Speculative Bubbles - An introduction and application of the Speculation Elicitation Task (SET)

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Abstract

We introduce the speculation elicitation task (SET) to measure speculative tendencies of individuals. The resulting SET-score allows us to investigate the role of individual speculative behavior on experimental asset market bubbles. The experimental results show that overpricing in asset markets composed of subjects with a high propensity to speculate (high SET-score) is significantly higher than in markets composed of subjects with a low propensity to speculate (low SET-score). We conclude that speculative tendencies are an important driver of price bubbles in experimental asset markets.

Keywords: Speculation, Experimental Asset Markets, Finance
JEL: C90, D40, D84, G10

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1 Introduction

Res tantum valet quantum vendi potest. (A thing is worth only what it can be sold for.)

A rich history of theoretical models in the financial literature show that speculative tendencies of investors can fuel asset bubbles.[1] Empirically, however, it remains a challenge to identify and test the influence of speculators. Furthermore, the fundamental value of assets cannot be observed directly. The experimental finance literature solves this problem by keeping both the fundamental value and the information flow under direct control of the experimenter (Bloomfield and Anderson, 2010). But even in controlled experimental asset markets it remains a challenge to obtain data on speculative behavior and its effect on asset market prices. One reason is that the price formation process in multi-period continuous double auction markets is dynamic and endogenous. This complicates the identification of speculative tendencies at the individual level.

Despite attempts to identify speculators ex post due to their trading behavior (see further below), there is no direct elicitation method to measure speculative tendencies in individuals. In this paper, we offer such a test, the Speculation Elicitation Task (SET). The SET measures speculative tendencies in a one shot asset market setting, but without market feedback that may confound price formation. We then use the resulting SET-score to analyze the effect of individual's speculative tendencies on bubble formation in the Smith et al. (1988) asset market design.

The SET is based on the bubble game introduced by Moinas and Pouget (2013). It involves an asset commonly known to have zero fundamental value traded in a sequential market with three traders. At each point in the sequence, an incoming trader chooses between either (i) accepting a buy offer and offering it to the next trader in line at a higher price, or (ii) rejecting the buy offer, effectively leaving the current owner stuck with a worthless asset. The last trader in the sequence cannot sell the asset anymore. Thus, when buying the asset, traders speculate on not being last and on being able to sell it to the next trader at a higher price. Traders do not know their position in the market sequence, but they receive a signal on their position in the form of the price offered to them: the higher the price, the higher the probability of being last in the sequence. The bubble game is a similar game-theoretic solution as the centipede game. Due to backward induction neither trader buys the asset and a price bubble is not able to form.

In their experiments, however, Moinas and Pouget (2013) find substantial trading and a 'snowball effect', where the propensity to enter bubbles increases in the required number of reasoning steps and in the probability not to be last. The authors interpret the latter result as evidence for some element of rationality in subjects' decision to speculate on higher prices. Moreover, Moinas and Pouget (2013) show that buying in the bubble game can solve an individual rationality condition (IRC), i.e., the utility of buying is larger or equal to the utility of not buying, as long as the believed probability of someone next in line buying is large enough. This reasoning is captured by the Quantal Response Equilibrium (QRE) model of Rogers et al. (2009) in which traders depart from the no-bubble Nash equilibrium due to the assumption of a less than perfect payoff responsiveness of others traders and the uncertainty concerning this responsiveness. This means that even at those prices at which a trader is sure to be last, he is still believed to buy with a certain probability. Since this probability increases in the offered price, the QRE predicts the snowball effect described above. Moinas and Pouget (2013) find that the QRE provides the

[1] Early papers assuming rational expectations and full information suggest that investing in a growing bubble can be rational if a number of restrictions on the asset and trading environment are met (see, e.g., Blanchard and Watson, 1983). Subsequent heterogeneous agents models (HAM), which allow for trader heterogeneity in rationality and/or information, echo this conclusion (Froot et al., 1992; Madrigal, 1996; Hong and Stein, 1999). Here, a central idea is the "greater fool theory" where asset prices that deviate from their fundamental value can be justified rationally under the belief that another party (a 'greater fool' or 'noise trader') is willing to pay an even higher price (De Long et al., 1990).

best explaination for the buying behavior in the bubble game, indicating that traders believe their fellow traders to make mistakes.[2] This finding is in line with the 'greater fool theory' by De Long et al. (1990) and also applies to our definition of speculation where a trader buys a worthless asset based on the expectation that another (noise) trader down the line mistakenly buys at an even higher price.

To obtain the SET-score from the bubble game, we exploit the bubble game's property of monotonously decreasing probabilities not to be last by translating the set of buy offers into a scale measure of the propensity to speculate.[3] In contrast to the experimental design of Moinas and Pouget (2013) in which subjects decide on only one price, we elicit buy orders for every possible price. If subjects have a high propensity to speculate they buy the asset, even at a high price. If subjects have no propensity to speculate they never buy, not even at the lowest price. In our experimental setting, each subject goes through a list of potential prices and decides whether to buy or not. Subjects start with the highest price to make backward induction more salient. Moving down the list, the first price at which a subject is willing to buy the asset determines the SET-score; a measure for the subject's maximum propensity to speculate. Following the logic of the aforementioned QRE, people with high SET-scores should expect higher error rates amongst their fellow participants than traders with lower SET-scores. This follows from the fact that only the assumption of higher error rates of others satisfies a trader's IRC for buying at high prices.

