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# Pyramid schemes ⋆

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ABSTRACT

We invite experiment participants to invest their endowment in a pyramid scheme with a negative expected return. In two samples, one from the general U.S. population and one from a major German university involving higher stakes, more than half invest regardless of their age, gender, income, and trust and fairness beliefs. Higher risk tolerance positively correlates with investment in both populations, whereas preference for positively-skewed risk, and lower cognitive skills explain investment only in the general U.S. population. We vary the level of assistance provided to participants in inferring the distribution of payoff from the pyramid scheme in four treatments, and find that only those requiring no further extrapolation of information are successful in reducing investment.

## 1. Introduction

Pyramid schemes are usually marketed as investments: a participant exchanges a joining fee for a solidified position in the pyramid. The joining fee then becomes a dividend and is awarded disproportionately to those who joined the scheme earlier than later. Many people fall for such schemes. The Federal Trade Commission (FTC) estimates that 400,000 people in the United States fell victim to some pyramid scheme in 2017 (Anderson, 2019), and in 2019, an estimated US$3.25 billion were invested in 60 different Ponzi schemes (Iacurci, 2020). [1] These victims' financial, personal, and social well-being are often devastated when the schemes inevitably collapse. An extreme example is the Albanian Civil War of 1997, in which more than 2000 people were killed and the government fell. The civil war was precipitated by the collapse of hugely popular pyramid schemes, which in 1996 had liabilities worth half

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[1] FTC considers a person to be a victim "if they purchased a membership in a pyramid scheme, were told that they would realize a promised level of earnings, and then earned less than half of that promised amount".

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the Albanian GDP and had two-thirds of the Albanian population as investors (Jarvis, 2000). The graveness of such consequences confronts us with the question: What makes people join pyramid schemes?

While pointing to the cajolery, deception, and manipulation that often accompany real-life pyramid schemes may offer an easy answer, it diverts our attention from the *intrinsic* nature of a pyramid scheme: the complexity of outcome and payoff inference, the potential high earnings which increases with the number of investors, and a skewed payoff distribution in which most people lose money. These features appear in other economic prospects that are perfectly legal with arguably minimal deceptive tactics, such as "superstar" industries (Rosen, 1981), and (at least some) cryptocurrencies. Understanding behavioral responses to such prospects therefore carries implications for career choices, income inequality, and financial system stability.

To answer this question, we created a simple pyramid scheme without deception in a pre-registered experiment. Participants are provided with a chance to invest in the scheme and be placed randomly into the pyramid. The random placement eliminates beliefs about one's position in the pyramid, or the ability to convince others to join, allowing us to focus on the behavioral response to a "bare-bones" pyramid scheme.

Strikingly, in our baseline setup conducted with participants from the U.S. general population recruited via Amazon MTurk, 58 percent chose to invest in the pyramid scheme, despite passing a comprehension test on the scheme before being allowed to invest. In a replication experiment with students of a large German university with higher stakes, 57 percent chose to invest. Investment choice is uncorrelated with age, gender, education, income, trust, and fairness beliefs. While risk tolerance explains a small percentage of investment, there is little supporting evidence for pyramid investment due to skewness preferences.

It is one thing to understand the mechanics of a pyramid scheme and another to draw the relevant inferences from available information. In a complex context like a pyramid scheme, there are multiple approaches to reach the optimal decision, and we remain agnostic about the decision-theoretic mechanism behind participants' choices. Yet ultimately, the critical realization for this problem is the high probability of losing money. Can participants be assisted to come to this realization? If so, what kind of assistance is effective?

We tested four interventions, each of which provided information to participants, varying in the assistance with information processing. These treatments are (in ascending order of assistance given):

**Examples** Participants were given an example pyramid tree and its associated payoff distribution that may realize based on the number of investors they chose. They can sample more example trees if they wish. No further assistance in interpreting, summarizing or applying the data was given.

**Small Pyramid** Participants were given an example of a small pyramid tree, and were asked to make an investment decision at each position of this small tree, before making their decision in the large pyramid scheme. Besides directing participants' attention to the profit and loss at each possible position in the small pyramid example, no assistance was given in summarizing or applying their findings to a large-scale pyramid.

**Backward Induction** Participants were given an example of a large pyramid tree, and were forced to calculate the payoffs of investors at the lowest three levels, before making their decision in the large pyramid scheme. The task directed participants' attention to the part of the pyramid that loses money. Participants in Backward Induction can apply their findings directly to a large pyramid, without having to extrapolate from a small-scale example.

**Payoff Distribution** Participants were shown the payoff distribution stemming from the number of investors they chose. No further summary is needed to arrive at the average payoff distribution in the large-scale pyramid. They can further sample different numbers of investors if they wish.

Out of these four interventions, Payoff Distribution and Backward Induction are effective in reducing pyramid investment rates, but Examples and Small Pyramid are not. Technically, all four interventions illuminate the probability of making a loss via data. Nonetheless, the level of assistance provided for information processing has a significant impact.

If information processing is driving the differences, one would expect participants with higher cognitive skills to be less likely to invest. This conjecture receives partial support in our experiments. In the general U.S. population sample, participants who pass the quiz on the instructions with fewer attempts are less likely to invest. Likewise, those who win the race game (Dufwenberg et al., 2010; Gneezy et al., 2010; Cardella, 2012) more often (signifying higher backward induction capability) are less likely to invest. In the Small Pyramid and the Backward Induction treatments, where additional calculations are required, participants who make correct calculations are markedly less likely to invest in the pyramid scheme. Nonetheless, in the university student sample, neither the quiz nor the race game performance explain pyramid investments. Notably, despite a significantly better race game performance, university students invest in the pyramid scheme at practically the same rate as the general U.S. population.

More generally, our findings imply that how consumers are given information is as important as the information content itself. Beshears et al. (2009) and Kozup et al. (2008) report contrasting findings on whether investors' behaviors respond to the provision of summary information on investment products. Notably, the two studies use different summary formats. The format that is effective in inducing changes is "much briefer and emphasizes comparisons between a fund and the universe of similar funds" (Beshears et al., 2009, p. 3). This is consistent with our findings that, in a complex context, effective interventions are those that emphasize critical information and require little extrapolation. Meanwhile, having better cognitive skills is helpful for consumer protection in general, but its effect may be subject to diminishing returns.

Close to our paper are three studies that explore pyramid-like schemes: Antler (2018), Sadiraj and Schram (2018) and Bosley et al. (2019). Antler (2018) proposes a theoretical model for multi-level marketing schemes, which is sustainable via agents' coarse beliefs.

The model offers insights into distinguishing multi-level marketing, which is legal, from pyramid schemes. For our purposes, though, we prefer testing the fundamental features of pyramid-like schemes. Sadiraj and Schram (2018) investigated investment decisions in Ponzi schemes with sequential multi-period decision-making with both informed and uninformed decision-makers. Different from ours, their setup comprised small groups with either 12 or 16 participants, and an underlying asset that was distributed as interest payments should a participant withdraw from the scheme. They found Ponzi schemes collapse faster with higher interest rates. Our study expands this line of work to pyramid-like schemes without an underlying asset, but with a large number of potential investors.

Bosley et al. (2019) ran a lab-in-the-field experiment eliciting participants' decisions upon being offered a pyramid scheme investment opportunity. Like us, they did not deceive participants about the mechanics of the scheme and the population size. However, their participants' payoffs did not depend on other participants' decisions. Their treatment involves a prompt asking participants to "think carefully about [their] odds of winning" (Bosley et al., 2019, p. 3), which was ineffective in reducing investment. By introducing treatments varying the assistance for participants to "think carefully", we are able to distinguish between the efficacy of different interventions.

## 2. Model

An initiator starts a pyramid scheme by sending $n$ invitations uniformly randomly to the $N$ agents in the economy. Upon receiving an invitation to join the scheme, each agent decides whether to accept or reject the invitation. If an agent rejects, he leaves the game. If he accepts, he becomes a member of the scheme and $n$ additional invitations will be sent on his behalf uniformly randomly to the population that has not yet received an invitation. To abstract away from agents' effort of recruiting members to the scheme, invitation generation is completely exogenous. The agents receiving these invitations will decide whether to join in the same manner. The game ends either when all agents have received an invitation, or when all current outgoing invitations are rejected.

The population size is common knowledge. However, when receiving an invitation, an agent does not know where he stands in the pyramid tree: he does not know the size of the population that has not yet received an invitation, nor does he know how many other invitations are sent along with his.

If agent $i$ accepts an invitation from agent $j$, $i$ is known as $j$'s *immediate descendant* and $j$ is $i$'s *parent*. Upon joining, each member of the scheme pays an amount $x$ to his parent. When a member acquires descendants, he pays his parent a fraction $\delta$ of the proceeds from all of his immediate descendants. Agents who reject the invitation receive nothing and pay nothing. The structure of the game and the payoff functions are common knowledge.

Because each agent can receive an invitation at most once, and he does not know his position in the pyramid tree, each agent has only one information set in this game. Thus, an agent's (behavioral) strategy can be described by the probability of acceptance when he receives an invitation. We consider Nash equilibria in which each agent's acceptance probability is optimal given other agents' strategies. [2]

It is obvious that an equilibrium exists: every agent rejecting the invitation is an equilibrium. In fact, this is the only equilibrium when no agent is risk seeking. To see why, notice that this is a zero-sum game in terms of monetary payoffs. Since the initiator never loses money, the expected monetary payoff to any agent receiving an invitation must be negative, and strictly so if at least one agent accepts with positive probability. It is therefore never optimal for a risk neutral or risk averse agent to accept.

Notice that this is a dominant strategy argument: a risk neutral or risk averse agent should always reject regardless of what other agents do. [3] The strategy remains unaffected if some other agents are risk seeking or make sub-optimal choices. Consequently, in our setup, a fully rational individual is distinguished from a victim by the ability to realize that the scheme is an unfair lottery, rather than the ability to understand other individuals' actions at each possible information set of the game. Thus, the investment decision cannot be solely explained by the agent's anticipation of others' mistakes (e.g., quantal response, McKelvey and Palfrey, 1995), his inability to draw inferences from other agents' actions (e.g., cursed equilibrium, Eyster and Rabin, 2005), or his inability to distinguish between different nodes of other agents (e.g., analogy-based expectation, Jehiel, 2005). [4]

## 3. Experimental design

The experiment was programmed and conducted with the software o-Tree (Chen et al., 2016). We describe here the experiments with participants recruited from Amazon MTurk. See Section 5 for the replication with university students.

