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

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A R T I C L E I N F O

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A B S T R A C T

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 (Baseline), and whether the very 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 treatments Baseline and Risk. Finally, we show that beliefs regarding the asset's value and others' participation explain individual market participation.

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 and 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).

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[1] In 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.

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(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, like 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 can usually not 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 was frequently 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 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 cryptocurrencies[2] 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. 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 belief if the token has a value higher than zero. The token is randomly assigned to one of those investors 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 with proceeds going to the previous token holder. 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 are: 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

2 For 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 by 2022 (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.

3 Collectibles 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.

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

(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 entertain 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) and proposed a theory of heterogeneous expectations. They proposes 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.

[5] Like 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.

[6] In 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.

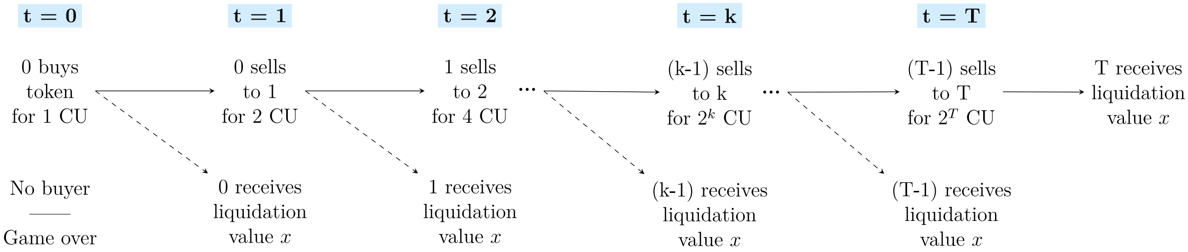

Fig. 1. Timeline. This figure illustrates the timeline of the greater fool game. Investor $i = \{0, 1, \dots, T\}$ indicates a buyer in a particular market period. The solid horizontal arrows indicate the consequence when there is a buyer for the token, while the dashed diagonal arrows illustrate the 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 "currency unit". In our study 1 CU was 1 Eurocent.

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 (Frederick, 2005)—as individual tasks. At the end of the experiment, participants filled out a questionnaire (see Online 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 student subjects participated in the experiment. The target sample size was derived by ex-ante power calculations (see Section B in the Online Appendix for details). The average payout for participants in the experiment was €14.50, and the average duration of a session was 35 min. Screenshots of the software and instructions in English are provided in Online 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 min. 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.

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 would double 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.[8]

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. Fig. 1 illustrates the timeline of a market.

As detailed in the following paragraph, subjects participated in four markets. Only in the baseline condition the intrinsic token value was known to be zero with certainty. In the other three markets, the token's liquidation payoff could be either high (H)

[7] Because 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.

[8] We set the maximum period to 11 to prevent subjects from overspending, thereby guaranteeing that participants could not leave the laboratory with a loss. This approach is standard practice in experimental finance and economics.

Table 1
Treatment design. Groups were assigned either to 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 $\frac{1}{46\,656}$—that is, when six independent dice throws showed the number six each.

Treatment	Token value	Information about other value
BASELINE: RISK 0	€0 certain	
RISK 10	€0 or €10	"six dice show the number 6 each"
RISK 30	€0 or €30	"six dice show the number 6 each"
RISK 100	€0 or €100	"six dice show the number 6 each"
BASELINE: AMBIGUITY 0	€0 certain	
AMBIGUITY 10	€0 or €10	No information
AMBIGUITY 30	€0 or €30	No information
AMBIGUITY 100	€0 or €100	No information

or zero. The token's realized liquidation value was private information to its final holder and remained ambiguous information to the others (except in the baseline condition, in which the value was zero with certainty, which was common information). In addition to their bidding behavior, participants in each period 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 accurate,[9] 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 the treatment variations the value of the token was either €0 with a probability of $\frac{46655}{46656}$ or €H with a probability of $\frac{1}{46656}$.[10] We set H = 10, 30, and 100 in three independent markets, 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 was determined by an independent 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 correct.[11] After reading the instructions, participants were required to answer two questions regarding the outcome of two hypothetical market periods[12] and two questions regarding the general mechanics of the game.[13] Additionally, we asked one treatment-specific question immediately before the corresponding market started.[14] All questions are provided in the instructions in Online 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

[9] We 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 liquidation payoff of the token was €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.

[10] 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.

[11] We 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.

[12] For 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)?"

[13] For 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?"

[14] For 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?"