To test whether and how the individual propensity to speculate impacts the formation of price bubbles in asset markets, we split the subject population in SET-score tertiles and assign each tertile to one of three independent but otherwise similar SSW markets.[4] We hypothesize that, if speculation plays a role in driving bubbles, we should observe systematically higher overpricing in markets with high SET-scores than in markets with low SET-scores. The rationale behind this hypothesis originates from the fact that the SET and the SSW market are very much related in the informational aspects, the rational outcome as well as the thought process needed to form speculative bubbles: in both settings backward induction coupled with full information on the fundamental value leads to a no-bubble Nash equilibrium. Accordingly, the logic behind the QRE can not only be applied to the bubble game/SET but also to buying behavior in the SSW.

Specifically, as with the SET, buying an asset above the fundamental value in the SSW should only be considered when the assumed probability of reselling for a higher price in one of the subsequent periods is high enough to satisfy a trader's IRC. Given that traders with high SET-scores should theoretically assume higher error rates amongst their fellow participants, they should also be more willing to speculate and buy at higher prices in the SSW. We therefore expect to see larger price bubbles in SSW markets populated by individuals with high SET-scores than in markets populated by individuals with low SET-scores.[5]

Our results show that the vast majority of subjects is willing to speculate following the backward snowball effect described in Moinas and Pouget (2013). The results from the asset market experiments show that high SET traders drive asset market bubbles as price deviations from the fundamental value in the high SET-score markets are statistically and economically significantly higher than in low SET-score markets. These findings indicate a strong link between

[2] Moinas and Pouget (2013) also apply a number of other behavioral models to the bubble game data, notably the the Analogy-Based Expectation Equilibrium of Jehiel (2005) and the Cognitive Hierarchy model of Camerer et al. (2004). These models are closely related to the QRE in spirit, but perform worse in fitting the bubble game data. In this paper, we therefore focus on the QRE model.

[3] Note that this is not possible in the centipede game, where the probability not to be last is equal to 1 for each node except for the last node where it is 0.

[4] By assigning subjects to markets based on their SET-score we follow earlier studies that composed markets according to trader characteristics to study bubble formation, such as prior market experience (Dufwenberg et al., 2005) or gender (Eckel and Füllbrunn, 2015).

[5] As the composition of a market is not known, a bubble can be sustained after the first period by speculators who unknowingly feed on each other.

the average individual propensity to speculate (average SET-score of traders) and the formation of price bubbles in asset markets.

This paper contributes to and complements recent studies that attempt to identify trader types and their role in bubbles in experimental asset markets by applying simulations or a scoring method to SSW trading data *ex post* (Haruvy and Noussair, 2006; Baghestanian et al., 2012). Although these approaches are intuitive, it is very difficult to detect speculative behavior ex post in SSW markets. First, it is not possible to control the proportion of speculative traders in the markets as this proportion can only be detected after the fact. Speculative traders, however, can behave very differently, depending on the composition of the market. For instance, when randomly matched with many fundamental traders, a speculator may not have the opportunity to exhibit speculative behavior. When using an ex ante approach, as in this paper, it is possible to control market composition and therefore actively create the possibility for speculative behavior. Second, an ex post analysis of trader types requires (frequent) trading in a multi-period asset market in order to have enough data for the identification process. As trading behavior in such asset market setups is highly endogenous, observed speculative behavior may change over periods. This dynamic complicates the ex post classification and identification of speculative traders (Baghestanian et al., 2012). The SET, in contrast, allows to measure speculative tendencies in a one shot setting, without any feedback from other traders. Third, it is difficult to test the validity of ex post trader classification from asset market behavior as this requires running a second experimental asset market after the identification has taken place in a first market. Doing so, one will inherently run into problems associated with repetition effects of the same task (Haruvy et al., 2007). Because of these limitations, the question if and to what extend speculators cause bubbles has not yet been answered conclusively. We add to the current literature by providing direct experimental evidence that individual speculative tendencies indeed increase the likelihood for trading behavior that supports price bubbles. With the SET we further offer a new and easy-to-implement experimental task that can be used to measure subjects' individual propensity to speculate.

The paper is structured as follows. In section 2 we provide our general experimental setup and procedures. In section 3, we introduce the SET-design,the SET-score, and report the experimental results. In section 4, we assign subjects, depending on their SET-score, to three SSW markets and discuss the results. Section 5 concludes.