### 3.1. Experiment structure

Across five treatments we conducted with MTurk participants, 3060 participants accepted the HIT. Among them, 1032 participants finished the experiment. The discrepancy occurs because we allowed only those participants who answered all the quiz questions correctly within three attempts to proceed to the investment decision. This ensures high-quality data and is in line with the best practices when using online samples, and in particular MTurk (see e.g., Chmielewski and Kucker, 2020; Keith et al., 2023). Participants were

[2] Since each agent has only one information set and there is no proper subgame, Nash equilibrium coincides with subgame perfect equilibrium and perfect Bayesian equilibrium.

[3] Not invest, however, is not 'obviously dominant' (Li, 2017). This does suggest that a cognitively limited agent may fail to recognize it as a weakly dominant strategy.

[4] Since each agent has only one information set, analogy-based expectation has no bite in this game.

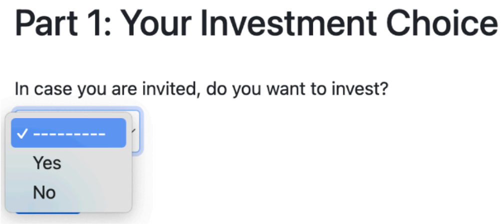



**Fig. 1.** The decision screen.

informed of this when accepting the HIT. Each participant could participate in one treatment only. The Baseline (205 participants), Examples (203 participants) and Payoff Distribution (204 participants) treatments were run simultaneously in June 2018. These were pre-registered in the AEA RCT Registry with the identifying number AEARCTR-0003057. A second Baseline (20 participants), Small Pyramid (200 participants) and Backward Induction (200 participants) treatments were run simultaneously in February 2019. These were pre-registered in the AEA RCT Registry with the identifying number AEARCTR-0003880. The second Baseline served two purposes: It replicated our initial findings in a smaller sample, and the investors therein served as matched participants in the first stage of the Small Pyramid treatment. The experiments lasted about 40 minutes and were conducted in English. The instructions do not use deception. Instructions for all the treatments are available in the online appendix. The average pay was $6.50, including $2 for passing the quiz; the corresponding hourly pay was higher than the hourly federal minimum wage at the time ($7.25).

Each participant was endowed with $4. This was larger than the MTurkers' average hourly earnings on the platform at the time (Hara et al., 2018). Participants were first given detailed information on how the pyramid scheme works and how payoffs are calculated. They were then given a quiz on the instructions. Passing the quiz within three attempts earned them $2, plus the ability to proceed.

Participants are then asked if they would like to invest their endowment in the pyramid scheme if they receive an invitation (see Fig. 1). We chose the strategy method, that is, asking for an ex-ante decision without informing participants whether they were invited, for several reasons. First, it matches our theoretical model, in which an agent does not know his position in the pyramid tree. Had participants' decision be elicited only when they were actually invited by another participant, the timing of the invitation could potentially convey information about their positions in the pyramid. [5] Second, the strategy method allows asynchronous elicitation of decisions from participants. All participants, regardless of their investment decision, made only one decision in relation to the pyramid scheme at their own timing. There is no "game play" and hence less concern about the active participation hypothesis (Lei et al., 2001). Third, the decision is less susceptible to emotions triggered by a game play. The downside of using the strategy method, however, is that the investment decision is not implemented if the participants do not receive an invitation. As the probability of being invited varies considerably over the relevant range of the number of investors, [6] the extent to which participants consider the possibility of not being invited is unclear. To account for this concern, we also analyze participants' prospects conditional on being invited into the scheme (see Table 4) and find no major differences.

For each treatment except the second Baseline, we invited participants to the experiment until about 200 participants had made an investment decision. We then randomly drew two participants as the starting points of a pyramid tree with two branches. We implemented the decisions of these participants. If a participant chose to invest, we randomly drew two other participants as immediate successors of this investor. If a participant chose not to invest, no further participants were chosen as his successors. The pyramid tree was constructed until either all participants were invited, or all participants who were drawn as successors chose not to invest. This tree construction algorithm may generate trees with very high levels even with relatively few investors, albeit with an exceedingly small probability. In the second Baseline, the tree was constructed in the same manner, but with only 20 participants. Fig. 2 depicts the realized tree in that treatment.

If a participant chose not to invest, he kept his $4. If a participant chose to invest but was not part of the constructed pyramid tree, he also kept his $4. If a participant chose to invest and was part of the pyramid tree, he paid the $4 endowment and earned $2 for each immediate successor who also invested, $1 for each second-degree successor who also invested, $0.5 for each third-degree successor who also invested, so on and so forth. In other words, we set the $\delta$ in our theoretical model to be 0.5.[7]

In each treatment except the second Baseline, participants were informed that there were a total of 200 decision-makers in the experiment before they made their investment decision. Investment decisions were made privately and without the knowledge of others' decisions. All task information in the experiment was common knowledge.

[5] Bosley et al. (2019) also asked their participants to make a one-off decision of investing or staying out in their lab-in-field experiment. In contrast to our experiment, their participants were informed of their position in the pyramid.

[6] See Online Appendix Figure A1. This probability is akin to the rate of contracting a disease in a typical contagion model. The probability of contraction remains low until the susceptible group (the investors) reaches about 50 percent of the population, increases rapidly thereafter, and then levels off.

[7] Some recent large scale pyramid schemes advertised much smaller returns (about 5 to 10 percent) from Level 1 recruits' investments; see e.g., the Texas State Securities Board's decision against Mirror Trading, a multi-level marketing scheme in cryptocurrency, , Texas State Securities Board (2020), and the court case against BitConnect, marketed as an investment fund in Bitcoin, articles 60–67, Securities (2021). Notice that in a "pure" pyramid scheme, a smaller rate increases the expected losses from investment, since more money is transferred to the top of the pyramid.

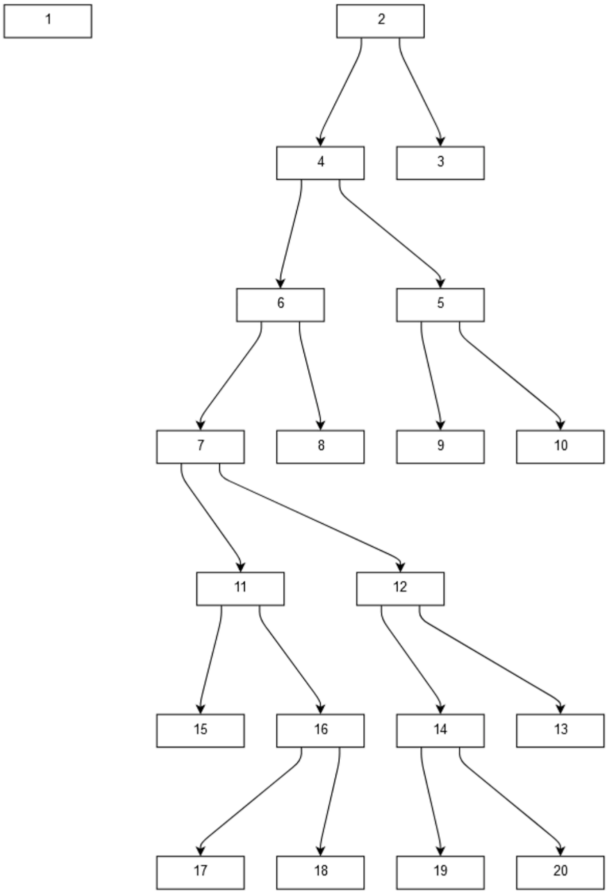



**Fig. 2.** The pyramid tree realized in the second Baseline treatment.

After their investment decision, participants answered a series of questions. They had to guess the number of investors among the 200 participants [8] and were paid \$1 minus the absolute difference between their guess and the actual number multiplied by \$0.1, if this amount was positive. They also made a dictator decision on how to distribute \$0.5 between themselves and another randomly-chosen participant in the treatment. At the end of each treatment, half of the participants were randomly chosen as dictators (the other half as recipients) and were paid accordingly.

We elicited risk attitudes using the probability equivalence method (Farquhar, 1984). In all treatments, participants chose between Option A and B, in which Option A gave a 50 percent chance each of winning \$1 or \$3 and Option B varied between a certain payment of \$1 and \$3 in increments of \$0.25.

In the second Baseline, Small Pyramid and Backward Induction treatments, we added a second lottery task to also directly measure risk attitudes in lotteries equivalent to pyramid investment decisions, and paid one of the lottery tasks randomly. In each additional lottery, Option A depicted the average payoff distribution of 10,000 simulated pyramid outcomes of 20, 40, 60, …, 200 investors out of 200 decision-makers, [9] while Option B was a certain payment of \$4. We will refer to these lotteries as “pyramid lotteries” hereinafter. There is an additional “pyramid guess lottery”, in which Option A depicted the average payoff distribution of pyramid outcomes when the number of investors equals the participant’s guess. Overall, participants made eleven pyramid lottery choices. They were not informed that these probability-payoff pairings were based on the pyramid scheme.

Participants then played the race game (Dufwenberg et al., 2010; Gneezy et al., 2010; Cardella, 2012), in which two players take turns to add 1, 2 or 3 to the current sum (starting at 0) until the sum reaches 15. The player who reaches 15 on his turn wins. To remove the role of beliefs about the matched partner’s action, we pitched participants against an optimally playing bot. The

8 In the second Baseline, which was conducted with 20 participants, we asked the participants to guess the number of investors in the earlier and identical Baseline session with 200 participants.

9 Since the number of possible payoffs in the pyramid scheme rapidly increases with increasing number of investors, we adjusted the payoffs and their probabilities in such a way to only include \$0, \$2, \$4,…,\$12, \$16,…,\$28 as payoff outcomes while preserving the expected value of the lottery. Payoffs are in \$4 increments beyond \$12 as the probabilities of receiving payoffs above \$12 are fairly small. The exact numbers can be seen in the instructions in the Online Appendix.

