associated to beliefs and the got-token indicator are shown in Figure C.3 in Appendix C, thereby supporting the evidence shown in Result 4. We show distributions of p-values for the various analysis forks and we can mainly support the general statement of Result 5. In particular, we show that suggestive evidence for significant (non-significant) findings remain suggestive (non-significant) in most of the universe. In terms of the coefficient associated with *LEVEL K*, each of the 1728 specifications are below the 5% significance threshold.²⁵ Interestingly, the majority of specifications even point toward a statistical significant association between level-k reasoning and bidding behavior as 1304 out of the 1728 analysis paths yield p-values below 0.5%. As such, our specified main analysis presented in Table 4 is one of the few that “only” showing suggestive evidence. Furthermore, the median test statistic of the coefficient associated with *LEVEL K* is -3.017, which, assuming an approximate normal distribution,

²⁵Given the possible combination of specifications in our multiverse, the sets of individual characteristics are included in 1728 of 3456 universes, respectively.

corresponds to a p-value of 0.003 in a two-sided test.²⁶

Similarly, 439 of 1728 specifications yield a p-value below 0.5% for the coefficient associated with *SELF-ASSESSED RISK* (1545 of 1728 paths are below the 5% suggestive evidence threshold). The median test statistic is 2.523, which under an approximate normal distribution, would indicate a p-value of 0.012, again in a two-sided test.

The coefficient regarding *NON-MALE* deserves special attention: Only 90 of the 1728 specifications yield a p-value below 0.5%, which would generally imply that we do not find an effect. However, 62.4% of specifications show a p-value of below 5%, thereby indicating suggestive evidence of an effect. This is also supported by the median test statistic of -2.15 (i.e., p-value of 0.032 in a two-sided test under an approximately and normally distributed null).

Finally, the tests regarding the other coefficients are all above the 5% significance threshold, thereby suggesting that we do not find an effect for these variables. In summary, we conclude that the multiverse analysis brings confirmatory evidence for Result 5. However, due to the exploratory nature of this analysis, we explicitly state that the interpretations of this finding, including the multiverse, should be handled with caution.

²⁶Here, we refer to a normal distribution because the t-distribution approaches the normal distribution when the degrees of freedom increase.

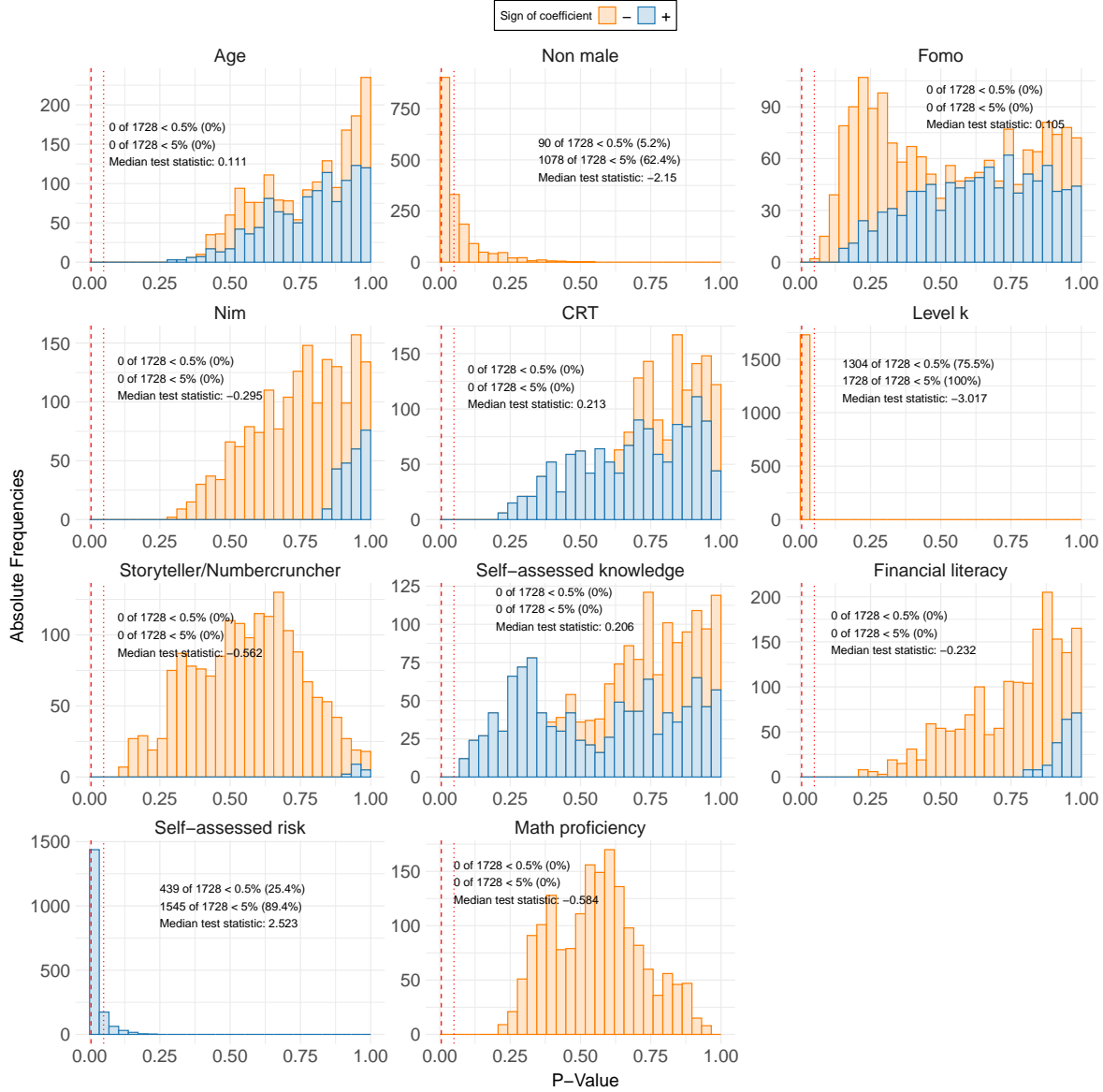


Figure 5: Histogram of p-values for individual characteristics. This figure depicts the distribution of p-values associated with the coefficients for participant characteristics. Additionally, the share of the universe yielding significant results (i.e., $p\text{-value} < 0.005$), suggestive evidence (i.e., $p\text{-value} < 0.05$), and the median test statistics (i.e., t-stat or z-stat, depending on the model) are depicted in each panel. Positive signs of the coefficients are coded in orange and indicate a positive correlation with individuals' bidding, while negative signs are in blue and indicate a negative association with individuals' bidding. *AGE* is an individual's current age when at the time of participating in the study. *NON-MALE* is a binary indicator for being of female or diverse gender, with the reference category being male. *FOMO* is an individual's index related to the fear of missing out. *NIM* is the number of times an individual consecutively hit a multiple of four, with higher numbers implying that the subject figured out the backward-inducing dominant strategy earlier (an integer between 0 and 4). *CRT* is participant's number of correct answers in the three-item cognitive reflection test (integer between 1 and 3). *LEVEL K* is participant's level of rationality in the beauty contest, with higher numbers indicating higher levels of rationality (an integer between 0 and 8). *STORYTELLER/NUMBER CRUNCHER* is subjects' self-assessed positioning of themselves of whether they are more of a storyteller or more of a number cruncher kind of person on an 11-point scale (0 = Storyteller; 10 = Number cruncher). *SELF-ASSESSED KNOWLEDGE* denotes subject's self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while *FINANCIAL LITERACY* is the number of correct answers in the Big Three financial literacy quiz. *SELF-ASSESSED RISK* is participants' self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks), and *MATH PROFICIENCY* denotes subjects' self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong).

7 Discussion

In our pre-registration and also in our paper, we termed our experiment the “greater fool game.” In what follows, we discuss the “greater fool” explanation and alternative explanations of the drivers for excessive bidding behavior and overvaluation. Of course, we acknowledge that there are potentially more alternative explanations, particularly for Results 1 – 3, but we want to limit the discussion to the most important ones (in our opinion):

The Greater Fool Theory: Across all periods, more than two-thirds of subjects (87.2%) expected that there will be at least one bidder in the upcoming period. This is an indication of a greater fool trading motive, as most subjects obviously believed that there are traders with inflated beliefs in the market to whom they can resell the asset at a higher price in subsequent periods (Miller, 1977; Aliber et al., 2015). Examining the determinants of bidding behavior in our *BASELINE* treatment—an evident case of the greater fool game—again shows that variables related to greater fool trading motives (i.e., the got-token indicator and expectations regarding the number of upcoming bidders) are statistically significant and indicate the expected direction, thereby reinforcing the greater fool theory as a potential explanation of the behavior we observe (see column 1 of Table C.5 in Appendix C).