2 General procedure in the experiments

Our experimental sessions consisted of three parts to be described in more detail below. In part one, we elicited the SET-score as well as subjects' beliefs concerning the SET-scores of the other participants. In part two, subjects with high, medium and low SET-scores traded in SSW asset markets. In part three, we administered the cognitive reflection test (Frederick, 2005) (CRT), a lottery choice list (Holt and Laury, 2002), a questionnaire with context dependent risk related questions (Bonin et al., 2007) and questions on demographics. Part one and two were fully incentivized. In part three, the risk elicitation and the CRT were incentivised.[6]

A total of 117 students participated in 4 sessions, with 27 subjects in session 1 and 30 subjects each in sessions 2-4. Each session lasted about 1 hour and 45 minutes and the average earnings per subject were 22.50 euros. All payments were made in cash and in private at the very end of the experiment. All tasks were computerized using z-Tree (Fischbacher, 2007) and subjects were recruited using ORSEE (Greiner, 2004). The sessions were conducted in the period from March

[6] Find the instructions in section A in the appendix.

to May 2014 at the NSM Decision Lab at the Radboud University Nijmegen, The Netherlands. Table A.1 in appendix D provides descriptive statistics of the subjects in the experiment.

3 The SET

3.1 Design

The SET is based on the bubble game by Moinas and Pouget (2013) which consists of a sequence of three traders who can either accept or reject to buy an asset with a fundamental value equal to zero for a certain price. Buying the asset for the offered price means investing one euro initial capital and automatically offering it to the next trader in the sequence. The payoff is either ten euros if the next trader decides to buy, or zero if the next trader rejects to buy or if no next trader exists. Not buying the asset means keeping the one euro initial capital. The design is summarized in figure 1. If trader three knows his position in the sequence, it is straight forward that he will reject to buy due to an immediate loss. Knowing this, trader two will reject to buy as well, and so does trader one. Hence, no one accepts an offer to buy in the no-bubble Nash equilibrium.

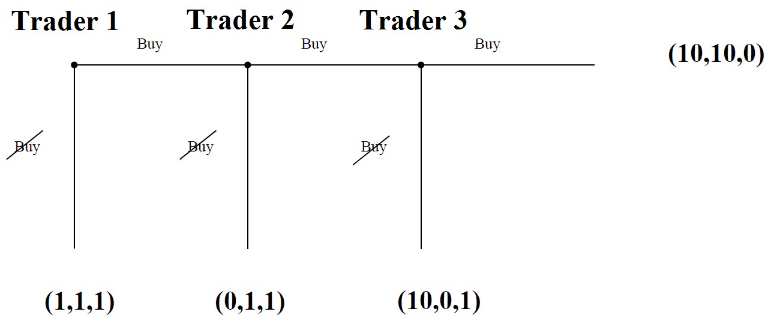


Figure 1: Sequence of the SET

***Notes*:** The first trader in line is offered to buy the asset at a randomly drawn price $P_1 \in \{10^0, 10^1, 10^2, 10^3, 10^4\}$. When the first trader rejects, the game ends and all traders earn their one euro initial capital. When the first trader accepts, the asset is offered to the second trader in the sequence at a price $P_2 = 10 \times P_1$, i.e., $P_2 \in \{10^1, 10^2, 10^3, 10^4, 10^5\}$. When the second trader rejects, the game ends, the first trader earns zero, and the second and the third trader earn the one euro initial capital. When the second trader accepts, the first trader sells the asset and earns ten euros. The asset is then offered to the third trader in the sequence at a price $P_3 = 10 \times P_2$, i.e., $P_3 \in \{10^2, 10^3, 10^4, 10^5, 10^6\}$. When the third trader rejects, the game ends, the second trader earns zero, and the third trader earns the one euro initial capital. When the third trader accepts, the second trader sells the asset and earns ten euros. The third trader buys the asset even though being last in the sequence and is unable to resell. Thus, the third trader loses the one euro initial capital and earns zero.

Traders have no information about their position in the sequence, i.e., each trader has an equal chance of being either first, second or third in the sequence. However, information about a trader's position in the sequence can be inferred after the price is revealed. The price offered to the trader in the first position is randomly drawn from a set $P_1 \in \{10^0, 10^1, 10^2, 10^3, 10^4\}$ with a known triangular distribution.[7] The price offered to the second trader in the sequence is then $P_2 = P_1 \times 10$, and the price offered to the third trader is $P_3 = P_2 \times 10 = P_1 \times 100$. Thus,

[7]For higher prices an external financial investor pays the difference. Earnings are divided between the financial

for any price offered, Bayes' rule provides the probabilities of being first, second or third in the trading sequence. Note that for an offer $P = 10^6$ the probability of being last is equal to one. As P_1 is capped, backward induction rules out a bubble Nash equilibrium given all traders are rational and this rationality is common knowledge. Hence, independent of whether the traders know their position in the sequence, neither trader accepts an offer to buy in the no-bubble Nash equilibrium. Buy decisions are made simultaneously and independently meaning that subjects have no further information on the actions of other traders in their sequence.