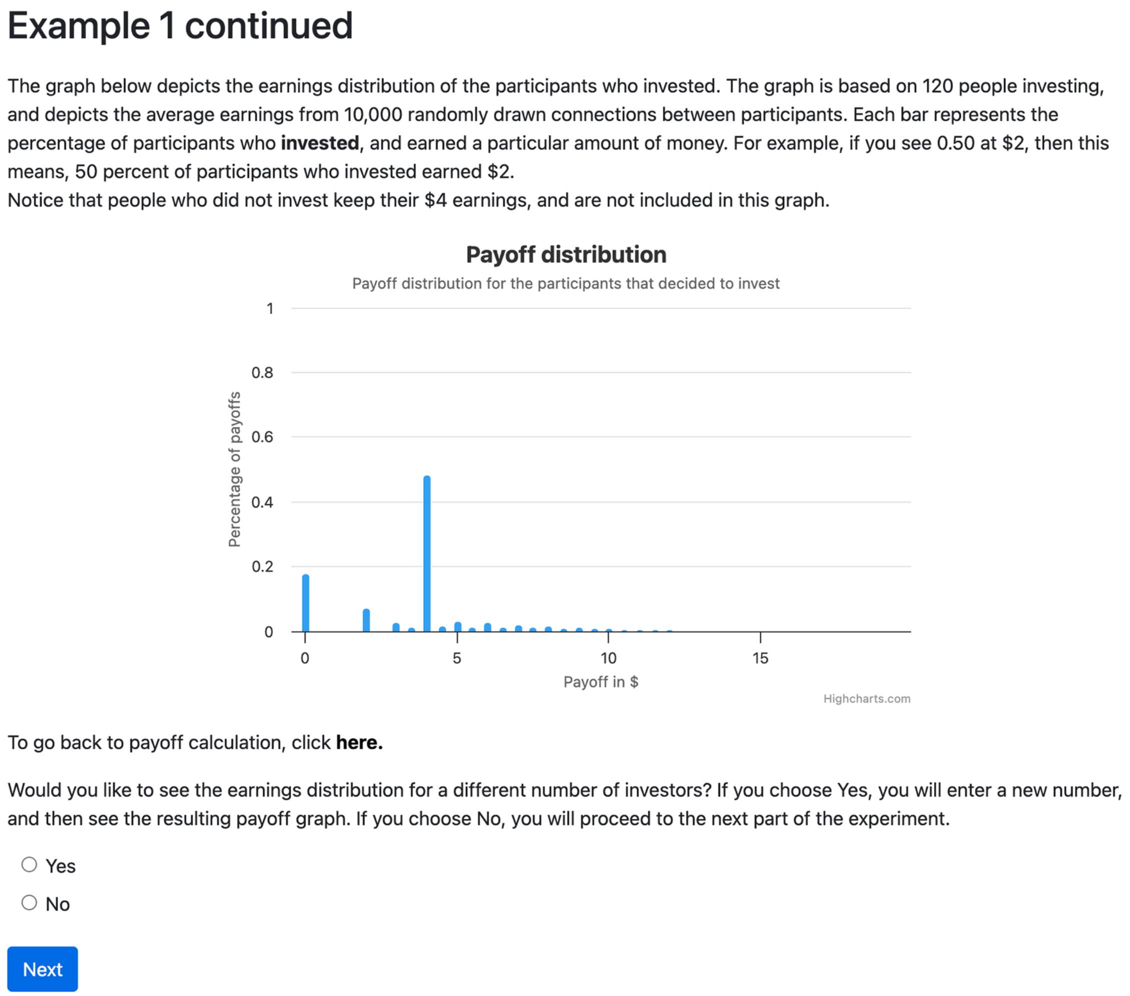



**Fig. 3.** An example figure in the Payoff Distribution treatment.

participant always starts, and wins if and only if he plays optimally to reach 3, 7, 11, and 15 on each of his turns. The game was repeated five times. Participants earned $0.1 for each round that they won.

Finally, participants answered some background questions about their age, gender, annual income, highest educational degree earned, how often they buy lottery tickets, whether they buy warranties, whether they think that most people can be trusted or are fair, and whether they lend their belongings to friends. In the second Baseline, Small Pyramid, and Backward Induction treatments, we also asked participants whether they held an investment account, a mortgage, a bank loan, a savings account, and stocks or shares at the time of the experiment, along with two questions measuring their financial literacy, for which they could earn $0.1 for each correct answer. In addition, all participants answered what they thought the experiment was about. [10] The experiment concluded with a feedback page.

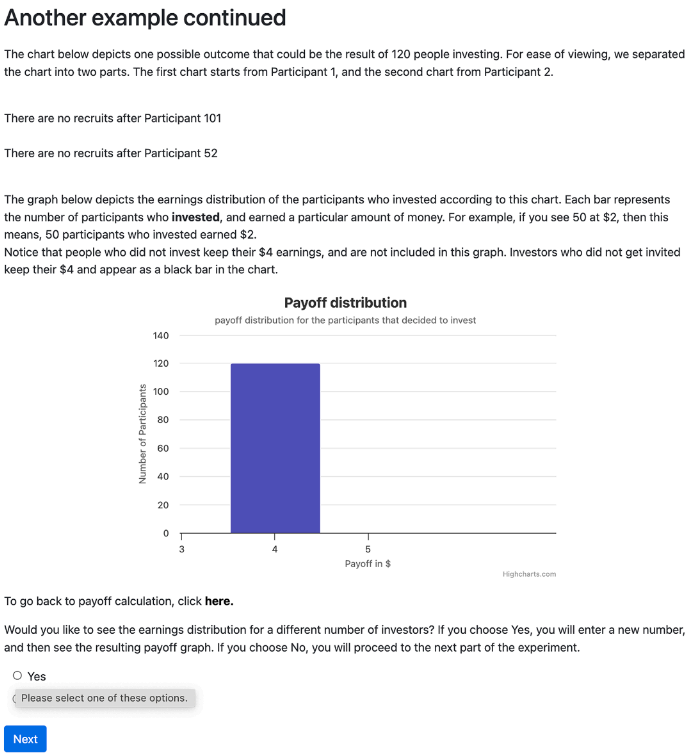
*3.2. Treatments*

We list the treatments here in the order in which they were run.

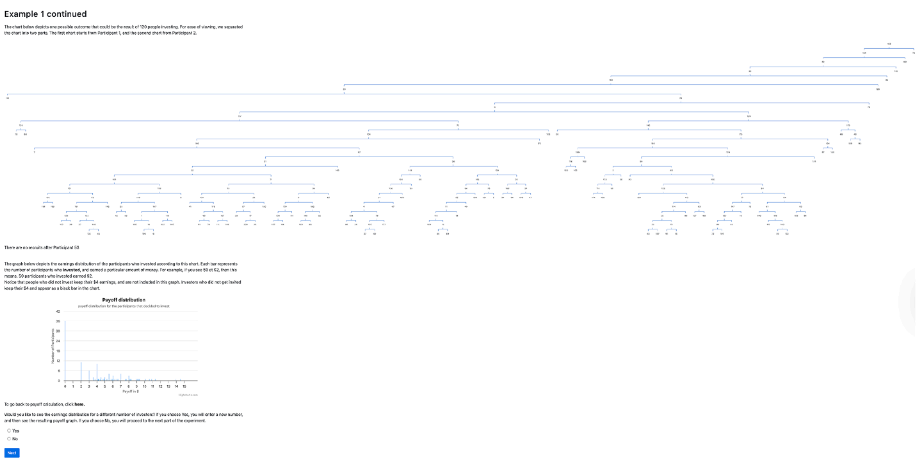
**Payoff Distribution Treatment**

Before making their investment decision, participants were asked to guess the number of investors out of 200 participants. They were then presented with the payoff distribution of investors averaged across 10,000 possible pyramids formed based on their guessed number of investors. Fig. 3 depicts the payoff distribution shown when a participant guesses 120 investors. Participants could try different numbers of investors and generate up to 20 payoff distributions.

[10] In the second Baseline, Small Pyramid and Backward Induction treatments, this question as well as their guesses on the number of investors were asked immediately after their investment decision.




(a) An example with 120 investors and no pyramid formed




(b) An example with 120 investors and a large pyramid formed

**Fig. 4.** Example figures in the Examples treatment.

**Examples Treatment**

Before making their investment decision, participants were asked to guess the number of investors out of 200 participants. They were then presented with a randomly generated pyramid tree with their guessed number of investors, along with the associated payoff distribution. Participants could try different or the same number of investors to generate up to 20 example pyramids. Fig. 4 shows two examples when a participant guesses 120 investors. These examples are randomly drawn. In Fig. 4a, a pyramid failed to form as the first two players both kept their endowment; while a substantial pyramid was realized in Fig. 4b.

**Backward Induction Treatment**

Before making an investment decision, participants were presented with the pyramid tree that arises when 200 out of 200 participants invest. The bottom three levels of this tree were highlighted with different colors, and participants had to calculate the payoff of a