Overvaluation of small probabilities: One important feature of Prospect Theory (Kahneman and Tversky, 1979) is the misweighting of probabilities, particular the overweighting of small probabilities. This preference can, on aggregate, also explain investors’ preference for lottery-like stocks on financial markets (Kumar, 2009). In particular, in the *RISK* and *AMBIGUITY* conditions, one can expect that overweighting of small probabilities plays a role, as the true probabilities for the high outcome of the assets are merely $\frac{1}{46656}$. We indirectly test its effect by comparing individuals’ beliefs regarding the probability of the token having a higher value than €0 (i.e., the first belief measure) between treatments. When regressing these beliefs on treatment dummies (i.e., column 1 in Table C.6; exploratory analysis), we find no significant difference between beliefs in the *BASELINE* and *RISK* markets, thereby indicating that individuals’ own subjective belief regarding the token value does not change due to a small probability of a high outcome being introduced. However, *RISK* treatments do increase individuals’ beliefs regarding the number of bidders in the current and following period as indicated by significant coefficients for *RISK* dummies (i.e., columns 2 and 3 in Table C.6, respectively). The same accounts for markets in the *AMBIGUITY* treatment, in which all beliefs are significantly higher than those in the *BASELINE*. We conclude that the overvaluation of small probabilities regarding the token’s value is not

an explanation for the high prices we see in our experiment. However, what could explain the substantial increase in prices compared to the *BASELINE* might be the positive effect of high outcomes with small probabilities on anticipated market participation (i.e., expectation regarding current and following number of bidders). As such, the introduction of positively skewed assets might be an important driver of greater fool expectations. What our results rather clearly eliminated is the ignorance of small probabilities in the market setting with resale option, as prices in *RISK* and *AMBIGUITY* were significantly higher than those in *BASELINE*.

Lack of outside options for trading (active participation hypothesis): Finally, one motive of engaging in trading in these markets is the lack of outside options while participating in the experiment, thus inducing an experimenter demand effect (Zizzo, 2010). In an early study, Lei et al. (2001) provided subjects with an outside option similar to trading in a market of Smith et al. (1988) type. Thus, they tested the “active participation hypothesis” that an overvaluation of assets can emerge due to the lack of alternatives, thereby “forcing” subjects to trade and thereby bidding prices up. Lei et al. (2001) found no support for this hypothesis, as overvaluation still emerges in the presence of outside options. We, unfortunately, cannot completely exclude the role of a lack of outside options for bidding behavior and price formation. However, in our design, participants had the option to abstain from bidding, which enabled for an early end of the session and, thus, and increased hourly pay. More generally speaking, the argument of lack of outside options could be applied to all laboratory asset market experiments run during the previous, as the lack of alternatives could have potentially created excess demand for the assets. However, we leave this aspect open for future research.

8 Conclusion

In our study, we conducted laboratory financial markets to investigate the market dynamics of asset markets with zero (or close to zero) fundamental values. We found that in markets where the fundamental value of the token was known to be zero with certainty (*BASELINE*) and no trade should take place according to standard intrinsic value theory, prices were positive and markets ended, on average, in period 5 (out of 11). Second, we reported that prices in markets with uncertainty regarding the fundamental value were substantially higher compared to markets in the *BASELINE* condition with average prices of over €2.56 in *RISK* and above €5.12 in *AMBIGUITY*. This finding is remarkable, as the expected fundamental values—assuming risk-neutrality—are only fractions of a cent, never exceeding €0.0021. Third, we provided evidence of increasing prices with increasing

prospective higher values of the asset. Finally, we reported that subjective beliefs regarding the participation of others and regarding the token’s value are positively correlated with the probability of engaging in these markets. Thus, the behavior in our markets aligns with the greater fool theory, with bids driven primarily by the belief in the ability to resell at a higher price to someone else, and, to some extent, by uncertainty about the fundamental value. As a related point, we found suggestive evidence that level-k reasoning, risk aversion, and gender (i.e., female and diverse) are negatively associated with participation.

Our study has several limitations. First, as discussed in the previous section, we can accommodate for certain alternative explanations of the drivers of overvaluation, but not perfectly so. However, we have statistical evidence for the greater fool motive—as revealed by subjects’ beliefs that other traders will be willing to purchase the asset at inflated prices in subsequent periods—is a main driver of our findings. Second, we ran the study with student subjects and it is not perfectly clear whether the findings will be the same with real-world investors or finance professionals. The literature has mixed results in this regard, as some studies show no behavioral differences between students and finance professionals, while others do (e.g., [Kirchler et al., 2018](#); [Holzmeister et al., 2020](#); [Razen et al., 2020](#); [Weitzel et al., 2020](#)).

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Appendices

A Experimental Software

Welcome to this experiment!

We are researchers from the University of Innsbruck and Luxembourg who are interested in asset market behavior. In this experiment data on your decisions and demographics information about you will be collected. However, all data collected will be anonymized and only used for scientific research purposes.

The experiment consists of a total of four tasks, where you will complete the first two tasks within a group. For this you will be grouped with 4 other randomly selected participants at the beginning of the experiment. In this group of 5 you will do the two tasks where you interact and where your actions influence the outcomes of the other group members. Then, you will go through the last two tasks by yourself.

Information on your payoff will be shown on a separate screen at the end of the experiment

If you want to continue please click on *I agree and want to participate*.

How do you wish to proceed?

☐ *I agree and want to participate*

Next

Figure A.1: Disclaimer page, beginning of the experiment

Task 1: Pick a number

This is the initial task of the experiment.

Every participant in your group chooses a number between **0 and 100**. The winner is the one whose number is **most closely to $\frac{2}{3}$ of the average** of all chosen numbers.

If, for example, the numbers of the **5** group members are **0, 10, 20, 30, 40**, the average number is **20.00** ($= 100.00 / 5$). Two thirds of the average are **13.33** ($= \frac{2}{3} \times 20.00$). Therefore, the participant who chooses **10**, which is closest to 13.33, would be the winner.

By choosing your number in this task, you earn your endowment of **€12.00** for the experiment. If you are the winner in this task, you earn an additional **€5.00**.



To enable a swift experiment, your decision time will be limited to 5 minutes. If you reach the timeout before making a decision, the computer will decide for you, which might affect your payout.

Your Guess

Please pick a number from 0 to 100:

Next

Figure A.2: Beauty contest

Instructions I
Instructions II
Instructions III
Quiz I
Quiz II
Quiz III
Quiz IV

Instructions

This is the main task of the experiment. You are going to participate in **4 independent** markets trading a non-divisible token up to **11 periods per market**. **The default value of the token is zero**. If another value is possible, it is shown on the screen. It is only the other value if 6 independent dice each roll the number 6. The possible values are publicly announced on the screen from the beginning of and throughout the market. Every participant has identical information.

You start each market with your earned endowment of **€12.00 in your account**. One market will be randomly chosen for payment. The chosen market will be revealed to everyone only at the end of the experiment. Your earnings in the chosen market will be paid to you in private.

There are **two possible sources of income** in this part of the experiment:

- **The token value:** in case you are the owner of the token at the end of the market, additionally you will also receive the value of the token, which will be added to your account.
- **Account:** If you buy the token, the price you pay is subtracted from your cash account; if you are the owner of the token and sell it to another participant, the price you receive is added to your cash account. The final value of the account is your earning in this market.

Each of the market rounds proceeds as follows:

There are 5 participants in the market throughout the experiment. You are one of them. **The composition of your group of market participants never changes.**

In each period, you and the other 4 participants bid to buy or decide not to bid for the token at the announced period price.

Next

Figure A.3: Instructions I (RISK)

Instructions I
Instructions II
Instructions III
Quiz I
Quiz II
Quiz III
Quiz IV

Instructions

This is the main task of the experiment. You are going to participate in **4 independent** markets trading a non-divisible token up to **11 periods per market**. **The default value of the token is zero**. If another value is possible, it is shown on the screen, but no probability of occurrence of this second value is revealed at any time. The possible values are publicly announced on the screen from the beginning of and throughout the market. Every participant has identical information.

You start each market with your earned endowment of **€12.00 in your account**. One market will be randomly chosen for payment. The chosen market will be revealed to everyone only at the end of the experiment. Your earnings in the chosen market will be paid to you in private.

There are **two possible sources of income** in this part of the experiment:

- **The token value:** in case you are the owner of the token at the end of the market, additionally you will also receive the value of the token, which will be added to your account.
- **Account:** If you buy the token, the price you pay is subtracted from your cash account; if you are the owner of the token and sell it to another participant, the price you receive is added to your cash account. The final value of the account is your earning in this market.

Each of the market rounds proceeds as follows:

There are 5 participants in the market throughout the experiment. You are one of them. **The composition of your group of market participants never changes.**

In each period, you and the other 4 participants bid to buy or decide not to bid for the token at the announced period price.

Next

Figure A.4: Instructions I (AMBIGUITY)

[Instructions I](#)[Instructions II](#)[Instructions III](#)[Quiz I](#)[Quiz II](#)[Quiz III](#)[Quiz IV](#)

In period 1, the buyer pays the price of €0.01 to the experimenter and becomes the first owner of the token. The buyer is chosen randomly among the bidders.

In period 2 and all later periods the price always doubles from period to period and the buyer pays the price to the latest owner and becomes the new owner of the token. The buyer is randomly chosen among the bidders of the period. Each bidder will be chosen with equal probability to become the new owner, whether s/he was a previous owner of the token or not.

The following table shows you the prices for the token in each period:

Prices across periods in the market
In period 1 , the price is €0.01 .
In period 2 , the price is €0.02 .
In period 3 , the price is €0.04 .
In period 4 , the price is €0.08 .
In period 5 , the price is €0.16 .
In period 6 , the price is €0.32 .
In period 7 , the price is €0.64 .
In period 8 , the price is €1.28 .
In period 9 , the price is €2.56 .
In period 10 , the price is €5.12 .
In period 11 , the price is €10.24 .

Next

Figure A.5: Instructions II

Instructions I
Instructions II
Instructions III
Quiz I
Quiz II
Quiz III
Quiz IV

Each market ends, automatically after period 11 is completed. The market may end early before reaching period 11 if one of the following conditions is met: The market ends if there is **no bidder in a given period**, or if there is **no bidder other than the latest owner of the token**. The latest owner of the token learns and receives the value of the token after the market ends.

At the end of the market you are informed of the earnings in that market. Then a **new and independent** market with a **new** token will start.