To develop the SET-score, we modified the experimental design of Moinas and Pouget (2013) in two ways. First, instead of presenting the subjects with just one buy decision at a particular price, we elicited subjects' buy decisions for each price possible given the set of initial prices. We asked each subject "Do you want to buy the asset at $1,000,000$?", "Do you want to buy the asset at $100,000$?",..., "Do you want to buy the asset at 1?".[8] Note that we started with the highest possible price where a buy decision immediately leads to zero payoff. We used this procedure to facilitate backward induction. The SET provides a clear switching price P^S for which a subject rejects to buy at prices $P > P^S$ and accepts to buy at prices $P \leq P^S$. To provide a score, we rank the decisions to buy from 0 (never buy) to 7 (always buy). Our SET-score is then defined by the rank of the switching price P^S, see table 1. For example, the switching price $P^S = 100$ refers to a SET-score of 3. A low SET-score reflects a low propensity to speculate while a high SET-score indicates a high propensity to speculate. An increasing SET-score implies that subjects try to sell to a greater fool who is present with a decreasing probability.

Table 1: Construction of the SET-score

Buy at or below price	Never	10^0	10^1	10^2	10^3	10^4	10^5	10^6
Probability of being last (%)	0	0	0	23.08	28.57	46.15	57.14	100
SET-score	0	1	2	3	4	5	6	7

Notes: The probabilities of being first, second or third in line were rounded to integers in the instructions.

Finer SET-score scales can easily be created by increasing the cap on P_1, but doing so is a two-edged sword. On the one hand, more levels allow for a more elaborate scale as more decisions are made and more heterogeneity in speculation becomes possible. On the other hand, a design with many levels might include superfluous decisions and could take up too much time. A second change we made to the original design of Moinas and Pouget (2013) was tripling the opportunity costs for speculation. This increase was applied after running pilots using a one euro initial capital. We found the distribution of SET-scores resulting from this setup to be heavily skewed towards the higher SET scores indicating a higher propensity to speculate. Subjects only needed to presume a small winning probability (at least $1/10$) to let the expected earnings from buying exceed one euro. With the calibration to three euro, subjects have to presume a probability of at least $3/10$, which allows us to better differentiate between speculation types in the population.[9]

After the SET, subjects were asked to state their beliefs regarding the SET-scores of the other session participants. For each possible buying price, subjects had to state their belief about how many of their fellow subjects in the same session started buying at that point. Accuracy of beliefs was incentivised as explained in the instructions in section A.4 in the appendix (incl. a screenshot).

investor and the participant such that the participant always earn 10 euro. See Moinas and Pouget (2013) for details.

[8] Please see the screen shot and additional explanations in the appendix A.

[9] In fact, with a starting capital of three euro the distribution of SET-scores shifted more towards the center, meaning that subjects were responsive (in the expected direction) to increased opportunity costs. The results from the pilot with one euro starting capital are available upon request.

3.2 Implementation

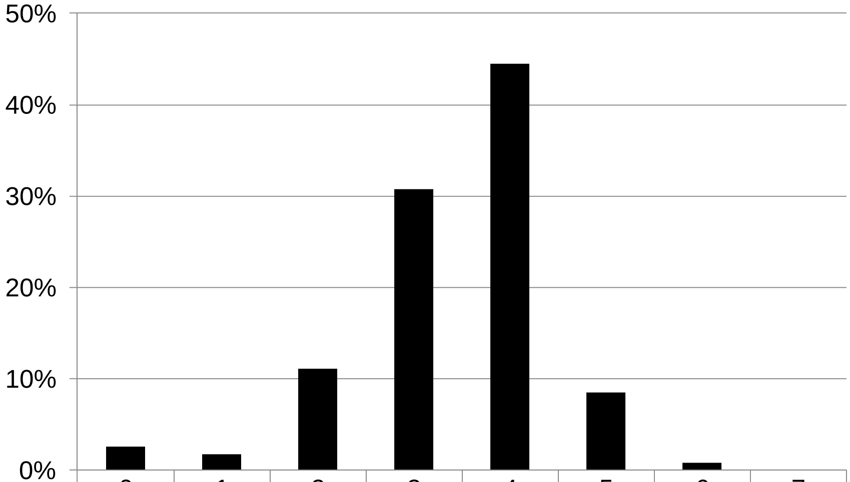
After subjects entered the lab, instructions on the bubble game (the basics of the SET) were read aloud (see section A.1), followed by on-screen comprehension questions (see appendix A.2). Subject were given time to complete seven comprehension questions. We allowed several attempts to answer, but a subject could only move on to the next question once the current question had been answered correctly. Then the correct answers were publicly announced and thoroughly explained. After having explained the basics of the SET, we provided the procedural instructions on the subjects' screen (see appendix A). These instructions made clear that the bubble game has to be played not for one but for all possible prices, and that one price would be randomly chosen to calculate their earnings. We clearly indicated that these on-screen instructions were the same for all participants. To get a consistent buy decision for the whole list of prices, we clearly communicated that if subjects decide to buy at a certain price P^S, they are assumed to also buy for each price below P. We allowed subjects to check and revise their decisions before confirming their final decision. The final payoff (paid out at the end of the experiment) for a subject i was calculated as follows. First, one of the seven prices was randomly drawn with equal probability to be the price the trader faced. Second, subject i's position was randomly drawn. Third, the remaining two positions were filled with two randomly drawn subjects j and k from the subjects in the room. Finally, subject i's payoff was calculated on the basis of all the three subjects' decisions.[10]