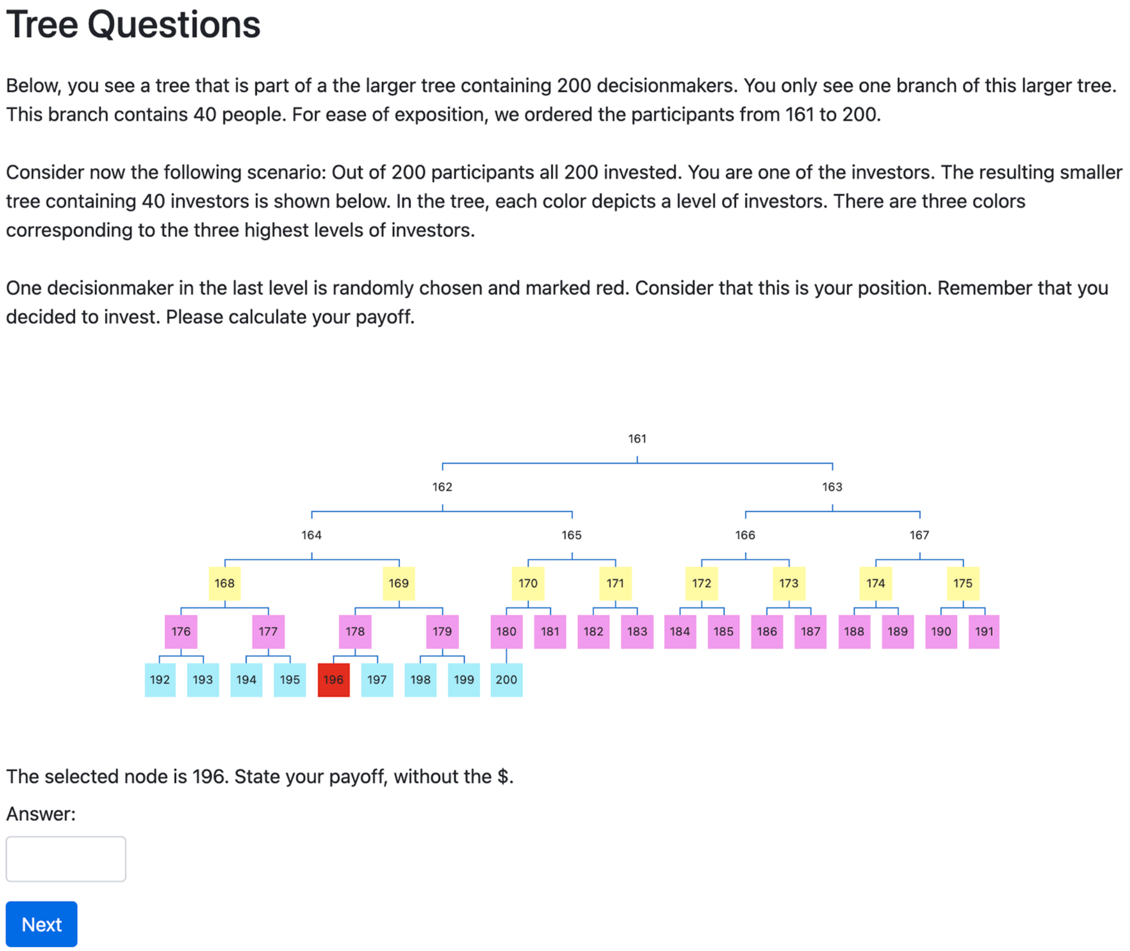



**Fig. 5.** Task screen in the Backward Induction treatment.

randomly chosen player in each of the three levels, starting from the last. They proceeded to their pyramid investment decision if they calculated all three payoffs correctly within five attempts. If their answers were not correct after five attempts, they were provided with the correct answers and a detailed explanation. In addition, immediately after they completed their calculation, all participants were presented with an explanation that 50 percent of investors belong to the lowest level of the tree, where investors earn nothing; 25 percent belong to the second lowest level, where investors break even; and the remaining 25 percent earn more than their investment. Fig. 5 depicts a screen in Backward Induction where participants work on the lowest level.

**Small Pyramid Treatment**

Participants were first presented with a pyramid tree with eight positions. They then had to decide whether to invest at each of the eight possible positions under the assumption that participants in the other seven positions invested. Thus, they chose whether to invest eight times. Fig. 6 depicts the screen where participants work through the small pyramid. They then proceeded to the pyramid game with 200 participants. At the end of the experiment, one of the two parts was chosen for payment: if the first part was chosen for payment, one of the eight positions was randomly selected for payment.

To facilitate payments in the first part of the Small Pyramid Treatment (if it is drawn), we ran the second Baseline (New Baseline) parallel to the Small Pyramid treatment and informed the participants of the second Baseline that their decisions might be used in another session, and that they might earn additional money as a result. Participants in the second Baseline remained anonymous. We randomly selected investors from the second Baseline as participants in the small pyramid to determine their additional payments, if any.

## 4. Results — MTurk sample

The average MTurk participant was 36.5 years old with an annual gross income of $44,482 (see Column 1, Table 1). This is somewhat younger than the U.S. median age (38.2) with a higher self-declared income than the per capita annual gross income at the time ($33,831) (Bureau, 2019). 44.7 percent of our sample were female, lower than the female share in the U.S. (51.3 percent).

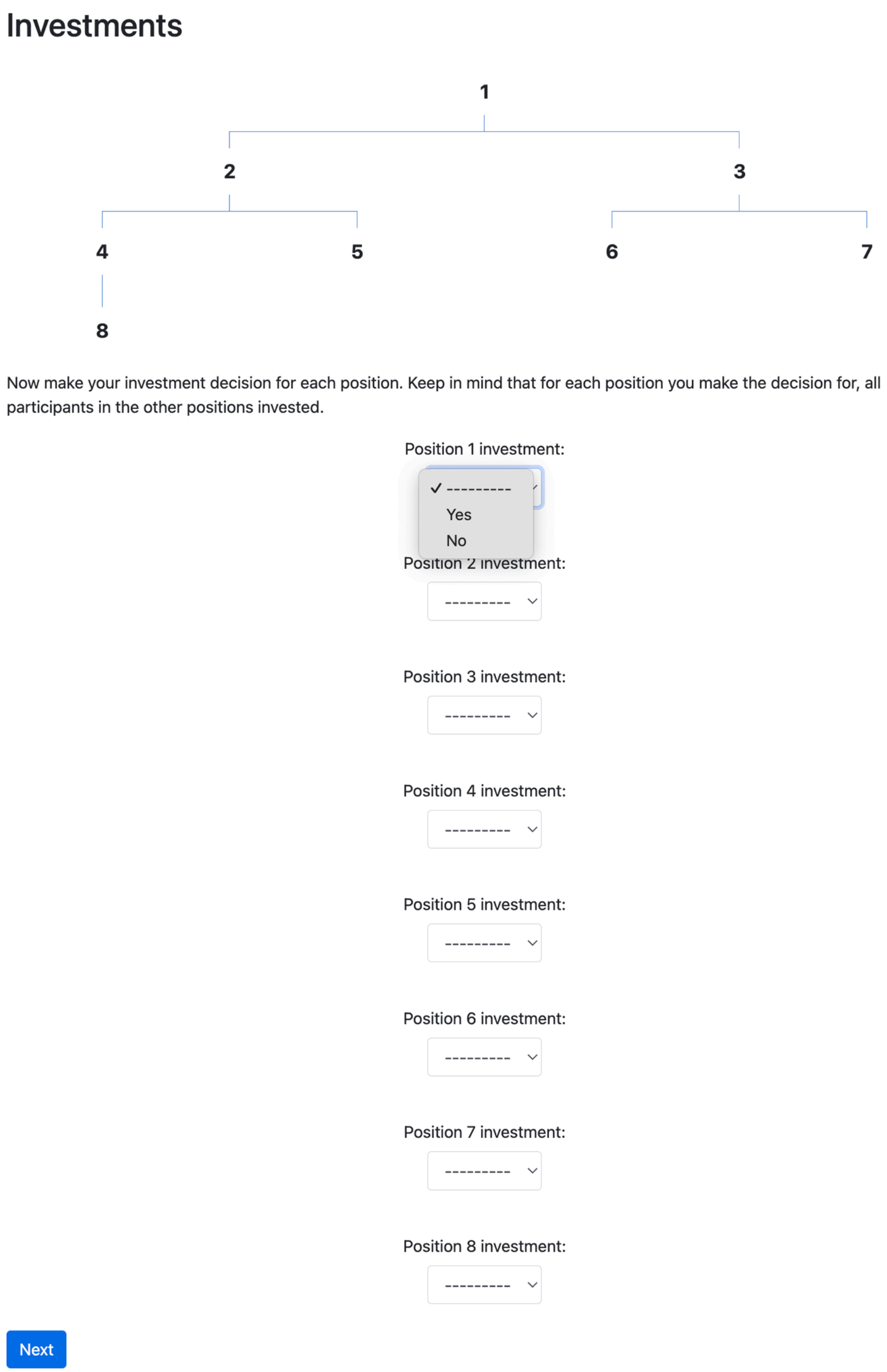



**Fig. 6.** Task screen in the Small Pyramid treatment.

**Table 1**
MTurk and student sample characteristics comparison.

| | MTurk | Student | *p* |
|---|---|---|---|
| Age | 36.51 | 24.84 | *** |
| | (10.20) | (3.778) | |
| Female | 0.447 | 0.510 | |
| | (0.497) | (0.502) | |
| Annual Gross Income | 44,482 | 10,803 | *** |
| | (32267) | (14602) | |
| Years of Schooling | 15.406 | - | |
| | (2.590) | | |
| Buys Lottery Monthly | 0.214 | 0.067 | *** |
| | (0.410) | (0.252) | |
| Never Buys Warranty | 0.468 | 0.673 | *** |
| | (0.499) | (0.471) | |
| Never Lends | 0.626 | 0.279 | *** |
| | (0.484) | (0.451) | |
| Risk Seeking | 0.142 | 0.136 | |
| | (0.349) | (0.344) | |
| Trusts Most People | 0.547 | 0.587 | |
| | (0.498) | (0.495) | |
| People Are Fair | 0.556 | 0.337 | *** |
| | (0.497) | (0.475) | |
| Percent Kept in DG | 67.79 | 71.49 | |
| | (25.23) | (21.76) | |
| Race Games Won | 0.854 | 1.683 | *** |
| | (1.331) | (1.818) | |
| Quiz Attempts | 1.903 | 1.740 | * |
| | (0.655) | (0.654) | |
| Financial Literacy | 1.614 | 1.750 | * |
| | (0.539) | (0.478) | |
| Investment Account | 0.526 | 0.471 | |
| | (0.500) | (0.502) | |
| Mortgage | 0.395 | 0.000 | *** |
| | (0.489) | (0.000) | |
| Loan | 0.302 | 0.077 | *** |
| | (0.460) | (0.268) | |
| Savings Account | 0.852 | 0.837 | |
| | (0.355) | (0.372) | |
| Stocks | 0.502 | 0.490 | |
| | (0.501) | (0.502) | |
| Pyramid Lottery Guess | 0.229 | 0.301 | |
| | (0.421) | (0.461) | |
| Observations | 1032 | 104 | |

Notes: Means of variables collected in all the MTurk experiments and the university student sample. Standard deviations are in parentheses. *p* column depicts the results of a two-sided two-sample *t*-test for Age, Income, Percent Kept in DG, Race Games Won, Quiz Attempts, Financial Literacy, and Pyramid Lottery Guess, and the test of proportions for the rest of the variables. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Percent Kept in DG depicts the percentage participants kept from their endowment which was 50 cents for the MTurk pool, and 100 euro for the laboratory pool. The dictator choice was implemented for all participants of the MTurk pool, and for one pair of the laboratory pool. For information on the construction of the other variables, see notes of Online Appendix Table A1. In the MTurk pool, the variables Financial Literacy, Investment Account, Mortgage, Loan, Savings Account, and Stocks are only collected in the second wave of the experiment, and they are therefore based on a sample size of 420. We omitted years of schooling in the university student pool, as no meaningful comparison can be made within and between the samples based on years of schooling. Risk Seeking only comprises participants whose answers are consistent in the probability equivalence risk elicitation method.

Our sample completed an average of 15.41 years of schooling, higher than the U.S. average of 13.50 (Programme, 2018). The trust and fairness measures are the same as in PEW surveys, [11] and our sample's response is not markedly different from representative U.S. samples in these two questions (Rainie et al., 2019).