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 for their first prediction. Thereafter, every bidding decision and prediction elicitation was restricted to a maximum of 20 s. 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.[15]

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.[16] 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.[17] 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 s 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 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.[18] 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), Crawford and Iriberri (2007), and Nagel (1995).

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.

$$r_t^i = \mu_t^i + w_t^i, \tag{1}$$

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:

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

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

[15] A timeout occurred only in 0.8% of bidding decisions and 2.81% of belief elicitations.

[16] The 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.

[17] 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.

[18] The 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).

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,[19] —that is.,

$$p_t \leq F. \tag{3}$$

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 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[20]:

$$r_T^i = \mu_T^i \tag{4}$$

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

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

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

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" theory (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 Eq. (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

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

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

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 diminished 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. Fig. 2 illustrates the relative frequencies of final transaction prices by treatment. This figure shows that the distribution of final transaction prices shifts toward higher amounts in markets in which the token payoff is greater than €0. This shift seems to be more pronounced in Ambiguity than in Risk. In the Baseline condition, in contrast, the final prices are rather uniformly distributed with no visible difference across Risk and Ambiguity treatments.[21] In the following section, we present the main findings based on our hypotheses, followed by exploratory results related to individual outcomes. Unless otherwise stated, all figures and regression models mentioned are pre-registered. Finally, we use the significance thresholds of Benjamin et al. (2018): a p-value < 0.05 is considered "suggestive evidence", and a p-value < 0.005 defines "statistical significance".

6.1. Market outcomes

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

Support: Panels A and B in Fig. 3 provide an overview of the average final transaction period and price across Baseline, Risk, and Ambiguity (Panel A) and across the higher token values (Panel B). Furthermore, Figure C.1 in the Online 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 transaction prices above €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.

[21] Before conducting the experiment, it could not be taken for granted that the differences would be small, as the ambiguity effect might have been substantial and spillover effects could have varied considerably across treatment conditions.

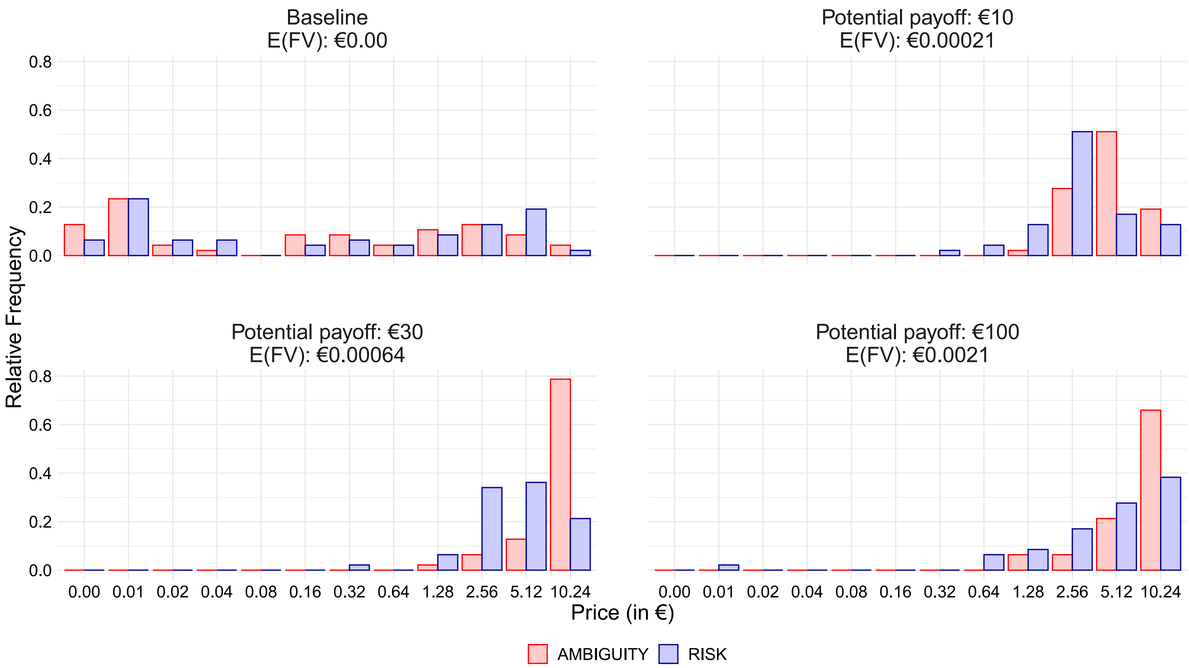

Fig. 2. Final prices. This figure illustrates the relative frequency of final transaction prices across treatments. In Baseline, the token value was €0 with certainty, while in all other treatments the token had a value of €10, or €30, €100 with a probability of $\frac{1}{46656}$, respectively. In Risk, participants were informed about this probability (i.e.,"when six dice show 6 at the same time"), while in Ambiguity this information was not known to participants.