Following your bid in a given period, you will be asked to enter your expectation of the token's value, and how sure you are about this value. You will also be asked your expectation about the number of bidders in the market in the ongoing and the following period. Specifically, you guess the number of bidders among the other 4 participants in the ongoing period and also in the following period. At the end of a market, one period-prediction is selected for possible payment.

The market that is selected for payment will be revealed to **everyone after the last market ends**. If your period-prediction (on value and number of bidders) is correct, a payment of €1.00 is added to your earnings if that market is chosen for payment.

To enable a swift experiment, your decision time will be limited in each period, for which you will see a countdown for the last 15 seconds on the screen. In the first period of the first market you will be given 3 minutes for your decision. Use this time for the careful reading of the onscreen instructions. If you reach the timeout before making a decision, the computer will decide for you, which might affect your payout. Also, we require your active decision-making. If you fail to make active decisions, we will consider your participation as inactive and you won't receive any payoff.

You can review the instructions at any point in time while making your decision. Because of the timeout of the periods, however, it will be impossible to re-read the instructions entirely. So please make sure that you have understood the instructions before you press the button to continue the experiment.

Before we move on to start the market, we are going to ask you quiz questions to enhance your overall understanding.

Start Quiz

Figure A.6: Instructions III

[Instructions I](#)
[Instructions II](#)
[Instructions III](#)
[Quiz I](#)
[Quiz II](#)
[Quiz III](#)
[Quiz IV](#)

Quiz I:

Given the following information, please answer the question below.

Current price	Value
€1.28	€0.00 or €30.00

The value of the token in this market is **€0.00** or **€30.00**. It is €30.00 only if six dice (showing the numbers 1 to 6 with equal probability, thrown at the beginning of the market) all show 6 at the same time.

If you are the owner of the token at the end of the market, what are the minimum and maximum amounts that will be credited to your account?

Minimum

Maximum

Check

Figure A.7: Quiz I (RISK)

[Instructions I](#)
[Instructions II](#)
[Instructions III](#)
[Quiz I](#)
[Quiz II](#)
[Quiz III](#)
[Quiz IV](#)

Quiz I:

Given the following information, please answer the question below.

Current price	Value
€1.28	€0.00 or €30.00

The value of the token in this market is **€0.00** or **€30.00**.

If you are the owner of the token at the end of the market, what are the minimum and maximum amounts that will be credited to your account?

Minimum

Maximum

Check

Figure A.8: Quiz I (AMBIGUITY)

Instructions I
Instructions II
Instructions III
Quiz I
Quiz II
Quiz III
Quiz IV

Quiz II:

Given the following information, please answer the question below.

Current price	Value
€2.56	€0.00

The value of the token in this market is **€0.00** with certainty.

If you are the owner of the token at the end of the market, what are the minimum and maximum amounts that will be credited to your account?

Minimum

Choose... ▾

Maximum

Choose... ▾

Check

Figure A.9: Quiz II

Instructions I
Instructions II
Instructions III
Quiz I
Quiz II
Quiz III
Quiz IV

Quiz III:

Given the following information, please answer the question below.

If you are the owner of the token and you sell the token to another participant in the market, what amount is added to your account - the price or the value?

☐ Price
☐ Value

Check

Figure A.10: Quiz III

[Instructions I](#) [Instructions II](#) [Instructions III](#) [Quiz I](#) [Quiz II](#) [Quiz III](#) [Quiz IV](#)

Quiz IV:

Given the following information, please answer the question below.

If you are the owner of the token and you decide to sell the token, but no participant in the market bids to buy the token, what amount is added to your account - the price or the value?

☐ Price

☐ Value

Check

Figure A.11: Quiz IV

Quiz:
Given the following information, please answer the question below.

Current price	Value
€0.01	€0.00 or €100.00

The value of the token in this market is **€0.00** or **€100.00**. It is €100.00 only if six dice (showing the numbers 1 to 6 with equal probability, thrown at the beginning of the market) all show 6 at the same time.

If you are the owner of the token at the end of the market, what are the minimum and maximum amounts that will be credited to your account?

Minimum

Maximum

Figure A.12: Quiz specific before market with a high prospective value (RISK).

Quiz:
Given the following information, please answer the question below.

Current price	Value
€0.01	€0.00 or €100.00

The value of the token in this market is **€0.00** or **€100.00**.

If you are the owner of the token at the end of the market, what are the minimum and maximum amounts that will be credited to your account?

Minimum

Maximum

Figure A.13: Quiz specific before market with a high prospective value (AMBIGUITY).

Quiz:

Given the following information, please answer the question below.

Current price	Value
€0.01	€0.00

The value of the token in this market is **€0.00** with certainty.

If you are the owner of the token at the end of the market, what are the minimum and maximum amounts that will be credited to your account?

Minimum Choose... ▾

Maximum Choose... ▾

Check

Figure A.14: Quiz specific before market with sure fundamental value of €0

Market 1 of 4
Period 1 of 11
Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

Bid

Current price

Value

€0.01

€0.00

The value of the token in this market is **€0.00** with certainty.

Do you bid to buy the token for €0.01?

Yes

No

Account: €12.00

Instructions

Figure A.15: Bid to buy at fundamental value of €0 (i.e., BASELINE)

Market 1 of 4
Period 1 of 11
Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

Expectations

What do you think is the token's value?

We told you before that in this market the only possible value of the token is **€0.00**. Please use the slider below to indicate in % how sure you are that the token's value is higher than €0.00. For help, you also see the corresponding statement according to your input on the slider below. In order to proceed, you also have to click the slider at least once.

€0.00

a higher value than €0.00

I am -% sure, that the value of the token is higher than €0.00.

How many of the others in your group do you think bid to buy in this round?

0

1

2

3

4

How many of the others in your group do you think will bid to buy in the following round?

0

1

2

3

4

Continue

Figure A.16: Belief at fundamental value of €0

Market 1 of 4

Period 2 of 11

Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

! You **bought** the token in the previous period for €0.01.

Bid

Instructions

Current price	Value
€0.02	€0.00

The value of the token in this market is **€0.00** with certainty.

Do you bid to buy the token for €0.02?

Yes

No

Account: €11.99 + Token

Figure A.17: Message when token bought

Market 1 of 4

Period 2 of 11

Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

! Your order to buy was unsuccessful.

Bid

Instructions

Current price	Value
€0.02	€0.00

The value of the token in this market is **€0.00** with certainty.

Do you bid to buy the token for €0.02?

Yes

No

Account: €12.00

Figure A.18: Message when bid was not successful

Market 1 of 4

Period 2 of 11

Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

⚠️ You didn't bid to buy in the previous round.

Bid

Current price
€0.02

Value
€0.00

The value of the token in this market is **€0.00** with certainty.

Do you bid to buy the token for €0.02?

Yes
No

Account: €12.00

Instructions

Figure A.19: Message when no bid was given previous period

Market 1 of 4

Period 3 of 11

Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

⚠️ You **sold the token in the previous period for €0.02.**

Bid

Current price
€0.04

Value
€0.00

The value of the token in this market is **€0.00** with certainty.

Do you bid to buy the token for €0.04?

Yes
No

Account: €12.01

Instructions

Figure A.20: Message when sold

Market 2 of 4
Period 1 of 11
Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

Bid

Instructions

Current price
€0.01

Value
€0.00 or €100.00

The value of the token in this market can be **€0.00** or **€100.00**. It is €100.00 only if six dice (showing the numbers 1 to 6 with equal probability, thrown at the beginning of the market) all show 6 at the same time.

Do you bid to buy the token for €0.01?

Yes

No

Account: €12.00

Figure A.21: Bid with a prospective high value (RISK)

Market 2 of 4
Period 1 of 11
Time left:

€0.01	€0.02	€0.04	€0.08	€0.16	€0.32	€0.64	€1.28	€2.56	€5.12	€10.24
-------	-------	-------	-------	-------	-------	-------	-------	-------	-------	--------

Bid

Instructions

Current price
€0.01

Value
€0.00 or €100.00

The value of the token in this market can be **€0.00** or **€100.00**.

Do you bid to buy the token for €0.01?

Yes

No

Account: €12.00

Figure A.22: Bid with a prospective high value (AMBIGUITY)

Market 4 of 4
Period 1 of 11
Time left:

€0.01
€0.02
€0.04
€0.08
€0.16
€0.32
€0.64
€1.28
€2.56
€5.12
€10.24

Expectations

Instructions

What do you think is the token's value?

We told you before that in this market the possible values for the token are **€0.00** and **€100.00**. Please use the slider below to indicate in % how sure you are that the token's value is higher than €0.00. For help, you also see the corresponding statement according to your input on the slider below. In order to proceed, you also have to click the slider at least once.

€0.00
€100.00

I am -% sure, that the value of the token is €100.00.

How many of the others in your group do you think bid to buy in this round?

☐ 0
☐ 1
☐ 2
☐ 3
☐ 4

How many of the others in your group do you think will bid to buy in the following round?