In the probability equivalence risk elicitation task, 14.2 percent of our sample were risk seeking, and 50.2 percent were risk neutral. On average, they kept 33.9 cents out of 50 in the dictator game, commensurate with typical rates observed in dictator experiments. They won 0.86 race games out of five, and needed 1.9 attempts out of a maximum of three to pass the quiz measuring their understanding of the pyramid game. There is little correlation between the risk measure, dictator behavior, quiz success, and demographics (see Online Appendix Table A2).

In the Backward Induction, Small Pyramid, and the second Baseline where additional questions on financial behavior, financial literacy, and pyramid lottery questions were administered, financial literacy was high. The average number of correct answers to the two financial literacy questions was 1.61. Most participants had investment and savings accounts and held stocks. When given the pyramid lottery based on their own guessed number of investors, only 22.9 percent chose to invest.

**Result 1.** *A majority of participants invest in a pyramid scheme.*

Fig. 7 shows the average investment rates in the pyramid scheme by treatment. To compare treatments, we use a two-sided test of proportions.Remarkably, 58 percent of the participants in the Baseline invest in the pyramid scheme. Two interventions are effective. The Payoff Distribution treatment leads to a 22.4 percent reduction in investment probability from the baseline ($p$-value $= 0.0074$). Backward Induction has an even larger effect, reducing investment rate by 35.1 percent from the Baseline ($p$-value $= 0.0001$). The other interventions are ineffective. Examples and Small Pyramid generate investment rates of 55.4 and 62.5 percent, respectively ($p$-values when compared with the Baseline are 0.619 and 0.321, respectively).

**Result 2.** *Providing participants with at least one payoff distribution is effective in reducing the probability of investment. So is forcing participants to calculate the payoffs at the lowest levels of the pyramid tree. In contrast, providing at least one example pyramid tree does not affect investment behavior. Neither does forcing participants to decide whether to invest at every position of a small pyramid.*

Recall that, in both Payoff Distribution and Examples, all participants see one distribution or example based on their guessed number of investors. Afterwards, participants in Payoff Distribution generated 0.77 new distributions on average, while participants in Examples generated 0.51 new examples. The difference in the average draws between the two treatments is statistically significant (two-tailed $t$-test $p$-value $= 0.006$). [12] Nonetheless, the effectiveness of Payoff Distribution versus Examples remains robust when additional draws are included as a control variable in our linear regression, see Online Appendix Table A3. [13]

Both Backward Induction and Small Pyramid force participants to work through an example. The two examples involve similar probabilities of profiting from the pyramid scheme. In the eight-person pyramid of Small Pyramid, only two out of eight positions (25 percent) make money. The corresponding rate in the Backward Induction 200-investor pyramid is 28 percent. The relative success of Backward Induction over Small Pyramid cannot be attributed to the use of a more favorable example in Small Pyramid.

Neither do Backward Induction participants comprehend the intervention better than Small Pyramid participants. The vast majority of participants (84.8 percent) in Small Pyramid correctly invest in profitable positions in the eight-investor tree. Only 27.3 percent ever invested in at least one money-losing position in the eight-investor tree. Those who invest at a money-losing position are also 29.9 percent more likely to invest in the pyramid game with 200 participants (see Online Appendix Table A4). In Backward Induction, 71.5 percent of participants correctly calculate the required payoffs, and those who do so are 21.8 percent less likely to invest in the pyramid scheme (see Online Appendix Table A5). Thus, the rate of correct decisions within the interventions are comparable across Small Pyramid and Backward Induction. Those who cannot make correct decisions within their intervention err in the 200-participant scheme at similar rates across the two interventions as well. In other words, the difference between these two treatments is not due to the understanding of the interventions themselves, but how the data and information from the interventions are being used in the pyramid scheme they face.

**Result 3.** *Among the general U.S. population, age, gender, education, income, trust, and fairness beliefs are not associated with pyramid investments. Dictator giving is positively correlated with pyramid investments, with a very small effect size.*

Table 2 reports the pooled linear regressions of the probability of investing in the pyramid scheme on treatment variables, demographic variables, and experimentally-elicited measures of risk, altruism, and cognitive ability. [14] Regressions for each separate treatment can be found in Online Appendix Table A6. Major differences are noted below where relevant. Model 1 includes the treatment variables only, with Baseline being the reference treatment. It confirms Result 2. Model 2 adds additional control variables.

[11] The trust question is "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?" Trust is coded as 1 if an individual chooses "most people can be trusted" and 0 otherwise. The fairness question is "Do you think most people would try to take advantage of you if they got a chance, or would they try to be fair?" The fairness measure is 1 if an individual chooses "Would try to be fair" and 0 otherwise.

[12] We thank an anonymous referee for pointing this out.

[13] In Payoff Distribution, the investment rates of those who made 0, 1 or 2 additional draws are 46, 46, and 40 percent, respectively. In Examples, the investment rates of those who made 0, 1 or 2 additional draws are 60, 54, and 28 percent, respectively.

[14] The results are qualitatively similar when we use a logistic or probit regression. We report linear regressions as the coefficients are easier to interpret. For ease of exposition, we excluded the financial literacy and behavior controls from the regressions. Their inclusion does not affect the results, does not improve the F statistic, and none shows a significant effect.

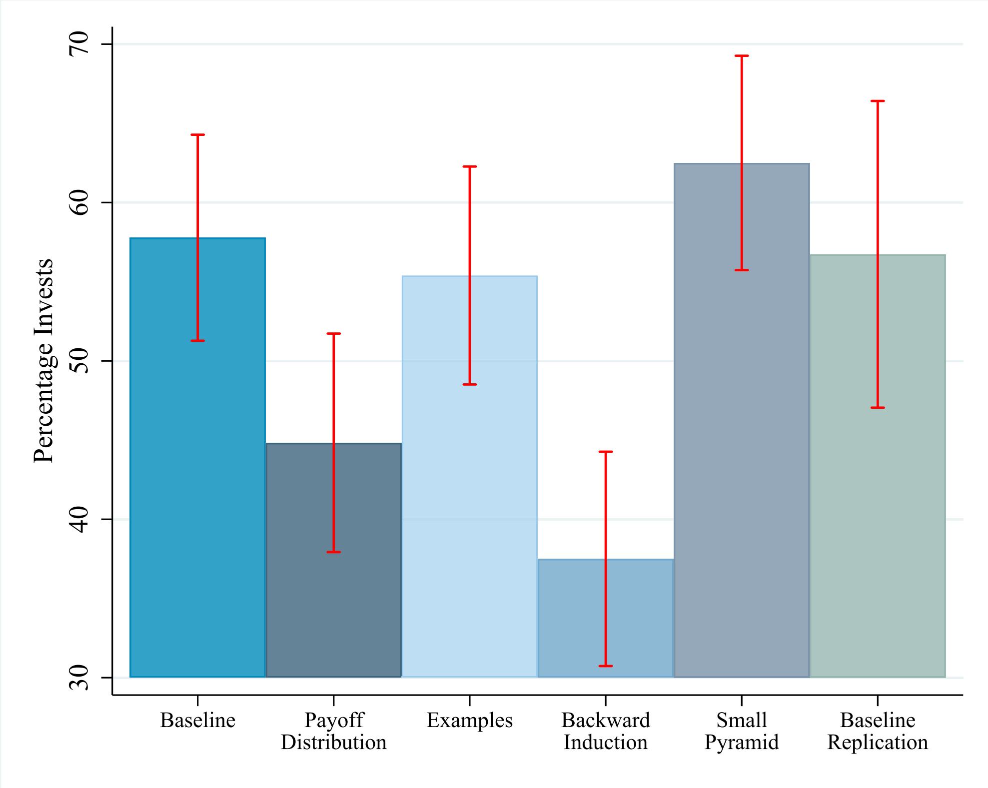



**Fig. 7.** Investment rates in the pyramid scheme.

Models 3–5 uses only data from Backward Induction (the reference treatment) and Small Pyramid. They include pyramid lottery decisions in the analysis. The results consistently show that a participant's age, gender, income, years of education, trust, and fairness beliefs have no effect on his investment in the pyramid scheme. Dictator giving is significantly positively correlated with pyramid investments except in the Backward Induction treatment, but the effect is very small. In pooled data, a person who keeps everything in the dictator game has about 0.5 percent lower probability of pyramid investment compared with someone who keeps nothing.

### 4.1. Cognitive skills

**Result 4.** *Among the general U.S. population, cognitive skills are negatively correlated with pyramid investments.*

Backward induction capability, as measured by the race game, is negatively correlated with investment in the pooled sample. Each race game won reduces investment probability by 2.9 percent. However, as 60.6 percent of all participants do not win any round of the race game, the negative correlation is driven by those who win in multiple rounds. [15]

The number of quiz attempts also matters. Each additional attempt increases the probability of investment by 7.2 percent in the pooled data. However, within each treatment, the effect of quiz attempts is statistically significant only in Examples and Small Pyramid. As previously mentioned, in the Backward Induction and Small Pyramid treatments, those who make correct calculations or decisions within the intervention are less likely to invest in the pyramid game. Thus, comprehension of instructions explains some of the investment decisions.

### 4.2. Risk preferences

**Result 5.** *Among the general U.S. population, real-life risk-taking behavior as well as elicited preferences for risk positively correlate with pyramid investments.*

[15] Categorizing participants into "never winners" and the rest does not explain pyramid investments, whereas categorizing them into "at-most-once winners" and the rest shows that the latter group is 10.7 percent less likely to invest. Of course, such a cutoff is arbitrary, and caution should be taken with interpretation. In fact, the effect of the race game performance disappears in Models 4 and 5, possibly because it only matters in the Backward Induction treatment when the sample is restricted to Backward Induction and Small Pyramid treatments.