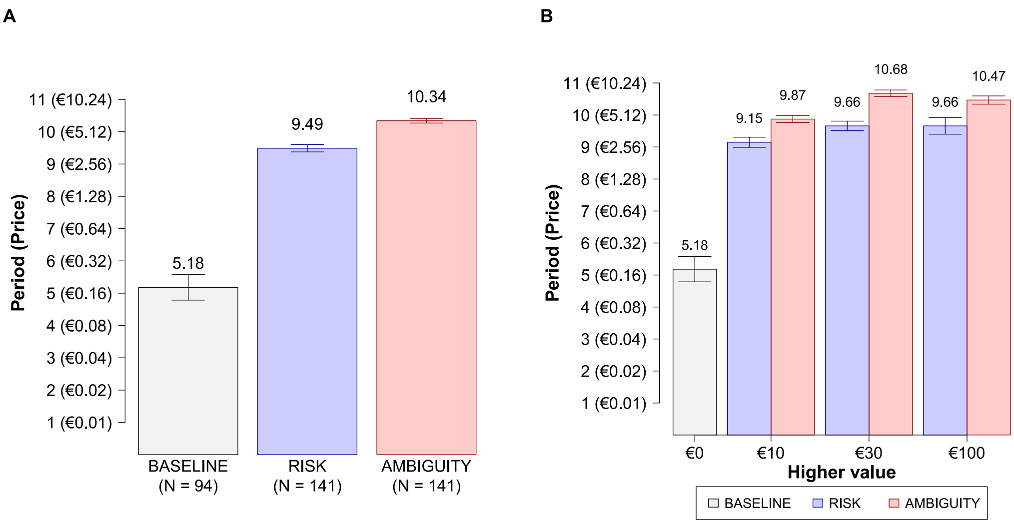

Fig. 3. Average final prices. This figure illustrates the average final transaction period and price across: (A) baseline and pooled uncertainty treatments and (B) baseline and uncertainty treatments ordered by higher prospective values. Note that the expected (fundamental) values are below €0.01 for given probabilities.

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 Fig. 3, market settings other than Baseline tend to end in later 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 Fig. 3). Additionally, as outlined in column (1) of Table 3, the coefficient for being in a market other than in the

Table 2

Sample descriptions. This table presents descriptive statistics of the sample characteristics as well as the outcome variables of 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	0.01				1	0.01			

baseline (i.e., Uncertain) is positive and highly significant.[22] We find strong support for *H2a*, thereby indicating that as soon as fundamentals climb above zero—in our case the probability of the token value exceeding zero is $\frac{1}{46656}$ and this yields expected fundamental values 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 prospective 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 the market further to overvalue token values. Discussing hypotheses *H2a* and *H2b* jointly, we observe a strong overvaluation of markets with non-zero fundamentals. As compared with 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

[22] We pre-registered using H1 robust standard errors in our models. However, due to the grouping nature of the data imposed by the experimental design and because we apply ordered logistic regressions, cluster robust standard errors are more appropriate. Results of non pre-registered robustness checks utilizing OLS models instead of ordered logistic regressions are shown in Tables C.1 and C.2 in the Online Appendix. Results remain qualitatively robust.

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.

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

* $p < 0.05$.
** $p < 0.005$.

bottom of the table.[23] 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). Here, ambiguous lotteries (where 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.

[23] For 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 for 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 analysis similar to the pre-registered one, which also includes interaction terms, is a subsample analysis that only includes markets other than Baseline. The results, presented in Table C.3 in Online Appendix C, are qualitatively the same.