3.3 Results

Figure 2 shows the distribution of SET-scores for all 117 subjects. Less than three percent chose not to buy at all while 97 percent of participants did speculate in the SET and were willing to buy the intrinsically worthless asset. Most subjects chose to buy at prices at or below 1,000 yielding an average SET-score of 3.42. Note that none of the subjects chose to buy at $P = 10^6$ (maximum SET-score of 7), where the probability to be last was equal to one, suggesting that subjects understood the game quite well.[11] The latter is also supported by the fact that all subjects provided the right answers to the seven comprehension questions within the time limit. We furthermore find no significant difference in the number of attempts between individuals with the lowest, middle and highest tertile of SET-scores (see section 4.1 for further details on this grouping) using a one-sided Jonckheere Terpstra test ($P = 0.124$).

[10] Example: Suppose $P = 1,000$ was drawn for subject i (suppose i chose to buy), and suppose i is drawn to be number 2 in line. Then we look at the decision of subject j for $P = 100$ (suppose j chose to buy) and of subject k for $P = 10,000$ (suppose k chose not to buy). Now the payoff for subject i is calculated according the decisions of all three (which is zero as k rejected to buy and i purchased from j).

[11] Also, only one subject (less than one percent of all subjects) bought at a SET-score of 6 (second highest price).



	0	1	2	3	4	5	6	7
%	2.56%	1.71%	11.11%	30.77%	44.44%	8.55%	0.85%	0.00%
N	3	2	13	36	52	10	1	0

SET-score

Figure 2: SET- score distribution

To investigate whether individual measures explain speculative tendencies in the SET, we ran an OLS regression with the SET-scores as dependent variable and all demographic variables and other measures elicited in part three of the experiment as independent variables. As the results in Table 2 show, the demographic control variables, as well as the CRT and the risk attitude measures from Holt and Laury (2002) and Bonin et al. (2007) are not statistically significant. A subject's belief about the others' SET-score, however, is significantly and positively correlated with a subject's own SET-score. Hence, on average, and in accordance with the greater fool theory, subjects who believe that others choose a higher P^S also choose a higher P^S themselves. Given the strong predictive power, we take a closer look at subjects' beliefs about others' SET-score. Looking at the chosen switching price, we observe that, given their beliefs regarding the switching points of the others, 84.6 percent of all subjects are within one step of their optimal decision under the expected utility framework assuming risk neutrality.[12] We furthermore find that more than 92 percent of subjects obtain a positive expected surplus (defined as the expected gain of buying minus the three euros obtained by deciding not to buy at all) of, on average, 1.63 euros. These results show that subjects indeed behave in accordance with their beliefs and seem to expect that, on average, a greater fool next in line will buy the asset from them.

[12] Going from a price of 1 to a price of 10 counts as 1 step, going from a price 1 to a price of 100 counts as 2 steps etc.. Please see appendix F for more information on the calculation of the optimal buy prices.

Table 2: Regression results on the SET-score.

Dependent	(1) SET score	(2) SET score
Session 2	-0.388*	-0.271
	(0.226)	(0.243)
Session 3	-0.263	-0.137
	(0.252)	(0.264)
Session 4	-0.167	0.019
	(0.240)	(0.247)
Belief SET	0.581***	0.563***
	(0.106)	(0.108)
CRT		-0.100
		(0.061)
Holt Laury		-0.019
		(0.046)
General Risk		0.076
		(0.052)
Age		0.018
		(0.038)
Female		0.210
		(0.172)
Foreign		0.185
		(0.234)
Econ		-0.042
		(0.472)
Constant	1.757***	1.118
	(0.429)	(1.061)
Observations	117	117
R-squared	0.318	0.375
Prob > F	0.000	0.000

Notes: Belief SET is the average believed SET score of others elicited at the end of part 1 of the experiment. Foreign is a dummy capturing a non-Dutch place of birth. Econ is a dummy for studying economics or business. The reported results do not change qualitatively when including the risk questions from Bonin et al. (2007). Heteroskedasticity-consistent standard errors in brackets. ***$p < 0.01$,**$p < 0.05$, *$p < 0.1$.

4 SSW Markets

4.1 Market composition and implementation

To consider the effect of speculation on price bubbles, we compare trading behavior in SSW markets composed of subjects who scored high in the SET to trading behavior in markets composed of subjects who scored low in the SET. In each session ($N = 30$ or $N = 27$), we ranked the elicited SET-scores from part one and split them into tertiles. The $N/3$ subjects with the highest SET-scores, representing the tertile of the session population with the highest propensity to speculate, were assigned to one market, henceforth "*H-market*". The $N/3$ subjects with the lowest SET-scores, representing the tertile of the session population with the lowest propensity to speculate, were assigned to another market, henceforth "*L-market*". The remaining subjects were assigned to a third market with medium SET-scores, henceforth "*M-market*". In case of ties, subjects were randomly assigned to one of either markets. Subjects knew that they were assigned to three separate markets of equal size, but were not aware of the fact that markets are composed in a certain way.[13] Hence, we are able to compare the performance of three SSW markets, differentiated by the population's propensity to speculate into L-/M-/H-markets, leaving all other parameters constant (even the stream of dividend payments).