**Table 2**
Probability of investment in the pyramid scheme.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Payoff Distribution | −0.130*** | −0.133*** | | | |
| | (0.05) | (0.05) | | | |
| Examples | −0.024 | −0.041 | | | |
| | (0.05) | (0.05) | | | |
| Backward Induction | −0.203*** | −0.204*** | | | |
| | (0.05) | (0.05) | | | |
| Small Pyramid | 0.047 | 0.047 | 0.234*** | 0.229*** | 0.242*** |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) |
| Age | | 0.001 | | −0.002 | −0.002 |
| | | (0.00) | | (0.00) | (0.00) |
| Female | | −0.026 | | −0.025 | −0.013 |
| | | (0.03) | | (0.05) | (0.05) |
| Annual Gross Income | | 0.000 | | 0.000 | 0.000 |
| | | (0.00) | | (0.00) | (0.00) |
| Years of Schooling | | 0.004 | | −0.002 | −0.000 |
| | | (0.01) | | (0.01) | (0.01) |
| Buys Lottery Monthly | | 0.069* | | 0.005 | 0.013 |
| | | (0.04) | | (0.06) | (0.06) |
| Never Buys Warranty | | −0.082*** | | −0.083* | −0.061 |
| | | (0.03) | | (0.05) | (0.05) |
| Never Lends | | −0.066** | | −0.037 | −0.062 |
| | | (0.03) | | (0.05) | (0.05) |
| Trusts Most People | | 0.012 | | −0.019 | −0.025 |
| | | (0.04) | | (0.06) | (0.06) |
| People Are Fair | | 0.019 | | 0.025 | 0.022 |
| | | (0.04) | | (0.06) | (0.06) |
| Amount Kept in DG | | −0.009*** | | −0.005** | −0.005** |
| | | (0.00) | | (0.00) | (0.00) |
| Race Games Won | | −0.029** | | −0.023 | −0.027 |
| | | (0.01) | | (0.02) | (0.02) |
| Quiz Attempts | | 0.072*** | | 0.080** | 0.107*** |
| | | (0.02) | | (0.04) | (0.04) |
| Risk | | 0.052*** | 0.039** | 0.037** | 0.050*** |
| | | (0.01) | (0.02) | (0.02) | (0.02) |
| Pyramid Lottery C1 | | | 0.061*** | 0.058*** | |
| | | | (0.01) | (0.01) | |
| Pyramid Lottery C2 | | | 0.030** | 0.034** | |
| | | | (0.01) | (0.01) | |
| Pyramid Lottery Guess | | | | | 0.255*** |
| | | | | | (0.06) |
| Constant | 0.578*** | 0.493*** | 0.213** | 0.366 | 0.197 |
| | (0.03) | (0.15) | (0.08) | (0.23) | (0.23) |
| $R^2$ | 0.0327 | 0.1510 | 0.1565 | 0.2042 | 0.1888 |
| Observations | 1032 | 1004 | 384 | 384 | 384 |

Notes: OLS estimates. The dependent variable is 1 if the participant chose to invest, and zero otherwise. Standard errors are in parentheses. ***, ** and * indicates statistical significance at the 1, 5 and 10 percent levels, respectively. Participants who switched more than once in the risk elicitation are excluded from the regressions. For brevity, Models 3–5 exclude financial literacy, investment account, mortgage, loan, savings account, and stocks as controls; none of them are significantly associated with the decision to invest, and the results remain qualitatively the same.

Although our pyramid scheme offers a negative expected return, there is also the possibility of high returns. Participants who are sufficiently risk seeking may therefore find it optimal to invest. To this end, we consider the relationship between self-reported real-life risk-taking behavior and lottery decisions.

In the pooled sample, participants who buy lottery tickets at least once a month are 6.9 percent more likely to invest. Those who purchase extended warranties and lend their possessions are 8.2 percent and 6.6 percent more likely to invest in the pyramid game, respectively. [16] Note, however, that these effects hold only in the pooled data but not in separate regressions per treatment, pointing to their high variance and low explanatory power. Neither financial literacy nor any of the financial behavior measures (stocks, mortgage, loan, investment or savings account) explain pyramid investments.

[16] Note that insuring against modest losses (e.g., by purchasing extended warranties) cannot plausibly be explained by risk aversion (Sydnor, 2010). Relatedly, in a costly voting experiment, Faravelli et al. (2019) found that those who buy lottery tickets as well as those who purchase extended warranties are more likely to vote, despite low odds of being pivotal.

Based on the probability equivalence method, each unit increase in the switching point in risk measurement—with 5 indicating risk neutrality—increases the probability of pyramid investment by 5.2 percent. As a result, those who are risk seeking are 23.5 percent more likely to invest compared with the rest. Risk seeking robustly correlates with investment across individual treatments except in Examples, where its effect is smaller and not statistically significant, see Online Appendix Table A7 for details. Nonetheless, since only 14.2 percent of our participants are risk seekers, risk seeking explains a very small percentage of pyramid investments.[17]

Could investment be driven by skewness preferences (Kraus and Litzenberger, 1976), though? In our pyramid scheme, skewness shifts from negative to positive with increasing number of investors: When the number of investors is low, the payoff distribution is negatively skewed. [18] Skew is around zero if half the decision-makers invest. With more than half investing, positive skew increases with the number of investors. [19] If pyramid investment becomes more attractive with increasing positive skew of the payoff distribution, we would observe this pattern in the pyramid lottery choices. The mean, variance, and skewness of these lotteries are depicted in the top panel of Table 4 in Section 4.4.

When making pyramid lottery choices, a majority of participants (54.3 percent) do not choose any lottery, including the one based on their guessed number of investors. Among the rest, 29.7 percent switch only once between the lottery and a certain payment of $4. Applying an unrotated principal component analysis of all pyramid lotteries shows two components with eigenvalues larger than 1. [20] In the first component, all eleven decisions have positive loadings. In the second component, the first five decisions load negatively, and the rest positive. The first component may be interpreted as capturing a general preference for lotteries, that is, participants' risk preferences. The second component is in line with a preference for right or left-skewed lotteries. As such, a risk averse individual would have a negative predicted value on the first component, whereas a risk seeker would have a positive one. Someone with a preference for positive skew would have a positive value in the second component, while someone with a preference for negative skew would have a negative value. In our pooled sample, 66 percent has a negative component score for the first component, and 76 percent has a negative component score for the second component.

Models 3 and 4 of Table 2 show that both components are significantly associated with participants' decision to invest in the pyramid scheme. Thus, a stronger preference for positively skewed lotteries is associated with a higher probability of pyramid investment, or alternatively, a stronger preference *against* positively skewed lotteries predicts a lower probability of investment. Model 5 drops the two components and uses participants' choice in the pyramid guess lottery, allowing a more straightforward interpretation: Those who chose to invest in the pyramid lottery based on their guessed number of investors are 25.5 percent more likely to invest in the pyramid scheme. However, as in the case of risk seeking preferences, this explains a relatively small fraction of pyramid scheme investing, as only 22.9 percent choose to invest in this pyramid lottery. [21]

### *4.3. Beliefs*

All participants made a monetarily incentivized guess on the number of participants who chose to invest in their session. Table 3 depicts regressions in the format of Table 2, [22] with the addition of the variable Guess. Across all model specifications, participants' guesses correlate highly significantly with their investment behavior. Including guesses in the regressions substantially increases the explained variance. When pooled across treatments, the average guess among non-investors is 65.7, while that among investors is 121.9 (two-sample $t$-test $p$-value $< 0.0001$). When Guess is included, the effect of Payoff Distribution vanishes, while the Backward Induction effect persists, albeit becoming smaller. Real-life risk-taking behavior shows up as significant only in the pooled sample, and not when each treatment is analyzed separately. Nonetheless, elicited risk measures remain predictive of investment decisions.

In Payoff Distribution and Examples, participants entered a non-incentivized guess pre-decision so that we could show them the associated payoff distribution or example tree. The average pre-decision guesses in Payoff Distribution and Examples are 97.8 and 92.1, respectively (two-sided $t$-test $p$-value $= 0.140$). The average post-decision incentivized guesses are 84.3 and 93.4, respectively (two-sided $t$-test $p$-value $= 0.0619$). In both treatments, participants who do not invest update their guesses downwards, while those who invest update their guesses upwards. Among non-investors, guesses decrease on average by 21.9 units (95 percent CI $= (-29.2, -15.7)$). Among investors, guesses increase by 12.4 units (95 percent CI $= (6.5, 18.4)$).

Our model offers no theoretical foundation for the correlation between guesses and behaviors—since not investing is the dominant strategy. It could be that beliefs cause behavior. Participants in Payoff Distribution and Examples began with similar priors, but updated their beliefs differently upon seeing distributions or examples. The difference in beliefs then channels into different investment

[17] For example, in Baseline, the investment rate among risk neutral or risk averse participants is 55.1 percent (108/196), and among the risk seekers it is 74.1 percent (20/27). Assuming that all other variables are distributed similarly across individuals with varying risk preferences, risk seeking explains approximately 5.1 investment decisions out of the observed 128.

[18] Pyramid lotteries with low number of investors are negatively skewed due to the large probability of not being invited and hence receiving $4.

[19] This is based on the ex-ante prospect of the scheme. If we consider a pyramid scheme prospect conditional on being invited, then skewness is always positive but U-shaped around half investing.

[20] A principal component analysis with all risk measures does not show a meaningful pattern between decisions in the probability equivalence method and pyramid lotteries. This signifies that these two measures capture different attributes or preferences. Therefore, we keep both measures in our analysis.

[21] Pooling the Backward Induction and Small Pyramid treatments, the average investment rate among those who did not invest in the pyramid guess lottery equivalent was 45.0 percent (144/320); among those who invested in the pyramid guess lottery equivalent, it was 69.5 percent (66/95).

[22] Variables that do not show significant effects in Table 2 are not reported here.

**Table 3**
Probability of investment in the pyramid scheme, controlling for guess.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Payoff Distribution | −0.043 | −0.033 | | | |
| | (0.04) | (0.04) | | | |
| Examples | 0.011 | 0.009 | | | |
| | (0.04) | (0.04) | | | |
| Backward Induction | −0.147*** | −0.136*** | | | |
| | (0.04) | (0.04) | | | |
| Small Pyramid | 0.006 | 0.009 | 0.141*** | 0.139*** | 0.148*** |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Guess | 0.006*** | 0.006*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Buys Lottery Monthly | | 0.061** | | −0.015 | −0.008 |
| | | (0.03) | | (0.05) | (0.05) |
| Never Buys Warranty | | −0.051** | | −0.083* | −0.067 |
| | | (0.03) | | (0.04) | (0.04) |
| Never Lends | | −0.045* | | −0.039 | −0.059 |
| | | (0.03) | | (0.04) | (0.04) |
| Amount Kept in DG | | −0.005*** | | −0.001 | −0.001 |
| | | (0.00) | | (0.00) | (0.00) |
| Race Games Won | | −0.013 | | −0.009 | −0.011 |
| | | (0.01) | | (0.02) | (0.02) |
| Quiz Attempts | | 0.047** | | 0.047 | 0.068** |
| | | (0.02) | | (0.03) | (0.03) |
| Risk | | 0.047*** | 0.036** | 0.037** | 0.046*** |
| | | (0.01) | (0.01) | (0.02) | (0.02) |
| Pyramid Lottery C1 | | | 0.043*** | 0.043*** | |
| | | | (0.01) | (0.01) | |
| Pyramid Lottery C2 | | | 0.031** | 0.029** | |
| | | | (0.01) | (0.01) | |
| Pyramid Lottery Guess | | | | | 0.206*** |
| | | | | | (0.05) |
| Constant | 0.011 | −0.156 | −0.232*** | −0.271 | −0.413** |
| | (0.04) | (0.12) | (0.08) | (0.21) | (0.21) |
| $R^2$ | 0.3399 | 0.4141 | 0.3720 | 0.3950 | 0.3877 |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 1032 | 1004 | 384 | 384 | 384 |

Notes: OLS estimates. The dependent variable is 1 if the participant chose to invest, and zero otherwise. Numbers in parentheses are standard errors. ***, ** and * indicates statistical significance at the 1, 5 and 10 percent levels respectively. In Models 3–5, Backward Induction serves as the benchmark. Controls include age, gender, income, years of schooling, trust and fairness beliefs.

behaviors. Alternatively, it could be that behavior causes beliefs. Again, participants in the two treatments began with similar beliefs. After encountering different interventions, they made different decisions. Projecting their own decision onto other participants would then lead to a correlation between beliefs and behavior.