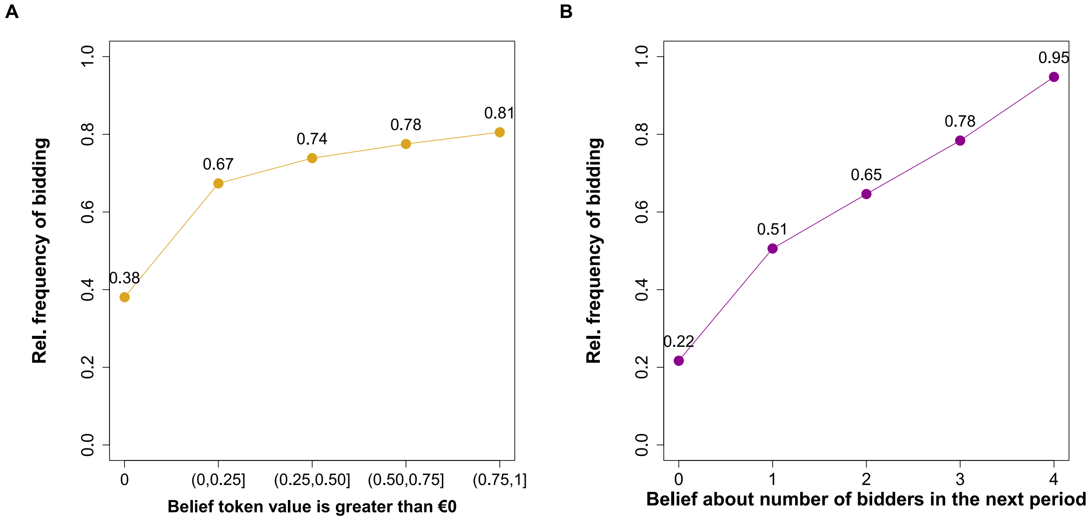

Fig. 4. Bids and beliefs. This figure illustrates the probability of bidding (i.e., willingness to buy the token) across belief measures, elicited after each bidding decision, respectively. Panel (A) depicts the share of bids across buckets of beliefs regarding the token value being greater than €0.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

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 and next round (*H4b*). Furthermore, individuals with the token in their possession are more likely to sell it immediately (this analysis was not pre-registered).

Support: We turn to individual bidding behavior and the role of beliefs and personal characteristics across various market settings. Fig. 4 and Table 4 present the results.[24] Note that we exclude observations from period 11 because we did not elicit individuals' beliefs 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.[25] Moreover, by expanding the set of explanatory variables in an additional, non-pre-registered analysis (see Table C.5 in Online 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 theory as explanation for trading in our markets. Finally, the results remain robust when controlling for a battery of individual skills and sociodemographic variables (see columns (3) of Table 4 and C.5, respectively). In the following 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.

[24] We 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.4, 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 Online Appendix C in Table C.4. The results remain quantitatively and qualitatively the same.

[25] These two beliefs are mostly uncorrelated, unless subjects correctly anticipate a zero liquidation payoff (i.e., $\rho = 0.06$ when excluding vs. $\rho = 0.16$ when including subjects who believe the token value is zero). When they assign a zero probability to a positive token value, their expected number of future bidders, which averages at 2.57, sharply lowers to 1.52. We also observe that participants who expect zero future buyers typically refrain from bidding unless they believe in a positive token value. A small share of subjects (a conditional 9.87%) seems confused, bidding despite indicating both of their beliefs as zero.

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 significant at the 5% level, we emphasize that the role of demographics, cognitive skills, and socioeconomic variables in bidding behavior should not be overinterpreted.[26]

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).[27] 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 presents the data analytical decisions along with specifications we consider for this study.[28] 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.[29] 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 with the modeling of the fomo-index. Here, multiple approaches might be suitable. Overall, we investigate 3456 meaningful specification combinations.

As shown in Fig. 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.5 in Online 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.[30] 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" provides suggestive evidence. Furthermore, the median test statistic of the coefficient associated with Level k is −3.017, which, assuming an approximate normal distribution, corresponds to a p-value of 0.003 in a two-sided test.[31] 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.

[26] To further support the robustness of our experimental setup, we connect our experiment to stylized facts about experimental asset markets known from prior literature. First, consistent with the findings from Smith et al. (1988) and Dufwenberg et al. (2010), markets in Baseline tend toward the fundamental value with experience of groups (i.e., number of market runs). However, as shown in Figure C.3 in Online Appendix C, this is not the case for markets in Risk and Ambiguity treatments. Moreover, the relevant literature documents that sophistication (i.e., Level k) and cognitive ability (i.e., Crt) are positively correlated with earnings in experimental asset markets (see, for example, Corgnet et al., 2018). In line with this literature, we find suggestive evidence of cognitive reflection being positively associated with average earnings (see Table C.10 in Online Appendix C). Contrasting this to findings reported in Result 5, we conclude that cognitive reflection is positively associated with exploiting the behavior of other participants in the market, while participants with higher sophistication tend to exhibit bidding behavior that reflects the token's fundamental value. Overall, in our greater fool game, the average performance of traders depends more on anticipating the irrationality of others than on the fundamental token value. Given that only one randomly chosen bidder gets the token, the payoff structure of our setup potentially obscures this general observation seen in previous literature. We thank one anonymous referee for guiding us in this valuable direction and contributing to the discussion. However, we want to explicitly point out that this was not part of our pre-registration and hence results and the interpretation should be considered with caution.