☐ 0
☐ 1
☐ 2
☐ 3
☐ 4

Continue

Figure A.23: Belief in markets with high prospective value

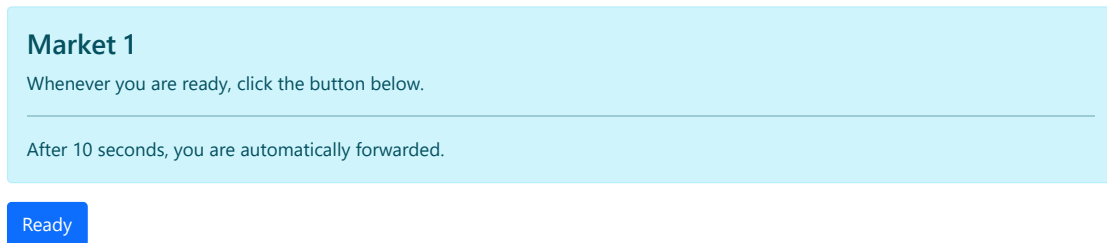


Figure A.24: Market beginning

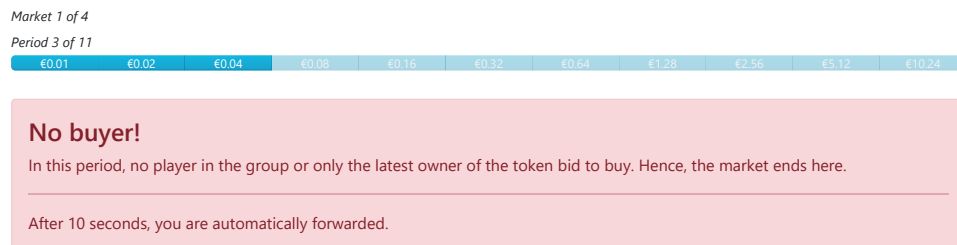


Figure A.25: Market early end

Results of Market 3


Your payoff in this market is €12.09.

After 10 seconds, you are automatically forwarded and a **new and independent** market will start.

Figure A.26: Result not a token holder

Results of Market 1

The following dice have been rolled:



Hence, the value of the token was €0.00.

Your payoff in this market is €11.99.

After 10 seconds, you are automatically forwarded and a **new and independent** market will start.

Figure A.27: Result token holder (RISK)

Results of Market 1

The value of the token was €0.00.

Your payoff in this market is €11.98.

After 10 seconds, you are automatically forwarded and a **new and independent** market will start.

Figure A.28: Result token holder (AMBIGUITY)

Game of 20

Finally, we ask you to take turns with a computer player in adding 1, 2 or 3 to a total, which is initiated at 0.

The computer player will begin by adding 1 or 2 or 3 to the total.

After the computer player has made the choice, you observe its choice and add either 1, 2 or 3 to the total.

After your choice, it is the turn of the computer player again. The computer player can, again, add 1, 2 or 3 to the total.

The **Game of 20** continues with you and the computer player taking turns. The **Game of 20** will end once the total reaches 20, and the winner is the player who makes the total reach 20.

If you are the winner in the game, **€1.00** will be added to your final payoff, otherwise nothing will be added to your final payoff.

When you have finished reading the instructions, start the game by clicking the button.

1

2

3

You:

Total: 0

Computer:

Start!

Figure A.29: Game of nim

Quiz game

In this task your time will be limited to 90 seconds to reply to a maximum of three questions. At the end, the computer will randomly choose one of the questions for payment. If your answer to the chosen question is correct, €1.00 Euro will be added to your final payoff.

Start when ready

Figure A.30: CRT intro

Quiz game

A hat and suit together cost 550 Euro. The suit costs 450 Euro more than the hat. What does the hat cost (in Euro)?

If it takes 10 machines to produce 10 items in 10 minutes, how many minutes would it take 20 machines to produce 20 items?

In a lake there is an algae stain, which doubles in size daily. If it takes the algae 32 days to cover the entire lake, how many days will it take the algae to cover half of the lake?

Next

Figure A.31: CRT

Questionnaire

Page 1 of 3

Please answer the following questions

Investing in a new project is most beneficial if I invest early.

☐

☐

☐

☐

☐

☐

☐

☐

☐

☐

☐

0

1

2

3

4

5

6

7

8

9

10

strongly

disagree

strongly

agree

I can easily resist temptations.

☐

☐

☐

☐

☐

☐

☐

☐

☐

☐

☐

0

1

2

3

4

5

6

7

8

9

10

strongly

disagree

strongly

agree

☐

☐

☐

☐

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0

1

2

3

4

5

6

7

8

9

10

strongly

disagree

strongly

agree

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strongly

disagree

strongly

agree

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strongly

disagree

strongly

agree

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strongly

disagree

strongly

agree

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strongly

disagree

strongly

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strongly

disagree

strongly

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4

5

6

7

8

9

10

strongly

disagree

strongly

agree

Next

Figure A.32: Fomo

Questionnaire

Page 2 of 3

Please answer the following questions

How do you see yourself: Are you rather a story teller or a number cruncher?

Story teller

Number cruncher

- ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

How do you assess your overall financial knowledge?

Very low

Very high

- ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

How do you see yourself: Are you a person who is fully prepared to take risks or do you try to avoid taking risks when doing investments?

Not willing to take risks

Very willing to take risks

- ☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

Suppose you had €100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you let the money grow?

- ☐ More than €102
☐ Exactly €102
☐ Less than €102
☐ Don't know
☐ Refuse to answer

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

- ☐ More than today
☐ Exactly the same as today
☐ Less than today
☐ Don't know
☐ Refuse to answer

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

- ☐ True
☐ False
☐ Don't know
☐ Refuse to answer

Next

Figure A.33: Field behavior and financial literacy

Questionnaire

Page 3 of 3

Please answer the following questions

Age:

 years

Gender:

Please select ▼

Self proficiency in math (0: very weak, 10: very strong):

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

Next

Figure A.34: Demographics

Thank you!

The experiment is now over. Below you can see the payoffs for the different tasks as well as your total payoff.

Task 1: Pick a number

Results	
Guesses among your group:	[5, 33, 43, 71, 98]
% of the average:	33.33
The best guess:	33
Your guess was:	5
Your additional payoff:	€0.00

Task 2: Markets

Market 1	Market 2	Market 3	Market 4
€1.89	€2.15	€14.01	€13.28

Token's value		Number of bidders in this period	Number of bidders in following period
Your prediction	99% sure that higher than €0.00	4	2
Actual	€0.00	4	5

The chosen market for your group was **Market 4**. Hence, your payoff out of this task is **€13.28**. Additionally, the period selected for possible payment is **Period 6**. Because your prediction was not correct, you do not receive an additional payoff of €1.00.

Task 3: Game of 20

You won the game! Hence you receive an additional payoff of €1.00.

Task 4: Quiz game

Correct answer	Your answer
50	9

You got the answer wrong. Hence, you do not receive an additional payoff for this task.

Summary

Your payoff	
Task 1: Pick a number	€0.00
Task 2: Markets	€13.28
Task 3: Game of 20	€1.00
Task 4: Quiz game	€0.00
Total:	€14.28

Continue

Figure A.35: Payoff screen

Thank you for participating in the experiment!

Figure A.36: The end

B A-priori Power Calculations

For determining a reasonable sample size, we conduct an a-priori power calculation on the level of groups continuing periods, which depends on being in the baseline or a treatment condition of the token having a potentially higher fundamental value. In particular, we simulate a simplified data generating process for the probability of a group passing a period, i.e. having demand by more than the current token holder in a given period. In order to do so we assume a group having a constant probability of passing the first period in the market within the baseline treatment. We then assume that this probability decreases in the prices of bids (i.e. period number) in an increasing rate (meaning that the decrease in probability of continuing period 2 is smaller than the decrease in probability of passing period 7 for example), i.e., we assume it is more likely that a the market for a group ends in higher periods than in lower periods. Furthermore, we assume that there are group individual effects. Finally, we then add a probability of passing the period if the group is within a treatment condition, i.e., we assume that it is more likely that a group continues a market where the expected value of the token is higher than €0. Taken together, we use the following linear model to determine the probability of a group continuing in a period:

$$y_{it} = \beta_0 + \alpha_i + \gamma_t + \beta_1 Treatment,$$

where y_{it} is the probability of group i continuing period t , β_0 is the baseline probability of passing a period, α_i is a group individual effect, γ_t is the negative period effect, and β_1 is the effect of being in one of the four treatment conditions.

To model the treatment effect, we rely on Cohen's h (Cohen, 1988), a measure for the distance between two proportions or probabilities. Given two probabilities p_1 and p_2 , Cohen's h is defined as:

$$h = \varphi_1 - \varphi_2, \quad \text{where} \\ \varphi_i = 2 \arcsin \sqrt{p_i}, \quad i \in \{1, 2\}$$

Given p_1 as the probability from the model above up until the treatment effect, we can back out a corresponding effect, given we assume a Cohen's h and rearrange the two equations just mentioned:

$$\beta_1 = p_2 - p_1 = \underbrace{\left[\sin \left(\frac{h + 2 \arcsin \sqrt{p_1}}{2} \right) \right]^2}_{p_2} - p_1$$

Of course, in order to do so we make the simplifying assumption that there is an average treatment effect of the token value having an expected value higher than €0, backed out in the terms of Cohen’s h . Moreover, we define $\beta_0 = 0.7$, $\alpha_i \sim \mathcal{N}(0, 0.01)$ and $\gamma_t = 1.02^t - 1$, where t is a round number indicator from 1 to 11.