Despite the positive correlation between guesses and investment, participants generally do not choose pyramid lotteries with a large number of investors. For example, only 10.7 percent (45 out of 420 in the MTurk sample) choose the 200-investor pyramid lottery (see Online Appendix Table A8), and the correlation between this lottery choice and investment is quite low (0.237). In other words, when the pyramid scheme's payoff distribution is presented to them in the form of a lottery, participants do not prefer schemes with a large number of investors, even though their investment in an actual scheme is positively correlated with their guess on the number of investors.

### 4.4. *Subjective probability*

Participants' behaviors in the pyramid scheme do not rule out the possibility that they overweight the small probability of profiting from the scheme. For this purpose, we make use of the eleven pyramid lotteries to investigate the role of subjective probabilities in investment decisions. The observed choices on these lotteries are reported in Online Appendix Table A8.

We consider an individual with risk neutral preferences over monetary outcomes, who weights probabilities as described by Prelec's (1998) one-parameter probability weighting function:

$$w(\pi;\alpha) = \exp\left[-(-\ln \pi)^{\alpha}\right],$$

**Table 4**
Pyramid lotteries: Imputed probability weighting parameters.

| | Payoff Statistics | | | Prelec's $\alpha$ |
|---|---|---|---|---|
| | Mean | Variance | Skewness | |
| PANEL A: Pyramid Lotteries with fixed number of investors | | | | |
| *Number of Investors* | | | | |
| 20 | 3.9542 | 0.1732 | -9.1602 | 0.5824 |
| 40 | 3.9501 | 0.1851 | -8.5486 | 0.7038 |
| 60 | 3.9425 | 0.2261 | -7.0002 | 0.7899 |
| 80 | 3.9336 | 0.3812 | -3.2186 | 0.8864 |
| 100 | 3.9209 | 1.6076 | 0.5314 | 0.9586 |
| 120 | 3.9028 | 7.5687 | 0.9472 | 0.9831 |
| 140 | 3.8730 | 13.1387 | 1.0836 | 0.9849 |
| 160 | 3.8323 | 17.8551 | 1.2361 | 0.9836 |
| 180 | 3.7866 | 21.6489 | 1.4057 | 0.9814 |
| 200 | 3.7364 | 24.3687 | 1.5567 | 0.9782 |
| PANEL B: Pyramid Lotteries given observed investment rate | | | | |
| *Investment Rate* | | | | |
| 0.375 (Backward Induction) | 3.9364 | 0.3145 | -4.3701 | 0.8603 |
| 0.448 (Payoff Dist.) | 3.9280 | 0.7329 | -0.5828 | 0.9275 |
| 0.554 (Examples) | 3.9118 | 4.4746 | 0.8671 | 0.9762 |
| 0.578 (Baseline) | 3.9070 | 5.8691 | 0.8899 | 0.9793 |
| 0.625 (Small Pyramid) | 3.8960 | 8.6458 | 0.9318 | 0.9822 |
| PANEL C: Pyramid Lotteries conditional on being invited | | | | |
| *Investment Rate* | | | | |
| 0.375 (Backward Induction) | 2.2831 | 5.3393 | 0.8071 | 0.6954 |
| 0.448 (Payoff Dist.) | 2.9967 | 7.3500 | 0.6640 | 0.8295 |
| 0.554 (Examples) | 3.7440 | 10.8016 | 0.6496 | 0.9632 |
| 0.578 (Baseline) | 3.7962 | 11.6286 | 0.6907 | 0.9721 |
| 0.625 (Small Pyramid) | 3.8374 | 13.1792 | 0.7852 | 0.9795 |

Notes: A pyramid lottery gives the same probability distribution over the same set of outcomes as in the pyramid scheme, given the number of investors or the investment rate. Panel A depicts the pyramid lotteries with fixed numbers of investors. Panel B depicts the pyramid lotteries with the number of investors fixed at the investment rate of each treatment. The payoff distributions used in the lotteries in Panels A and B are based on the pyramid game, thus individuals who are uninvited to the scheme are included with their $4 earnings. Panel C depicts pyramid lotteries as in Panel B, but the probabilities on the outcomes are calculated conditional on the individual being invited into the scheme. Mean, variance and skewness refer to the corresponding summary statistics of the pyramid lotteries. Prelec's $\alpha$ gives the threshold probability weighting parameter at which a risk-neutral individual is indifferent between the lottery and the certain option of obtaining $4. The lower the threshold $\alpha$, the heavier the probability weighting.

where $\pi$ is the objective probability. [23] The parameter $\alpha$ lies between 0 and 1. The lower the $\alpha$, the stronger the probability weighting. For all pyramid lotteries, the weighted expected payoff is decreasing in $\alpha$, i.e., the stronger the probability weighting, the more attractive the lottery.

We solve for $\alpha$ in

$$\sum_{v \in V} w\big(\pi(v); \alpha\big) v = 4$$

where each $v$ is a possible payoff (and $V$ is the set of all possible payoffs) and $\pi(v)$ is the objective probability of obtaining payoff $v$. The dependence of $\pi$ on the number of investors or the investment rate is suppressed for simplicity. The solved $\alpha$ indicates the "strength" of probability weighting required to make an otherwise rational individual indifferent between the lottery and $4 for certain. Any individual with $\alpha$ below this critical value would strictly prefer the lottery to a certain $4, and vice versa.

The imputed Prelec's $\alpha$'s are given in Panel A of Table 4 along with the means, variances, and skewnesses of the payoffs from the pyramid lotteries. First, note that when the lotteries are positively skewed, the critical $\alpha$'s are close to 1, meaning that the required weighting function is close to linear. These imputed $\alpha$'s are substantially higher (i.e., the weighting functions are closer to linear)

[23] One may argue that Prelec's one-parameter weighting function is a primitive form of probability weighting, and we have ignored a number of potential factors (e.g., gain vs. loss prospects). Nonetheless, we believe that it is a good benchmark to consider.

than the empirical estimates in the literature. [24] The high imputed $\alpha$'s are due to the relatively small expected loss in the pyramid scheme. Even at its lowest expected value (when all 200 participants invest), [25] the expected payoff from the pyramid lottery still stands at $3.74, which is 93.5 percent of the $4 outside option. Heavy overweighting on the "favorable events" is not required to bring the expected payoff of the lotteries to $4.

These results remain robust even if we use lotteries constructed based on the actual investment rate in the pyramid scheme (Panel B, Table 4), [26] or lotteries constructed based on probabilities *conditional on being invited into the scheme* (Panel C, Table 4). In either case, the critical $\alpha$'s are relatively high. More substantial adjustments to probabilities are required for investment in the Payoff Distribution and Backward Induction treatments, primarily because the pyramid scheme's expected value declines with fewer investors. Still, the imputed weights are within the range documented in the literature.

The high imputed $\alpha$'s may seem a good explanation of pyramid scheme investment. However, such a conclusion is inconsistent with the pyramid lottery choices. The critical $\alpha$ with 200 investors is higher than that with 80 investors, so we should expect a higher uptake of Pyramid Lottery 200 than Pyramid Lottery 80. However, the reverse is observed (see Online Appendix Table A8), which suggests that probability weighting — at least in Prelec's form — is not the main factor behind the pyramid lottery choices.

Neither are the observed pyramid lotteries choices consistent with salience theory (e.g., Bordalo et al., 2012; Dertwinkel-Kalt and Köster, 2019). The probability of obtaining a payoff above $4 is increasing in the number of investors. Thus, the gain prospect of the lottery becomes more salient as the number of investors increases. Nonetheless, participants prefer pyramid lotteries with fewer, not more, investors.

## 5. Replication

A potential explanation for high pyramid investment rates rests on the characteristics of the MTurk subject pool. If participants are not paying enough attention to the decision particulars under a relatively low-stakes environment, they may behave erroneously (or at least in a way that they would not do so if they "understood" the game). Our intervention treatments would then be measuring the extent to which participants' attention is diverted to the pyramid game detail. To mitigate such sample-related concerns, we replicated a higher-stakes version of our baseline with the students of the University of Cologne at the Cologne Laboratory for Economic Research (CLER) in December 2023. This study was preregistered at As Predicted, https://aspredicted.org/3434-rvnz.pdf.

We endowed participants with 24 euros each, double the hourly minimum wage at the time, and invited them to the pyramid scheme with 100 decision-makers. As before, we look at the behavior of those who answered the comprehension questions in a maximum of three tries. [27] The maximum possible earnings in this setup is about 133 euros, a considerable amount for this pool.[28] In line with the six-fold increase in the pyramid decision endowment, all the payoffs in our probability equivalence risk measure were multiplied by six. The pyramid lotteries correspond to the payoff distributions in the high stakes scheme when 10, 20, …, 100 persons invest in the scheme. Lastly, we adjust the dictator game so that participants decided how much to keep for themselves from 100 euros, and only one of the dictator decisions within each session was implemented. [29]

Table 1 compares the participant characteristics of the university student sample to the combined MTurk samples. As expected, German university students are younger and have lower income than U.S. MTurkers. The university sample is gender-balanced, while the MTurk pool is skewed towards males. Students buy lotteries and warranties less often, lend their belongings more often, and are less likely to have a loan. Their financial literacy is only marginally better than that of MTurk participants, whose scores are already quite high. The share of risk-seekers in these two populations is remarkably similar. Although university students' own fairness behavior is not different than that of the diverse pool of MTurkers in the dictator game, they are less likely to think people are fair. Finally, university students on average perform better in the two cognitive skill measures: race game and the number of quiz attempts, though only marginally so on the latter. As with the MTurk sample, there is very little correlation across the main demographic variables and risk and cognitive skill measures as well as dictator game sharing (see Online Appendix Table A9).