[27] Additionally, 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 (see Table C.6 in Online Appendix C).

[28] Note 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.

[29] We 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.4 suggests that no variance stems from the group random effect (see footnote 24).

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

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

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.

	Dep. variable: Bid		
	(1)	(2)	(3)
Beliefs:			
Higher value	0.023** (0.001)		0.023** (0.001)
Bidders next period	0.856** (0.023)		0.856** (0.023)
Personal characteristics:			
Age		−0.004 (0.014)	−0.002 (0.014)
Non-male		−0.351* (0.140)	−0.327* (0.138)
Fomo		−0.005 (0.058)	0.013 (0.057)
Nim		0.002 (0.063)	0.004 (0.063)
Crt		−0.026 (0.064)	0.025 (0.063)
Level k		−0.082* (0.030)	−0.075* (0.030)
Storyteller/Number cruncher		−0.003 (0.028)	−0.001 (0.027)
Self-assessed knowledge		−0.039 (0.032)	−0.017 (0.032)
Financial literacy		−0.085 (0.095)	−0.003 (0.093)
Self-assessed risk		0.080* (0.029)	0.068* (0.029)
Math proficiency		0.014 (0.036)	−0.023 (0.036)
Constant	−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

* $p < 0.05$.
** $p < 0.005$.

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.

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, 2, and 3, but we want to limit the discussion to the most important ones (in our opinion):

The Greater Fool Theory: Participants expected at least one bidder in the upcoming period in 87.2% of all observations across periods. This is an indication of a greater fool trading motive, as most subjects obviously believed that there are traders with