One run in the simulation looks as follow: We begin with a group starting in the baseline condition (i.e., the token has a fundamental value of €0 in period 1. Based on the probability calculated with the model above we then draw a binary variable whether the group continues in the market or not. If it continues, the next period starts where a new probability is calculated and a new binary variable is drawn. This could go up to 11 periods like in our experimental setting. If the group has passed period 11 or if the binary draw is 0, the group starts off with the next market in period 1. In our experiment, groups participate in total of 4 markets (i.e. 1 baseline and 3 within-subject treatment conditions), where we assume for simplicity that the first market is always the baseline condition, and markets 2 to 4 are the treatment conditions. This process is repeated for N groups. Data collected is then the group ID, period number, market number and the binary whether the period is continued or the market ends in the given period. Power is given in how many of 1000 runs a logit regression²⁷ can detect a given treatment effect

We run simulations where we vary the number of groups (i.e. from 10 to 100) and Cohen’s h (i.e., 0.2, 0.35 and 0.5 following Cohen (1988) for small, medium-to-small and medium effect sizes). Results from these simulations are shown in Figure B.1. Assuming a small-to-medium effect size of $h = 0.35$ and a significance threshold of $\alpha = 0.5\%$ (see e.g., Benjamin et al., 2018), we would need approximately 45 groups to detect an effect with a power of 80%. As we also have another treatment scenario about the level of uncertainty in a between-subject design, we double the number of groups (i.e., 45 for RISK and 45 for AMBIGUITY). Hence, we aim to collect a total of 90 groups consisting of 5 participants each, resulting in a total of 450 subjects.

²⁷Here, we regress the binary of the period continuing or not on the dummy of a group being in a treatment condition, also including period fixed effects and using cluster robust standard errors on group level

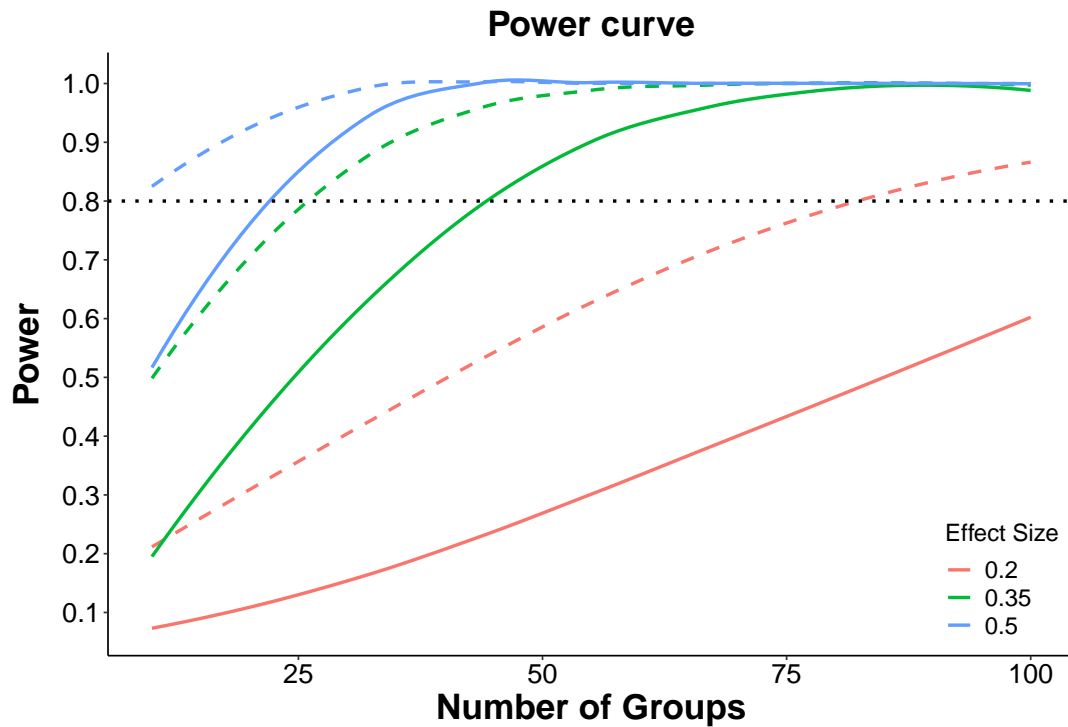


Figure B.1: Power curve for different effect sizes and significance levels. This graph shows the smoothed results of an a-priori power simulation for detecting a given treatment effect measured in Cohen's h (color coded) and a given significance threshold (the solid line represents a 0.5% while the dashed line represents a 5% significance threshold, respectively).

C Supplementary Figures and Tables

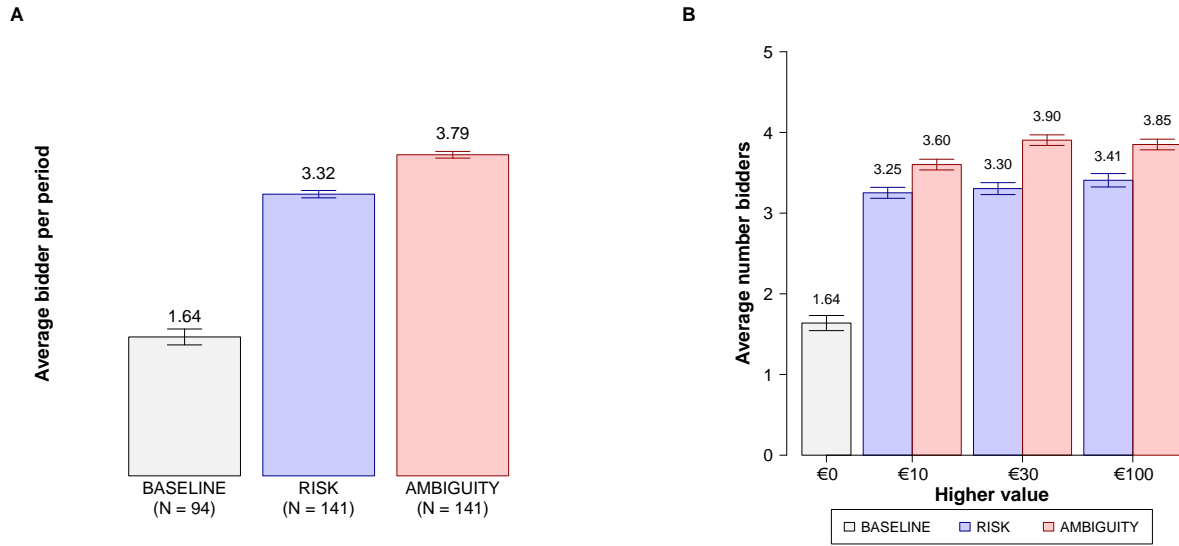


Figure C.1: Average number of bidders. This figure illustrates the average number of bidders across (A) treatments (pooled in higher prospective values and across periods), and (B) treatments and higher prospective values (pooled across periods), respectively.

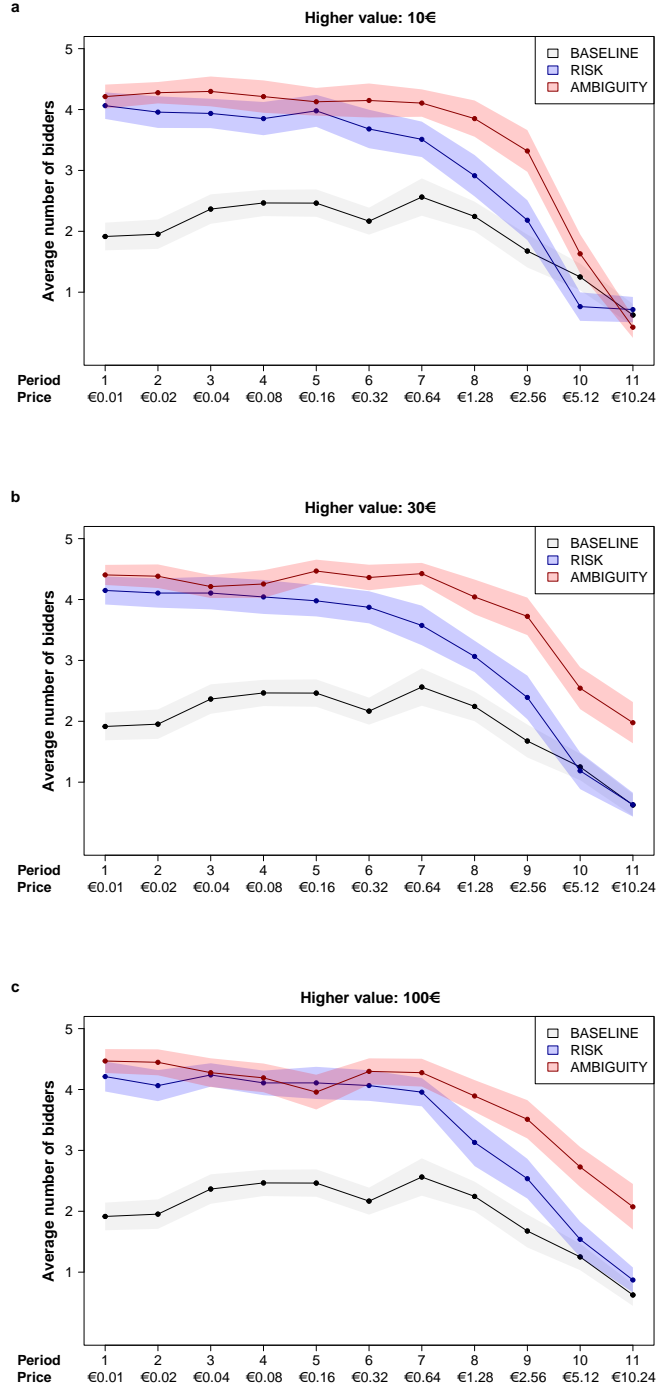


Figure C.2: Average number of bidders over treatments, higher values and periods. In (A) the token value is either €0 or €10, in (B) the token value is either €0 or €30, while in (C) the token value is either €0 or €100.