[24] Prelec (1998) informally stated that $\alpha = 0.65$ fits well with previous observations. Wu and Gonzalez (1996) estimate Prelec's $\alpha$ to be 0.74 using gain prospects. Bleichrodt and Pinto (2000) obtain estimates in the range of 0.533–0.589 in a medically-framed experiment. However, it should be cautioned that none of these previous experiments have considered probabilities as small as those involved in our experiment.

[25] The expected payoff is decreasing in the number of investors because the higher the number of investors, the higher the chance of being invited into the scheme, which gives an expected payoff below $4.

[26] The events for these lotteries are obtaining $0–$2, $2–$4,…,$10–$12,$12–$16,$16–$20,…,$24–$28, with the payoff in each event corresponding to the expected payoff conditional on the payoff falling into the bracket. Probabilities with a fixed number of investors are weighted by the binomial probability of having the number of investors given the investment rate and then summed. Since a binomial distribution with 200 draws is fairly concentrated around its mean, using the investment rate produces results similar to fixing the number of investors at the expectation. To ease inference, we order the treatments according to their investment rates.

[27] We aimed to recruit 100 participants, and the instructions regarding the pyramid payoffs reflect this. Since we did not know ex-ante how many participants would pass the quiz and finish the online experiment, we invited more than 100 participants. Twelve participants did not pass the quiz in three tries, received their show-up fee and left the experiment. The final number of observations is 104.

[28] The maximum possible payoff occurs when all but one person invests, and the non-investor is drawn at the first level. Then the top position in the single eventuated investor tree earns 133.5 euros from their investment.

[29] In the MTurk pool, dictator decisions predict pyramid investments, albeit with a small effect size. As people may be less altruistic with higher stakes (see, e.g., Larney et al., 2019), implementing a probabilistic but high-stakes replication of the dictator game may provide sharper evidence on this correlation.

**Table 5**
Probability of investment in the pyramid scheme: Student sample.

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Age | 0.008 | | |
| | (0.014) | | |
| Female | -0.104 | | |
| | (0.103) | | |
| Annual Gross Income | -0.000 | | |
| | (0.000) | | |
| Trusts Most People | -0.051 | | |
| | (0.106) | | |
| People Are Fair | -0.050 | | |
| | (0.113) | | |
| Percent Kept in DG | -0.002 | | |
| | (0.002) | | |
| Race Games Won | 0.001 | | |
| | (0.029) | | |
| Quiz Attempts | 0.062 | | |
| | (0.079) | | |
| Buys Lottery Monthly | | -0.012 | |
| | | (0.208) | |
| Never Buys Warranty | | 0.160 | |
| | | (0.108) | |
| Never Lends | | -0.097 | |
| | | (0.107) | |
| Financial Literacy | | -0.048 | |
| | | (0.106) | |
| Investment Account | | -0.251* | -0.181 |
| | | (0.129) | (0.123) |
| Loan | | 0.111 | 0.069 |
| | | (0.181) | (0.173) |
| Savings Account | | -0.119 | -0.089 |
| | | (0.133) | (0.131) |
| Stocks | | 0.201 | 0.166 |
| | | (0.128) | (0.123) |
| Risk | | 0.102** | 0.112*** |
| | | (0.046) | (0.042) |
| Pyramid Lottery C1 | | 0.043 | |
| | | (0.034) | |
| Pyramid Lottery C2 | | 0.049 | |
| | | (0.033) | |
| Pyramid Lottery Guess | | | 0.286*** |
| | | | (0.103) |
| Constant | 0.559 | 0.189 | 0.030 |
| | (0.451) | (0.285) | (0.213) |
| $R^2$ | 0.044 | 0.196 | 0.174 |
| Observations | 104 | 102 | 102 |

Notes: OLS estimates. The dependent variable is 1 if the participant chose to invest, and zero otherwise. Standard errors are in parentheses. ***, ** and * indicates statistical significance at the 1, 5 and 10 percent levels, respectively. Models 2 and 3 exclude two participants whose choices in the probability equivalence risk measure were inconsistent.

Our main result successfully replicates in the university student sample: The pyramid investment rate is on a par with that of the MTurk sample (56.7 versus 57.8 percent). This is despite the students' better performance in the cognitive skills tasks.

Table 5 reports the linear regressions of the probability of investment in the pyramid scheme on the controls. Unlike the MTurk pool, neither real-life risk-taking behavior nor cognitive skills significantly predict pyramid investments in the student pool. Those who have an investment account appear to be less likely to invest, but this effect is not robust across different regression specifications. Among the risk measures, only the probability equivalence method predicts pyramid investment in the expected direction — that is, the more risk seeking an individual, the higher his probability of investing in the pyramid scheme.

Neither principal component of the pyramid lottery choices predicts the pyramid investment in the student sample. However, those who chose to invest in the pyramid guess lottery were 28.6 percent more likely to invest in the pyramid game itself, which is slightly higher than the corresponding number in the MTurk sample (25.5 percent). As in the MTurk sample, the overall explanatory power of pyramid guess lottery choice is limited since the majority of student participants (72 out of 104) did not choose the pyramid guess lottery.

As in the MTurk sample, the higher the guessed number of investors, the higher the probability of investment. The average guesses of non-investors and investors are 34.2 and 63.9, respectively (two-sample $t$-test $p$-value $< 0.001$).

The replication of our main result with higher monetary stakes implies that widespread pyramid investment behaviors are not explained by lack of attention or gambling with "peanuts". As the students are highly educated and performed better on tasks proxying cognitive skills than MTurkers did, this replication indicates that neither cognitive sophistication nor comprehension of pyramid scheme mechanics immunizes individuals against pyramid schemes.

## 6. Discussion and conclusion

The findings from the intervention treatments, when evaluated together with the replication results, support the conjecture that participants fall for the pyramid scheme largely due to a lack of realization of the probability of losing money. When interventions alert them to this piece of information, participants were able to resist the scheme. This is consistent with the experimental literature on asset bubbles, in which a better understanding of the underlying asset value reduces bubbles (Kirchler et al., 2012; Huber and Kirchler, 2012). Also, as in the asset bubbles literature, there is no significant difference between the formats through which the information is given — as long as the cognitive tasks required are similar. In Huber and Kirchler (2012), providing participants with a figure of the asset value process and asking participants to give an estimate of the asset value are both effective in reducing bubbles. Likewise, our Payoff Distribution (providing a figure) and Backward Induction (asking participants to calculate the payoffs of those making losses) treatments are both effective in reducing pyramid investments. Nonetheless, we also show that interventions requiring participants to further process the provided information are ineffective. Even when participants correctly deduce the optimal action at every position in a small example (Small Pyramid), they still fail to *extrapolate* this conclusion to a larger scheme.

Since the seminal work of Wilcox (1993), a large literature has focused on how complex tasks affect choices. In these, complexity is defined by the increasing difficulty posed by the attributes of the task. [30] While we do not formally measure the complexity of our baseline and treatments—there are multiple approaches through which one can reach the correct decision, each with varying dimensions of varying complexity—one can regard the treatments requiring extra steps of data processing as more "complex". In this sense, our results indicate that information given in a more "complex" manner is less effective in helping decision-makers identify the optimal solution. Relatedly, it has been argued that computational complexity in determining the value of assets leads to financial market inefficiency (Bossaerts et al., 2018, 2024). Interestingly, human approximations to complex problems seem to be adapted to the difficulty at hand (Yadav et al., 2022). In light of this, one interpretation of our results is that the assistance given in our treatments changed the difficulty of the problem and hence elicited different approximations.

Generally, cognitive skills have a positive relationship with equilibrium play and a negative relationship with decision-making biases (Brañas-Garza and Smith, 2016; Brañas-Garza et al., 2019). In addition, performance in the cognitive reflection test or Raven's matrices, two common measures of cognitive skills, is highly correlated with behavior in backward induction games (Akiyama et al., 2017; Brañas-Garza et al., 2012; Carpenter et al., 2013; Fehr and Huck, 2016). However, the relationship between cognitive skills and risk preferences is not robust. For example, Frederick (2005) found that those who scored high in the cognitive reflection test were less risk averse than those who scored low, whereas Thomson and Oppenheimer (2016) found no such relationship. Our result that cognitive skills are negatively correlated with pyramid investment in the MTurk sample but not among the university students shows that better cognitive skills are not a panacea in deterring pyramid participation.

One may be concerned that our participants were investing out of social pressure. They may be worried either about reducing the payoffs of the person sending them the invitation, or blocking the investment prospects of those who would have been invited by them. This could potentially explain the small positive correlation between dictator game keeping and investment in the MTurk sample. Nonetheless, the same social pressure would have been present in real-life pyramid schemes, especially when they expand through social networks. A priori, it is unclear how other-regarding preferences would affect pyramid scheme investments. If potential participants realize the high probability of losing money, altruism may deter pyramid scheme investment due to the wish to foil the scheme for others. Likewise, if potential participants are aware of the uneven payoff distribution, inequality aversion may reduce the desirability of pyramid schemes.

Having said that, we did ignore the recruitment dimension of pyramid schemes in both our theoretical and experimental examination. If the number of descendants in the scheme depends on an investor's recruitment ability and effort, behavioral dimensions such as overconfidence may play a role. The effect of these dimensions on pyramid scheme investment is not necessarily straightforward, as they may be correlated with other preferential or cognitive traits.

## Data availability

Data will be made available on request.

[30] In experimental studies, a variety of task attributes have been tested as contributors to complexity, such as the number of choices or outcomes (e.g., Johnson and Bruce, 1997; Huck and Weizsäcker, 1999; Sonsino and Mandelbaum, 2001; Sonsino et al., 2002), the number of calculation steps required for a rational or correct solution (Carvalho and Silverman, 2019; Kalaycı and Serra-Garcia, 2016), and the difficulty of calculations such as requiring the use of Bayes' rule for a correct solution (Brown et al., 2019; Charness et al., 2007; Enke, 2020). Recently, Oprea (2020) identified the dimensions of complexity as characteristics of rules that increase costs to participants who need to apply these rules repeatedly.

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## Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jebo.2025.107398

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