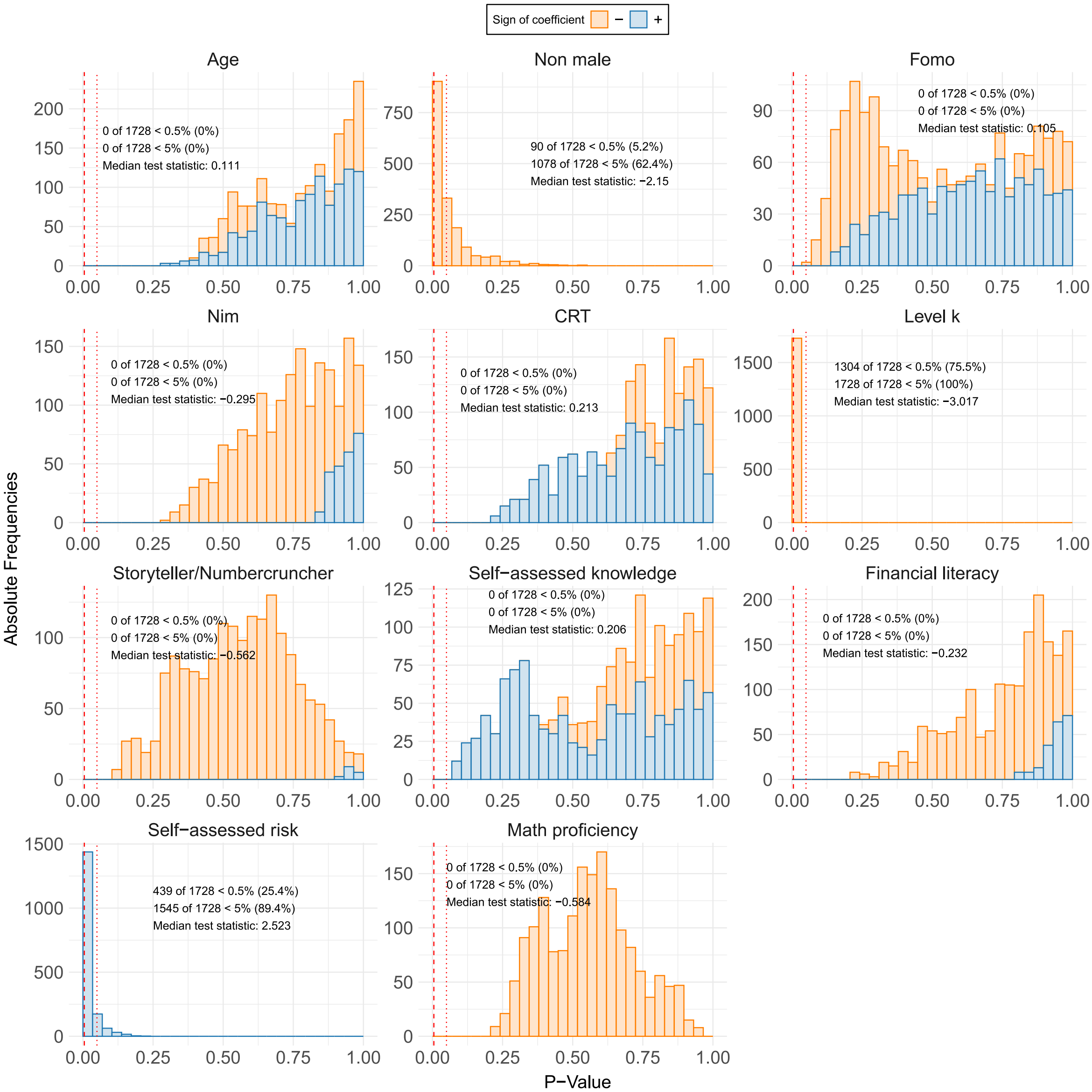

Fig. 5. Histogram of p-values for individual characteristics. This figure depicts the distribution of p-values associated with the coefficients for participant characteristics. Additionally, the share of the universe yielding significant results (i.e., p-value < 0.005), suggestive evidence (i.e., p-value < 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 blue and indicate a positive correlation with individuals' bidding, while negative signs are in orange and indicate a negative association with individuals' bidding. Age is an individual's current age 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 0 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). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 modeling	**Mean over all items**, product over all items, every questions by itself, principal component analysis (1st component)

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.7 in Online 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.8; 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.8, respectively). On average, individuals in the Risk treatment form beliefs of one additional bidder in current and future periods compared to individuals in the Baseline treatment, holding everything else constant. The same holds for markets in the Ambiguity treatment, in which all beliefs are significantly higher than those in the Baseline. Consequently, we cannot clarify whether the overvaluation of small probabilities or anticipated market participation is the predominant explanation for prices we see in Ambiguity treatments. The fact that both treatments show higher expected market participation – without a corresponding increase in value expectation – suggests an effect on second-order and higher-order beliefs about how a small probability event influences others in the market. Therefore, what could explain the significant increase in prices from Baseline to Risk markets, 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 may not only systematically increase anticipated market participation but also make these beliefs more persistent—that is, speculation itself is sustained. To further examine this possibility, we conducted an additional exploratory analysis, presented in Online Appendix C (see Table C.9). Supporting this claim, the results suggest that (i) participants in the Risk and Ambiguity conditions are less likely to abandon their greater fool expectations over the course of the market (see column (1)), and (ii) when they do, they tend to do so significantly later (see column (2)). We take these results as further evidence that greater fool beliefs explain the results better than probability misweighting.[32] However, what our results clearly show is that extremely small probabilities matter in a market setting with resale option and are not ignored, 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 could be 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," which suggests that an overvaluation of assets can emerge due to the lack of alternatives, "forcing" subjects to trade and thereby driving prices up. Lei et al. (2001) found no support for this

[32] Complementary to the results shown in Tables C.8 and C.9, Figure C.4 in Online Appendix C depicts the evolution of probability misweighting (i.e., Higher value) and greater fool expectations (i.e., Bidders next period) across periods and treatment conditions. In general, the graphs support what is discussed in this paragraph.

hypothesis, as overvaluation still emerged 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 an early end of the session and, thus, an increased hourly pay. More generally speaking, the argument of lack of outside options could be applied to almost all laboratory asset market experiments run during the previous decades, 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.

The key takeaway from our study is that the market price does not always equal the value assigned by the investor who buys an asset for keeps. Instead, the price can also reflect the expectations of market participants, or the expectations about others' expectations, regarding future prices. As we show, announcements, even of highly unlikely outcomes, can shape market beliefs about how others might behave. This observation helps to explain how and why narratives about potential outcomes fuel speculation on future market values,[33] or, in our terminology, how greater fool beliefs emerge.

The implications for investors and portfolio managers are that gains can be made from assets even when their prices exceed fundamental values. Brunnermeier and Nagel (2004) document how fund managers at the turn of the century recognized the dot-com bubble. However, rather than exiting the market, many chose to "ride the bubble"—a strategy that, while potentially lucrative, carried significant risk. Some ultimately stayed in the market too long, facing substantial losses when the bubble burst.