Table C.1: Ordered logistic regression - Subsample analysis. This table shows regression results of the last period of trading on a battery of dummy indicators for the higher potential token value and the type of uncertainty in the market. *HIGHER VALUE = 30* and *HIGHER VALUE = 100* are binary indicators for markets where the higher prospective token value is either €30 or €100, respectively, and with the reference category being a market where the higher potential value is €10. *AMBIGUITY* is a binary indicator for being in market where participants do not know the realization probability of the token having the higher value, with the reference category being markets where people know this probability (i.e., *RISK*). All models include controls for the market number to also account for learning effects. Coefficients are shown in terms of log-odds. Standard errors are indicated in parenthesis and clustered on group ID. *p<0.05; **p<0.005

	Dep. var: Round number reached
<i>HIGHER VALUE = 30</i>	0.909** (0.255)
<i>HIGHER VALUE = 100</i>	1.320** (0.367)
<i>AMBIGUITY</i>	1.200** (0.320)
<i>HIGHER VALUE = 30</i> x <i>AMBIGUITY</i>	1.343** (0.435)
<i>HIGHER VALUE = 100</i> x <i>AMBIGUITY</i>	0.153 (0.457)
# of Market	Yes
Pseudo R2	0.276
Observations	282
<i>HV 100 - HV 30 = 0</i>	0.411 (0.336)
<i>AMBIGUITY: HV 100 - HV 30 = 0</i>	-1.19 (0.516)*

Table C.2: Random effects logit regressions. This table shows results of random effects logit regressions of individual's decision to bid for the token in a given round (1: bid; 0: no bid) on (1) belief estimates and (2) including personal characteristics. The sample includes periods 1 – 10 and excludes timed-out observations (i.e., taking longer than 20 seconds without responding in all periods except the first one in the first market; in the first period in the first market the threshold was 3 minutes). *HIGHER VALUE* is an individual's own belief that the token value is greater than €0 in percentage value. *BIDDERS NEXT PERIOD* is an individual's belief of how many bidders there are in the next period (integer between 0 and 4). *TREATMENTS* is a battery of dummy indicators for each of our between-subject treatments, where the first term refers to being in a market where the probability of the higher token value is either known (i.e., *RISK*) or not known (i.e., *AMBIGUITY*), and the second term refers to the height of the other possible value (either €10, €30 or €100). The reference category for *TREATMENTS* is the *BASELINE* treatment, where the token value was known to be zero. *AGE* is individual's current age when participating in the study. *NON-MALE* is a binary indicator for being of female or diverse gender, with the reference category being male. *FOMO* is individual's mean score across all nine-items in the fear of missing out questionnaire where the items related to *TEMPTATION* and *SELF-DISCIPLINED* are reverse coded (continuous between 0 and 10). *NIM* is the number of times an individual consecutively hit a multiple of four, with higher numbers meaning that the subject figured out the backward-inducing dominant strategy earlier (integer between 0 and 4). *CRT* is the number of correct answers the subject provided in the three-item cognitive reflection test (integer between 1 and 3). *LEVEL K* is subject's level of rationality in the beauty contest, with higher numbers indicating higher levels of rationality (integer between 0 and 8). *STORYTELLER/NUMBER CRUNCHER* is subjects' self-assessed positioning of themselves of whether they are more of a storyteller or more of a number cruncher kind of person on an 11-point scale (0 = Storyteller; 10 = Number cruncher). *SELF-ASSESSED KNOWLEDGE* denotes subject's self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while *FINANCIAL LITERACY* is the number of correct answers in the Big Three financial literacy quiz. *SELF-ASSESSED RISK* is subjects' self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks), and *MATH PROFICIENCY* denotes subjects' self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong). All models include controls for treatments, market number and period (price) fixed effects. Coefficients are shown in terms of log-odds. Standard errors are shown in parenthesis. Nested random effects on subject ID in Group ID are included. *p < 0.05; **p < 0.005

	Dep. variable: Bid		
	(1)	(2)	(3)
<i>BELIEFS:</i>			
<i>HIGHER VALUE</i>	0.023** (0.001)		0.023** (0.001)
<i>BIDDERS NEXT PERIOD</i>	0.856** (0.023)		0.856** (0.023)
<i>PERSONAL CHARACTERISTICS:</i>			
<i>AGE</i>		-0.004 (0.014)	-0.002 (0.014)
<i>NON-MALE</i>		-0.347* (0.140)	-0.327* (0.138)
<i>FOMO</i>		-0.005 (0.058)	-0.013 (0.057)
<i>NIM</i>		0.003 (0.063)	0.004 (0.063)
<i>CRT</i>		-0.024 (0.064)	0.025 (0.063)
<i>LEVEL K</i>		-0.082* (0.030)	-0.075* (0.030)
<i>STORYTELLER/NUMBER CRUNCHER</i>		-0.003 (0.028)	-0.001 (0.027)
<i>SELF-ASSESSED KNOWLEDGE</i>		-0.038 (0.032)	-0.017 (0.032)
<i>FINANCIAL LITERACY</i>		-0.085 (0.095)	-0.003 (0.093)
<i>SELF-ASSESSED RISK</i>		0.080* (0.029)	0.068* (0.029)
<i>MATH PROFICIENCY</i>		0.014 (0.036)	-0.023 (0.035)
<i>CONSTANT</i>	-2.293** (0.120)	0.336 (0.548)	-1.999** (0.541)
Controls	Yes	Yes	Yes
Observations	16,005	16,005	16,005

Table C.3: Random effects logit regressions. This table shows results of random effects logit regressions of individual's decisions to bid for the token in a given round (bid=1; no bid=0) on (1) token possession and belief estimates, (2) personal characteristics, and (3) token possession, belief estimates and personal characteristics. The sample includes periods 1 – 10 and excludes timed-out observations. *GOT TOKEN* is a binary indicator for an individual being in the possession of the token (token in possession = 1; otherwise = 0). *HIGHER VALUE* is an individual's own belief that the token value is higher than €0 in %. *BIDDERS CURRENT PERIOD* is an individuals' beliefs how many bidders there are in the current period, while *BIDDERS NEXT PERIOD* is an individual's belief of how many bidders there are in the next period (integer between 0 and 4, respectively). *AGE* is an individual's age. *NON-MALE* is a binary indicator for being of female or diverse gender, with the reference category being male. *FOMO* is an individual's mean score across all nine-items in the fear of missing out questionnaire where the items related to *TEMPTATION* and *SELF-DISCIPLINED* are reverse coded (continuous between 0 and 10). *NIM* is the number of times an individual consecutively hit a multiple of 4, with higher numbers indicating that the subject figured out the backward-inducing dominant strategy earlier (integer between 0 and 4). *CRT* is the number of correct answers the subject provided in the three-item cognitive reflection test (integer between 0 and 3). *LEVEL K* is subject's level of rationality in the beauty contest, with higher numbers indicating higher levels of rationality (integer between 0 and 8). *STORYTELLER/NUMBER CRUNCHER* is subjects' self-assessed positioning of themselves of whether they are more of a storyteller or more of a number cruncher kind of person on an 11-point scale (0 = Storyteller; 10 = Numbercruncher). *SELF-ASSESSED KNOWLEDGE* denotes subject's self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while *FINANCIAL LITERACY* is the number of correct answers in the Big Three financial literacy quiz. *SELF-ASSESSED RISK* is subjects' self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks), and *MATH PROFICIENCY* denotes subjects' self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong). All models include controls for treatments, the market number and period (price) fixed effects. Coefficients are shown in terms of log-odds. Standard errors are shown in parenthesis. Random effects on subject ID are included. *p < 0.05; **p < 0.005

	Dep. variable: Bid		
	(1)	(2)	(3)
<i>GOT TOKEN</i>	-0.653** (0.062)		-0.652** (0.062)
<i>BELIEFS:</i>			
<i>HIGHER VALUE</i>	0.022** (0.001)		0.021** (0.001)
<i>BIDDERS CURRENT PERIOD</i>	0.788** (0.034)		0.787** (0.034)
<i>BIDDERS NEXT PERIOD</i>	0.352** (0.032)		0.351** (0.032)
<i>PERSONAL CHARACTERISTICS:</i>			
<i>AGE</i>		-0.004 (0.014)	-0.0002 (0.014)
<i>NON-MALE</i>		-0.351* (0.140)	-0.278 (0.143)
<i>FOMO</i>		-0.005 (0.058)	0.006 (0.059)
<i>NIM</i>		0.002 (0.063)	0.020 (0.065)
<i>CRT</i>		-0.026 (0.064)	0.020 (0.065)
<i>LEVEL K</i>		-0.082* (0.030)	-0.081* (0.031)
<i>STORYTELLER/NUMBER CRUNCHER</i>		-0.003 (0.028)	-0.005 (0.028)
<i>SELF-ASSESSED KNOWLEDGE</i>		-0.039 (0.032)	-0.011 (0.033)
<i>FINANCIAL LITERACY</i>		-0.085 (0.095)	-0.028 (0.096)
<i>SELF-ASSESSED RISK</i>		0.080* (0.029)	0.068* (0.030)
<i>MATH PROFICIENCY</i>		0.014 (0.036)	-0.034 (0.037)
<i>CONSTANT</i>	-2.794** (0.128)	0.342 (0.547)	-2.502** (0.562)
Controls	Yes	Yes	Yes
Conditional/Marginal R squared	0.633/0.457	0.479/0.242	0.635/0.47
Observations	16,005	16,005	16,005