As shown in table 3, the average SET-score in markets L, M, and H is 2.38, 3.63, and 4.32, respectively. To test whether SET-scores are indeed increasing from markets L to H, we use a one-sided Jonckheere Terpstra test in each session as SET-scores are independent across markets. We can reject the Null that no trend from L to H exist in each session in favor of the alternative that SET-scores increases from L to H ($p < 0.001$). Comparing only the L-markets to the H-markets, a Mann Whitney U test confirms statistically significant differences in SET-scores for each individual session as well ($p < 0.001$ in each session).

Table 3: SET-score descriptives.

MARKET	SET-Score	Mann Whitney U test
Avg: L vs. M	2.38 vs. 3.63	0.000
Avg: M vs. H	3.63 vs. 4.32	0.000
Avg: H vs. L	4.32 vs. 2.38	0.000
S1: L vs. M	2.5 vs. 4	0.001
S1: M vs. H	4 vs. 4.67	0.059
S1: H vs. L	4.67 vs. 2.5	0.000
S2: L vs. M	2.5 vs. 3	0.063
S2: M vs. H	3 vs. 4.2	0.000
S2: H vs. L	4.2 vs. 2.5	0.000
S3: L vs. M	2 vs. 3.7	0.000
S3: M vs. H	3.7 vs. 4.2	0.105
S3: H vs. L	4.2 vs. 2	0.000
S4: L vs. M	2.5 vs. 3.8	0.000
S4: M vs. H	3.8 vs. 4.2	0.051
S4: H vs. L	4.2 vs. 2.5	0.000

Notes: N=117. 'Avg' indicates average per market type (L, M, H) across all sessions (S). 'S1-L' stands for session 1, market 'L'. Each separate market consisted of 10 participants (session one had 10, 9, and 8 due to no-shows).

Before trading in the SSW market, subjects had a neutral trial period of 5 minutes to get used to the trading platform.[14] After the trial the traders entered the SSW market which we implemented in line with the standard literature (see Palan, 2013). Traders were able to buy and sell shares during a sequence of 15 double-auction trading periods, each lasting three minutes. At the end of every period, each share paid a dividend of 0, 8, 28, or 60 francs with equal probability. Note that the random draw for the dividend payment applied to all three markets resulting in identical dividends across all three markets within a session. Since the expected dividend equals 24 francs in every period, the fundamental value in period t equals $24 \times (16–t)$, i.e. 360 francs in period 1, 336 francs in period 2, ... and 24 francs in period 15. The initial endowments were

[13]In line with previous studies, e.g. Cheung et al. (2014); Levine et al. (2014), subgroups are composed without public knowledge on the determinants of selection. This ensures that our treatment variable, the degree of speculative tendency (average SET-score), constitutes the only difference between markets.

[14]For instructions see appendix B.

equal for all subjects and amounted to an initial cash balance of 2000 francs and two shares.[15] The exchange rate used was 300 francs for 1 euro.

4.2 Results

Figure 3 shows the difference between the median price path and the fundamental value, averaged over all four sessions for markets L, M, and H.[16] The figure clearly shows a significant difference in price bubbles between the L-markets and the H-markets: the average deviation from the fundamental value stays well below 100 francs in the L-markets, while the average price in the H-markets starts at 100 francs deviation and then clearly bubbles to more than 250 francs above fundamental value. The M-markets also bubble, but less than the H-markets and with a lower peak: the average M-prices stay between L and H for the first 12 out of 15 periods. In the last three periods, the M- and the H-markets follow a very similar price path as they converge to the fundamental value after their bubbles burst.[17]

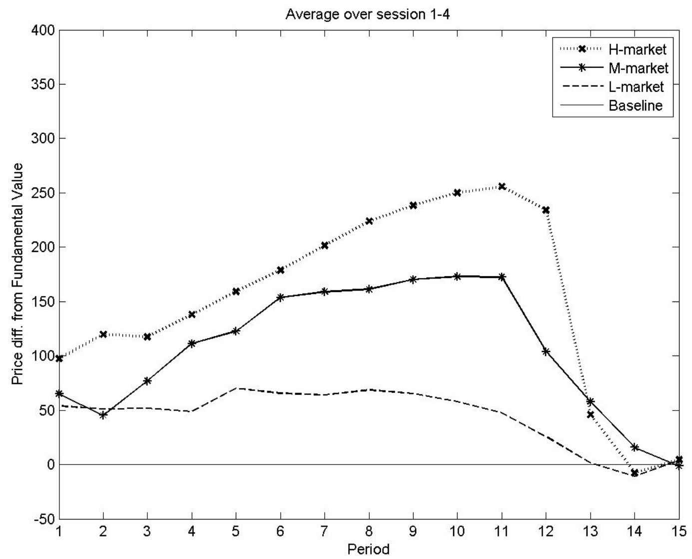


Figure 3: Time series of transaction price differences to fundamental value

Notes: The figure shows the average of median session prices of markets L, M, and H and the fundamental value (as solid horizontal line).