Our study has several limitations. First, as discussed in the previous section, we can accommodate 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. We did not elicit second or higher order beliefs as doing so would have significantly increased the complexity. Instead, this paper focuses on establishing the relevance of greater fool beliefs in subjects' decision-making. Determining whether greater fool beliefs stem more from second- or third-order beliefs, which is an intriguing question, requires further experiments.[34] Second, the potential maximum bid was common information—that is, €10.24 in period 11, and was fixed by applying the no-loss constraint, a standard approach in financial economic experiments. Similar to real speculative asset markets, introducing uncertainty around the investment horizon and hence not limiting potential gains through trading the token could further affect bidding behavior in this context. As such, participants' expectation of their highest possible gain through trading would not be capped from above. Finally, 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). As a result, the exclusive use of student subject pools limits the study's generalizability to real-world investors.[35] These limitations highlight open research questions that would be potentially interesting to explore in future studies.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Juergen Huber reports financial support was provided by Austrian Science Fund. Michael Kirchler reports financial support was provided by Austrian Science Fund. Tibor Neugebauer reports financial support was provided by Luxembourg National Research. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[33] Bitcoin advocate Michael Saylor famously predicted a bitcoin price of 13 million by 2045. Without further reflecting on the plausibility of this figure or the credibility of the source, our results suggest that such a public prediction can, for some time, entertain the imagination of some market participants.

[34] In this context we note that the modal level of reasoning is 2 in the sequential beauty contest game of Nagel (1995).

[35] For instance, the experimenter demand effect could be mitigated with professional investors. As stated above, we believe that the experimenter demand effect should be minimal in our experiment, as duration and hourly earnings depend on participants' early exit decisions. However, our anonymous referee argued that students may not value their time as highly as professional investors, who face higher opportunity costs and may place greater emphasis on early exits. Therefore, testing professionals in our experimental setup could provide further insight into the experimenter demand effect hypothesis.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.euroecorev.2025.105180.

Data availability

The replication package can be found on our OSF repository: https://osf.io/gszbw/.