Table C.4: Ordinary least squares regression. This table shows results of an OLS regression where the dependent variable is the number of bids across all markets for each individual, and the independent variables are a between-subject treatment indicator (1: *AMBIGUITY*; 0: *RISK*), and individual characteristics. *AMBIGUITY* is a binary indicator for individuals being in markets, where participants do not know the realization probability of the token having the higher value. The reference category is *RISK*, where participants see the realization probability. *AGE* is an individual's age. *NON-MALE* is a binary indicator for being of female or diverse gender, with the reference category being male. *FOMO* is an individual's mean score across all nine-items in the fear of missing out questionnaire where the items related to *TEMPTATION* and *SELF-DISCIPLINED* are reverse coded (continuous between 0 and 10). *NIM* is the number of times an individual consecutively hit a multiple of 4, with higher numbers indicating that the subject figured out the backward-inducing dominant strategy earlier (integer between 0 and 4). *CRT* is the number of correct answers the subject provided in the three-item cognitive reflection test (integer between 0 and 3). *LEVEL K* is subject's level of rationality in the beauty contest, with higher numbers indicating higher levels of rationality (integer between 0 and 8). *STORYTELLER/NUMBER CRUNCHER* is subjects' self-assessed positioning of themselves of whether they are more of a storyteller or more of a number cruncher kind of person on an 11-point scale (0 = Storyteller; 10 = Numbercruncher). *SELF-ASSESSED KNOWLEDGE* denotes subject's self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while *FINANCIAL LITERACY* is the number of correct answers in the Big Three financial literacy quiz. *SELF-ASSESSED RISK* is subjects' self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks), and *MATH PROFICIENCY* denotes subjects' self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong). Standard errors are clustered on group-level and shown in parenthesis. *p < 0.05; **p < 0.005

	Dep. variable: Number of bids
<i>AMBIGUITY</i>	3.555** (0.861)
<i>PERSONAL CHARACTERISTICS:</i>	
<i>AGE</i>	-0.017 (0.069)
<i>NON-MALE</i>	-1.680* (0.836)
<i>FOMO</i>	0.025 (0.345)
<i>NIM</i>	-0.030 (0.323)
<i>CRT</i>	-0.141 (0.317)
<i>LEVEL K</i>	-0.498* (0.184)
<i>STORYTELLER/NUMBER CRUNCHER</i>	-0.050 (0.139)
<i>SELF-ASSESSED KNOWLEDGE</i>	-0.287 (0.187)
<i>FINANCIAL LITERACY</i>	-0.516 (0.500)
<i>SELF-ASSESSED RISK</i>	0.579** (0.179)
<i>MATH PROFICIENCY</i>	0.184 (0.198)
<i>CONSTANT</i>	23.921** (2.406)
Observations	470
Adjusted R ²	0.103

Table C.5: Subsample analysis. This table shows results of random effects logit regressions of individual's decisions to bid for the token in a given round (bid = 1; no bid = 0) on token possession, belief estimates and personal characteristics for each treatment, respectively. The sample includes periods 1 – 10 and excludes timed-out observations. *GOT TOKEN* is a binary indicator for an individual being in the possession of the token (token in possession = 1; otherwise = 0). *HIGHER VALUE* is an individual's own belief that the token value is higher than €0 in %. *BIDDERS CURRENT PERIOD* is an individuals' beliefs how many bidders there are in the current period, while *BIDDERS NEXT PERIOD* is an individual's belief of how many bidders there are in the next period (integer between 0 and 4, respectively). *AGE* is an individual's age. *NON-MALE* is a binary indicator for being of female or diverse gender, with the reference category being male. *FOMO* is an individual's mean score across all nine-items in the fear of missing out questionnaire where the items related to *TEMPTATION* and *SELF-DISCIPLINED* are reverse coded (continuous between 0 and 10). *NIM* is the number of times an individual consecutively hit a multiple of 4, with higher numbers indicating that the subject figured out the backward-inducing dominant strategy earlier (integer between 0 and 4). *CRT* is the number of correct answers the subject provided in the three-item cognitive reflection test (integer between 0 and 3). *LEVEL K* is subject's level of rationality in the beauty contest, with higher numbers indicating higher levels of rationality (integer between 0 and 8). *STORYTELLER/NUMBER CRUNCHER* is subjects' self-assessed positioning of themselves of whether they are more of a storyteller or more of a number cruncher kind of person on an 11-point scale (0 = Storyteller; 10 = Numbercruncher). *SELF-ASSESSED KNOWLEDGE* denotes subject's self-assessed financial knowledge on an 11-point scale (0 = very low; 10 = very high), while *FINANCIAL LITERACY* is the number of correct answers in the Big Three financial literacy quiz. *SELF-ASSESSED RISK* is subjects' self-assessed risk tolerance on an 11-point scale (0 = not willing to take risks; 10 = very willing to take risks), and *MATH PROFICIENCY* denotes subjects' self-assessed proficiency in mathematics on an 11-point scale (0 = very weak; 10 = very strong). All models include controls for the market number and period (price) fixed effects. Coefficients are shown in terms of log-odds. Standard errors are shown in parenthesis. Random effects on subject ID are included. *p<0.05; **p<0.005

	Dependent variable: Bid						
	BASELINE	RISK10	RISK30	RISK100	AMBI10	AMBI30	AMBI100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>GOT TOKEN</i>	-0.974** (0.156)	-0.719** (0.173)	-0.743** (0.170)	-0.936** (0.183)	-0.921** (0.169)	-0.782** (0.190)	-0.872** (0.186)
<i>HIGHER VALUE</i>	0.019** (0.003)	0.025** (0.005)	0.035** (0.005)	0.020** (0.005)	0.029** (0.004)	0.031** (0.005)	0.024** (0.005)
<i>BIDDERS CURRENT PERIOD</i>	0.939** (0.092)	0.704** (0.093)	0.714** (0.090)	0.827** (0.105)	0.833** (0.101)	0.809** (0.123)	0.828** (0.107)
<i>BIDDERS NEXT PERIOD</i>	0.303** (0.088)	0.489** (0.087)	0.507** (0.090)	0.310** (0.098)	0.204* (0.098)	0.270* (0.113)	0.456** (0.104)
<i>AGE</i>	-0.024 (0.024)	-0.012 (0.024)	-0.015 (0.023)	-0.002 (0.026)	0.026 (0.034)	0.060 (0.044)	0.040 (0.040)
<i>NON-MALE</i>	-0.405 (0.254)	-0.533 (0.302)	-0.549 (0.284)	-0.349 (0.317)	-0.351 (0.260)	0.053 (0.325)	0.102 (0.305)
<i>FOMO</i>	-0.016 (0.107)	0.180 (0.126)	0.034 (0.116)	0.121 (0.130)	-0.101 (0.104)	0.031 (0.131)	-0.114 (0.126)
<i>NIM</i>	-0.117 (0.117)	-0.090 (0.142)	0.039 (0.131)	0.101 (0.152)	-0.058 (0.114)	-0.086 (0.146)	0.067 (0.142)
<i>CRT</i>	-0.063 (0.115)	-0.044 (0.137)	0.076 (0.131)	-0.026 (0.141)	0.028 (0.117)	0.149 (0.150)	0.173 (0.140)
<i>LEVEL K</i>	-0.077 (0.056)	-0.147* (0.062)	-0.127* (0.058)	-0.132* (0.063)	-0.009 (0.059)	-0.061 (0.074)	0.021 (0.070)
<i>STORYTELLER/NUMBER CRUNCHER</i>	-0.046 (0.051)	-0.002 (0.057)	-0.004 (0.054)	-0.045 (0.060)	0.080 (0.052)	0.028 (0.066)	-0.002 (0.062)
<i>SELF-ASSESSED KNOWLEDGE</i>	-0.067 (0.059)	0.052 (0.070)	0.080 (0.066)	0.001 (0.073)	-0.001 (0.058)	0.004 (0.073)	-0.014 (0.068)
<i>FINANCIAL LITERACY</i>	-0.032 (0.165)	0.099 (0.188)	0.091 (0.172)	0.212 (0.198)	-0.206 (0.191)	-0.105 (0.235)	0.021 (0.220)
<i>SELF-ASSESSED RISK</i>	0.075 (0.054)	-0.003 (0.065)	-0.024 (0.063)	0.044 (0.068)	0.068 (0.053)	0.191** (0.068)	0.158* (0.063)
<i>MATH PROFICIENCY</i>	0.117 (0.066)	-0.071 (0.073)	-0.074 (0.069)	-0.039 (0.077)	-0.091 (0.072)	-0.060 (0.092)	-0.068 (0.084)
<i>CONSTANT</i>	-1.970* (0.980)	-1.854 (1.123)	-1.732 (1.065)	-1.821 (1.175)	-2.119 (1.204)	-3.777* (1.661)	-2.771* (1.395)
Conditional/Marginal R squared Observations	0.697/0.438 2,607	0.686/0.439 2,201	0.669/0.45 2,240	0.675/0.402 2,151	0.596/0.389 2,276	0.648/0.347 2,296	0.628/0.356 2,234

Table C.6: Treatment effects on beliefs. This table shows ordinary least squares regressions of the elicited belief estimates in each period on dummy indicators for each treatment specifically and controls. The sample excludes timed-out observations (i.e., taking longer than 20 seconds without responding in all periods except the first one in the first market; in the first period in the first market the threshold was 3 minutes). The reference category in all models is the *BASELINE* treatment, i.e., markets where the value of token was known to be zero with certainty. *HIGHER VALUE* is individual's own belief that the token value is greater than €0 in %. *BIDDERS CURRENT PERIOD* is an individuals' beliefs how many bidders there are in the current period, while *BIDDERS NEXT PERIOD* is an individual's belief of how many bidders there are in the next period (integer between 0 and 4, respectively). Treatment indicators are a combination of the information provided to participants about the realization probability of the token having a higher value (i.e., either *RISK* or *AMBIGUITY*), and the potential value the token can take on (i.e., either €10, €30, €100). Dummies including *RISK* indicate markets where participants knew that the token is only worth the higher value when six dice, thrown at the beginning of the market, show all six at the same time (i.e., a probability of $\frac{1}{46656}$). Dummies including *AMBIGUITY* indicate markets where participants did not get any information about the probability of the token being worth a higher value. Controls include period and market number fixed effects, and timed-out observations (i.e., taking longer than 20 seconds without responding in all periods except the first one in the first market; in the first period in the first market the threshold was 3 minutes) are excluded. Standard errors are indicated in parenthesis and clustered on group ID. *p<0.05; **p<0.005