To measure the magnitude of price bubbles we follow the literature and compute two bubble measures provided by Stöckl et al. (2010). The *relative absolute deviation* (RAD) measures mispricing as the average absolute deviation from the average fundamental value, and the *relative deviation* (RD) measures overpricing as the average deviation from the average fundamental value.[18] Table 4 reports the RAD and RD by market and by session, and the average over all

[15]Deviating from the 'Design 4' parameters used in the literature, we increased the cash-to-asset ratio to allow for higher price bubbles in the markets (see, e.g., Haruvy and Noussair, 2006).

[16]See appendix C for session-specific price paths.

[17]Note that in contrast to earlier experiments price deviations are positive from the start as sufficient cash was available right from the beginning.

[18]The RAD is defined as $\frac{1}{T}\sum_{t=1}^{T}\frac{|P_t - FV_t|}{FV}$ while the RD is defined as $\frac{1}{T}\sum_{t=1}^{T}\frac{P_t - FV_t}{FV}$.

sessions.[19] RAD and RD have almost equal values indicating that prices are in general above the fundamental value. In the following we therefore focus on the RD.[20] In each session, overpricing is lower in L-markets than in H-markets. On average, L-markets are overpriced by 23 percent, while in H-markets the average overpricing is close to 78 percent. Thus, overpricing is more than three times higher in H-markets than in L-markets. To compare the two markets, we use a test proposed by Haruvy and Noussair (2006). We treat the difference between the average price and the fundamental value in each period of each session as the relevant unit of observation yielding 15 observations (this assumes that the difference between price and fundamental value is independent over periods and results in giving equal weight to all periods in all sessions). We then evaluate the hypothesis that the difference in the L-markets is equal to the difference in the H-markets using a Wilcoxon signed rank test.[21] The results in Table A.3 show that we can reject the Null for each session and for the average of all sessions ($p = 0.011$ for session two and $p \leq 0.001$ for all other tests).[22] Hence overpricing is significantly higher in H-markets than in L-markets.

While table 4 shows a clear trend in RD in session three and four, this is not the case for sessions one and two. This is due to the fact that differences in SET-scores between markets in the first two sessions are less pronounced, as shown in table A.3. In session one, the SET-scores are not significantly different between markets M and H at a 5 percent level. This may explain the lower RD in the H-market. In session two, the SET-scores in the L- and M-market are statistically not different, which may explain the higher RD in the L-market. To test for a trend, we evaluate the Null that $RD_L = RD_M = RD_H$ against the alternative that $RD_L < RD_M < RD_H$. As observations are not independent within a session, we make use of Page's Trend Test (Page, 1963) with $m = 4$ and $n = 3$. We can reject the Null at a significance level of 5 percent indicating a significant trend of increasing overpricing as we move from L to M to H.[23] Thus, we can conclude that overpricing significantly increases in the average SET-score of the market.

Table 4: Bubble measures.

	RAD			RD		
Session\Market	L	M	H	L	M	H
1	8%	55%	45%	8%	53%	45%
2	25%	15%	71%	19%	11%	69%
3	50%	81%	94%	50%	81%	94%
4	17%	88%	106%	17%	88%	106%
Average	25%	60%	79%	23%	58%	78%

Notes: N=117. Relative absolute deviation is measured as $RAD = \frac{1}{15}\sum_{t=1}^{15}\frac{|P_t - FV_t|}{Mean(FV)}$, and (the average of) the relative deviation is measured as $RD = \frac{1}{15}\sum_{t=1}^{15}\frac{P_t - FV_t}{mean(FV)}$. Each separate market consisted of, on average, 10 participants.

[19] Table A.2 in appendix D provides further bubble measures used in the literature.

[20] The reported statistical tests yield qualitatively identical results for the RAD.

[21] Thus, for each session we evaluated the Null that $(P_t^H - FV_t) - (P_t^L - FV_t) = 0$, and across sessions we evaluated the Null that $\frac{1}{4}\sum_{i=1}^{4}(P_{t,i}^H - FV_t) - \frac{1}{4}\sum_{i=1}^{4}(P_{t,i}^L - FV_t) = 0$ with i being the session ID.

[22] Using a Wilcoxon signed rank test on the differences in RD with only four observations, we find the difference to be weakly significant (p=0.068).

[23] Note that markets in a session may not be completely independent of each other, due to equal dividend draws across markets and other shared session characteristics, like the weather, the day of the week, or the time of the day. As markets may be less independent within a session than across sessions we apply Page's trend test to compare markets. Using Cuzick's Test yields a p-value of 0.031 and a one-sided Jonckheere-Terpstra Test yields a p-value of 0.014.