References

Akiyama, E., Hanaki, N., Ishikawa, R., 2017. It is not just confusion! strategic uncertainty in an experimental asset market. Econ. J. 127 (605), 563–580.
Aliber, R.Z., Kindleberger, C.P., McCauley, R.N., 2015. Manias, Panics, and Crashes: A History of Financial Crises. Springer.
Ammann, M., Burdorf, T., Liebi, L., Stöckl, S., 2022. Survivorship and delisting bias in cryptocurrency markets. Available at SSRN 4287573.
Athey, S., Parashkevov, I., Sarukkai, V., Xia, J., 2016. Bitcoin Pricing, Adoption, and Usage: Theory and Evidence. Stanford University Graduate School of Business Research Paper No. 16-42, Available at SSRN: https://ssrn.com/abstract=2826674.
Benjamin, D.J., Berger, J.O., Johannesson, M., Nosek, B.A., Wagenmakers, E.-J., Berk, R., Bollen, K.A., Brembs, B., Brown, L., Camerer, C., et al., 2018. Redefine statistical significance. Nat. Hum. Behav. 2 (1), 6–10.
Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., Menkveld, A.J., 2023. Equilibrium bitcoin pricing. J. Financ. 78 (2), 967–1014.
Biais, B., Bossaerts, P., 1998. Asset prices and trading volume in a beauty contest. Rev. Econ. Stud. 65 (2), 307–340.
Brunnermeier, M., Nagel, S., 2004. Hedge funds and the technology bubble. J. Financ. 59 (5), 2011–2040.
Carlé, T.A., Lahav, Y., Neugebauer, T., Noussair, C.N., 2019. Heterogeneity of beliefs and trade in experimental asset markets. J. Financ. Quant. Anal. 54 (1), 215–245.
Cheah, E.-T., Fry, J., 2015. Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. Econom. Lett. 130, 32–36.
Chen, D.L., Schonger, M., Wickens, C., 2016. OTree—An open-source platform for laboratory, online, and field experiments. J. Behav. Exp. Financ. 9, 88–97.
Corgnet, B., Desantis, M., Porter, D., 2018. What makes a good trader? On the role of intuition and reflection on trader performance. J. Financ. 73 (3), 1113–1137.
Crawford, V.P., Iriberri, N., 2007. Level-k auctions: Can a nonequilibrium model of strategic thinking explain the winner's curse and overbidding in private-value auctions? Econometrica 75 (6), 1721–1770.
Damodaran, A., 2017. Narrative and Numbers: The Value of Stories in Business. Columbia University Press.
Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. J. Eur. Econ. Assoc. 9 (3), 522–550.
Dufwenberg, M., Sundaram, R., Butler, D.J., 2010. Epiphany in the game of 21. J. Econ. Behav. Organ. 75 (2), 132–143.
Ellsberg, D., 1961. Risk, ambiguity, and the Savage axioms. Q. J. Econ. 75 (4), 643–669.
Frederick, S., 2005. Cognitive reflection and decision making. J. Econ. Perspect. 19 (4), 25–42.
Harrison, J.M., Kreps, D.M., 1978. Speculative investor behavior in a stock market with heterogeneous expectations. Q. J. Econ. 92 (2), 323–336.
Holzmeister, F., Huber, J., Kirchler, M., Lindner, F., Weitzel, U., Zeisberger, S., 2020. What drives risk perception? A global survey with financial professionals and laypeople. Manag. Sci. 66 (9), 3977–4002.
Huber, J., Kirchler, M., Stefan, M., 2014. Experimental evidence on varying uncertainty and skewness in laboratory double-auction markets. J. Econ. Behav. Organ. 107, 798–809.
Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica (ISSN: 00129682, 14680262) 47 (2), 263–291.
Keynes, J.M., 1936. The General Theory of Employment, Interest and Money. Macmillan and Co..
Kirchler, M., Huber, J., Stöckl, T., 2012. Thar she bursts: Reducing confusion reduces bubbles. Am. Econ. Rev. 102 (2), 865–883.
Kirchler, M., Lindner, F., Weitzel, U., 2018. Rankings and risk-taking in the finance industry. J. Financ. 73 (5), 2271–2302.
Kumar, A., 2009. Who gambles in the stock market? J. Financ. 64 (4), 1889–1933.
Lei, V., Noussair, C.N., Plott, C.R., 2001. Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality. Econometrica 69 (4), 831–859.
Lusardi, A., Mitchell, O.S., 2011. Financial literacy around the world: an overview. J. Pension Econ. Financ. 10 (4), 497–508.
Maafi, H., 2011. Preference reversals under ambiguity. Manag. Sci. 57 (11), 2054–2066.
Malkiel, B.G., 1999. A Random Walk Down Wall Street: Including a Life-Cycle Guide to Personal Investing. WW Norton & Company.
Miller, E.M., 1977. Risk, uncertainty, and divergence of opinion. J. Financ. 32 (4), 1151–1168.
Moinas, S., Pouget, S., 2013. The bubble game: An experimental study of speculation. Econometrica 81 (4), 1507–1539.
Nagel, R., 1995. Unraveling in guessing games: An experimental study. Am. Econ. Rev. 85 (5), 1313–1326.
Neugebauer, T., 2010. Moral impossibility in the petersburg paradox: A literature survey and experimental evidence.
Palan, S., 2013. A review of bubbles and crashes in experimental asset markets. A Collect. Surv. Mark. Exp. 197–217.
Pénasse, J., Renneboog, L., 2022. Speculative trading and bubbles: Evidence from the art market. Manag. Sci. 68 (7), 4939–4963.
Przybylski, A.K., Murayama, K., DeHaan, C.R., Gladwell, V., 2013. Motivational, emotional, and behavioral correlates of fear of missing out. Comput. Hum. Behav. 29 (4), 1841–1848.
Razen, M., Huber, J., Hueber, L., Kirchler, M., Stefan, M., 2021. Financial literacy, economic preferences, and adolescents' field behavior. Financ. Res. Lett. 40, 101728.
Razen, M., Huber, J., Kirchler, M., 2017. Cash inflow and trading horizon in asset markets. Eur. Econ. Rev. 92, 359–384.
Razen, M., Kirchler, M., Weitzel, U., 2020. Domain-specific risk-taking among finance professionals. J. Behav. Exp. Financ. 27, 100331.
Scheinkman, J.A., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Political Econ. 111 (6), 1183–1220.
Simonsohn, U., Simmons, J.P., Nelson, L.D., 2020. Specification curve analysis. Nat. Hum. Behav. 4 (11), 1208–1214.
Smith, V.L., Suchanek, G.L., Williams, A.W., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica 1119–1151.
Weitzel, U., Huber, C., Huber, J., Kirchler, M., Lindner, F., Rose, J., 2020. Bubbles and financial professionals. Rev. Financ. Stud. 33 (6), 2659–2696.
Zizzo, D.J., 2010. Experimenter demand effects in economic experiments. Exp. Econ. 13, 75–98.