	<i>Dependent variables: Beliefs</i>		
	<i>HIGHER VALUE</i>	<i>BIDDERS CURRENT PERIOD</i>	<i>BIDDERS NEXT PERIOD</i>
	(1)	(2)	(3)
<i>RISK 10</i>	-0.641 (1.723)	1.011** (0.076)	0.932** (0.076)
<i>AMBIGUITY 10</i>	26.798** (1.822)	1.301** (0.075)	1.286** (0.076)
<i>RISK 30</i>	-1.361 (1.680)	1.023** (0.076)	0.941** (0.076)
<i>AMBIGUITY 30</i>	23.180** (1.905)	1.430** (0.081)	1.392** (0.082)
<i>RISK 100</i>	-2.809 (1.698)	1.164** (0.079)	1.126** (0.079)
<i>AMBIGUITY 100</i>	14.538** (1.932)	1.520** (0.079)	1.454** (0.080)
<i>CONSTANT</i>	20.098** (1.606)	1.943** (0.069)	1.911** (0.066)
Controls	Yes	Yes	Yes
Observations	17,707	17,664	16,553
Adjusted R ²	0.171	0.268	0.244

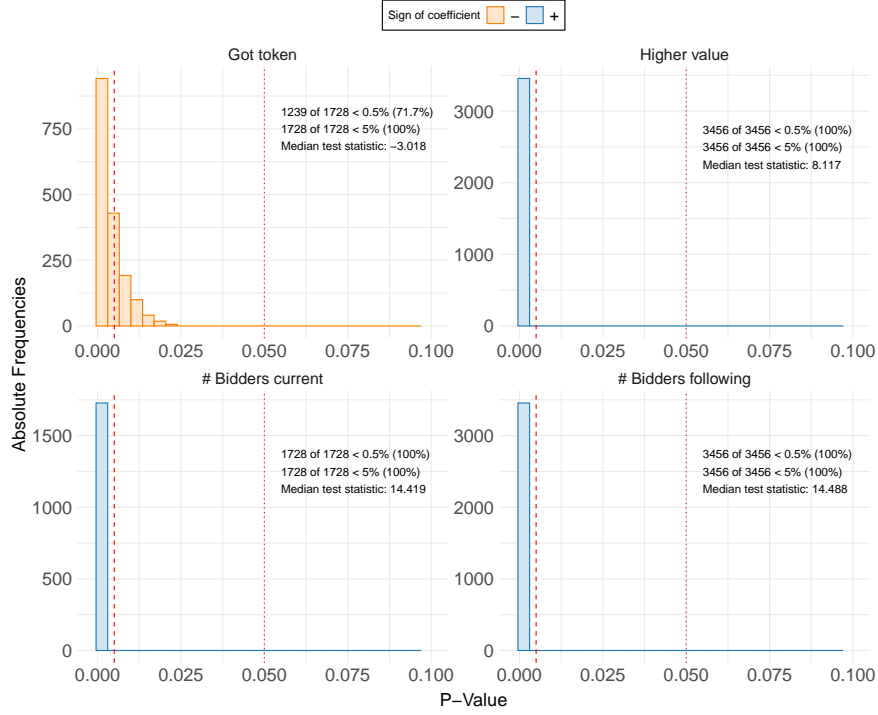


Figure C.3: Histogram of p-values for token possession and belief estimates.

This figure shows the distribution of p-values associated with the coefficients for participant characteristics. Additionally, the share of universe yielding significant results (i.e. p-value < 0.005), suggestive evidence (i.e., p-value < 0.05), and the median test statistics (i.e., t-stat or z-stat, depending on the model) are depicted in each panel. Positive signs of the coefficients are coded in orange and indicate a positive correlation with individuals' bidding, while negative signs are in blue and indicate a negative association with individuals' bidding. *GOT TOKEN* is a binary indicator for an individual being in the possession of the token (1 = token in possession; 0 = otherwise). *HIGHER VALUE* is an individual's own belief that the token value is greater than €0 in %. *BIDDERS CURRENT PERIOD* is an individuals' beliefs how many bidders there are in the current period, while *BIDDERS NEXT PERIOD* is an individual's belief of how many bidders there are in the next period (integer between 0 and 4, respectively).

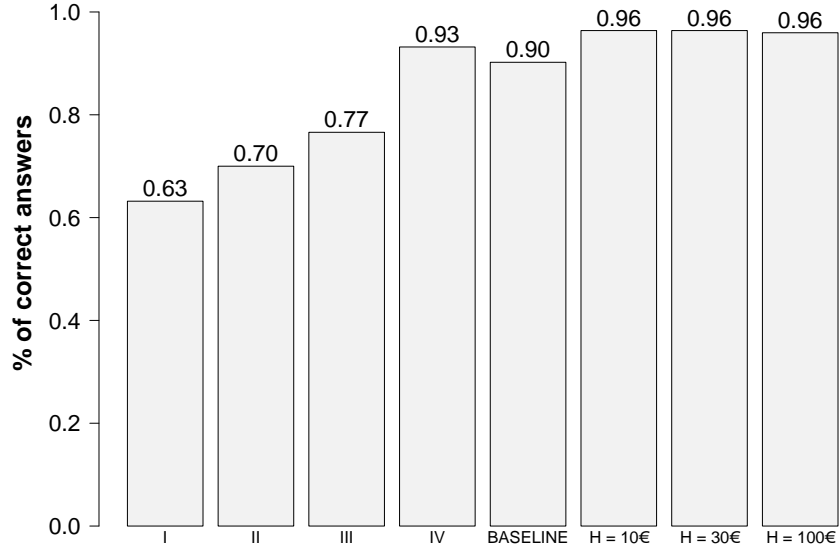


Figure C.4: Share of correct answers in comprehension checks. This figure shows the share of correct answers for each of the eight comprehension check questions, respectively. Questions I-IV were asked right after the instructions of the greater fool game. The remaining questions were asked immediately before the corresponding market began. *BASELINE* corresponds to the market where the token value is €0 with certainty, while $H = €0$ to $H = €100$ correspond to markets where the token value can be higher than €0 with a probability of $\frac{1}{46656}$ (*RISK* and *AMBIGUITY* markets pooled).

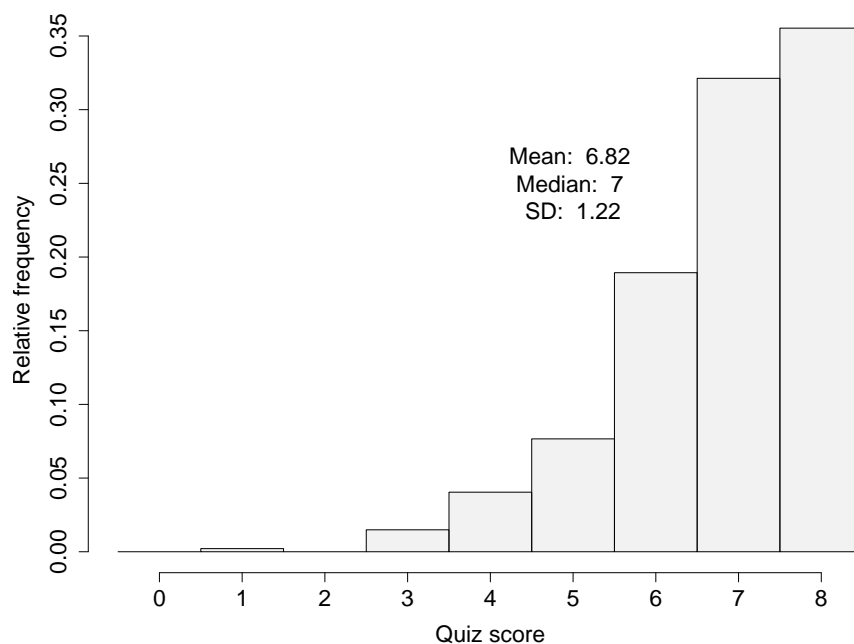


Figure C.5: Histogram of quiz scores in total. This figure depicts the distribution of quiz scores among all participants. On average participants answered 6.8 questions correctly (SD =1.22).

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Armando Holz knecht, Jürgen Huber, Michael Kirchler, Tibor Neugebauer

Speculating in zero-value assets: The greater fool game experiment

Abstract

In a pre-registered laboratory asset market study, we investigate dynamics of asset markets with zero (or close to zero) fundamental values. We introduce the “greater fool asset market game” with a zero-value token, whose price doubles in each period. We design several treatments, which differ in terms of whether the fundamental value is zero for sure, and whether the rather low probability of non-zero fundamentals is known (Risk) or not (Ambiguity). We find that prices in markets with zero fundamental value are clearly above zero. Furthermore, we report that prices in treatment Ambiguity are substantially higher than those in the baseline and in treatment Risk. Finally, we show that beliefs regarding the asset’s value and others’ participation explain individual market participation.

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