5 Conclusion

In this paper we have introduced the speculation elicitation task (SET) designed to measure individual speculative tendencies. We confirm results from Moinas and Pouget (2013) that, even though assets have zero fundamental value, subjects are willing to buy these asset at positive prices. The SET does not only elicit decisions for one price, as in Moinas and Pouget (2013), but for a range of prices. We conclude that the higher a trader's maximum willingness to buy, as expressed by the SET-score, the higher a trader's propensity to speculate on a 'greater fool', who will buy at even higher prices.

We applied the SET-score in experimental asset market settings by composing separate markets with homogeneous trader types having similar low, medium, or high SET-scores. As expected, we observe significantly higher overpricing and bubble formation in high SET-score markets than in low SET-score markets in all sessions. In fact, we find that overpricing in the H-markets is more than three times higher than in the L-markets. Our results provide evidence that price bubbles in SSW market designs are at least partly driven by speculative behavior.

Overall, we find that the SET is able to elicit and measure speculative tendencies of individuals. Our approach is distinctly different from ex post identification of speculative trading behavior in SSW markets (Haruvy and Noussair, 2006; Baghestanian et al., 2012) as the SET-score measures speculative tendencies of individuals without market feedback and dynamics that may confound price formation.

The SET is easily implemented in the laboratory and the procedure only takes about 20 minutes. The SET provides us with the SET-score; an easy-to-interpret speculation measurement at the individual level that enables us to explore the influence of traders' speculative tendencies on bubble formation and crashes. Future studies may want to use the SET-score as a treatment variable (for example, to explore the influence of speculators on different market phenomena) or as an explanatory variable for trader and market characteristics.

References

Baghestanian, S., Lugovskyy, V., Puzzello, D., 2012. Individual behavior in experimental asset markets: theory and evidence. Tech. rep., Working Paper, University of Indiana.

Blanchard, O. J., Watson, M. W., 1983. Bubbles, rational expectations and financial markets. National Bureau of economic research Cambridge, Mass., USA.

Bloomfield, R., Anderson, A., 2010. Behavioral Finance: Investors, Corporations, and Markets. John Wiley & Sons, Ch. Experimental Finance.

Bonin, H., Dohmen, T., Falk, A., Huffman, D., Sunde, U., 2007. Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. Labour Economics 14 (6), 926–937.

Cheung, S. L., Hedegaard, M., Palan, S., 2014. To see is to believe: Common expectations in experimental asset markets. European Economic Review 66, 84–96.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990. Noise trader risk in financial markets. Journal of political Economy, 703–738.

Dufwenberg, M., Lindqvist, T., Moore, E., 2005. Bubbles and experience: An experiment. American Economic Review, 1731–1737.

Eckel, C. C., Füllbrunn, S., 2015. Thar'she'blows? gender, competition, and bubbles in experimental asset markets. The American Economic Review 105 (2), 1–16.

Fischbacher, U., 2007. z-Tree: Zurich toolbox for ready-made economic experiments. Experimental economics 10 (2), 171–178.

Frederick, S., 2005. Cognitive reflection and decision making. Journal of Economic perspectives, 25–42.

Froot, K. A., Scharfstein, D. S., Stein, J. C., 1992. Herd on the street: Informational inefficiencies in a market with short-term speculation. The Journal of Finance 47 (4), 1461–1484.

Greiner, B., 2004. The online recruitment system orsee 2.0-a guide for the organization of experiments in economics. University of Cologne, Working paper series in economics 10 (23), 63–104.

Haruvy, E., Lahav, Y., Noussair, C. N., 2007. Traders' expectations in asset markets: Experimental evidence. The American Economic Review 97 (5), 1901–1920.

Haruvy, E., Noussair, C. N., 2006. The effect of short selling on bubbles and crashes in experimental spot asset markets. The Journal of Finance 61 (3), 1119–1157.

Holt, C. A., Laury, S. K., 2002. Risk aversion and incentive effects. American economic review 92 (5), 1644–1655.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. The Journal of Finance 54 (6), 2143–2184.

Jehiel, P., 2005. Analogy-based expectation equilibrium. Journal of Economic theory 123 (2), 81–104.

Levine, S. S., Apfelbaum, E. P., Bernard, M., Bartelt, V. L., Zajac, E. J., Stark, D., 2014. Ethnic diversity deflates price bubbles. Proceedings of the National Academy of Sciences 111 (52), 18524–18529.

Madrigal, V., 1996. Non-Fundamental Speculation. The Journal of Finance 51 (2), 553–578.

Moinas, S., Pouget, S., 2013. The Bubble Game: An Experimental Study of Speculation. Econometrica 81 (4), 1507–1539.

Page, E. B., 1963. Ordered hypotheses for multiple treatments: a significance test for linear ranks. Journal of the American Statistical Association 58 (301), 216–230.

Palan, S., 2013. A review of bubbles and crashes in experimental asset markets. Journal of Economic Surveys 27 (3), 570–588.

Rogers, B. W., Palfrey, T. R., Camerer, C. F., 2009. Heterogeneous quantal response equilibrium and cognitive hierarchies. Journal of Economic Theory 144 (4), 1440–1467.

Smith, V. L., Suchanek, G. L., Williams, A. W., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica: Journal of the Econometric Society, 1119–1151.

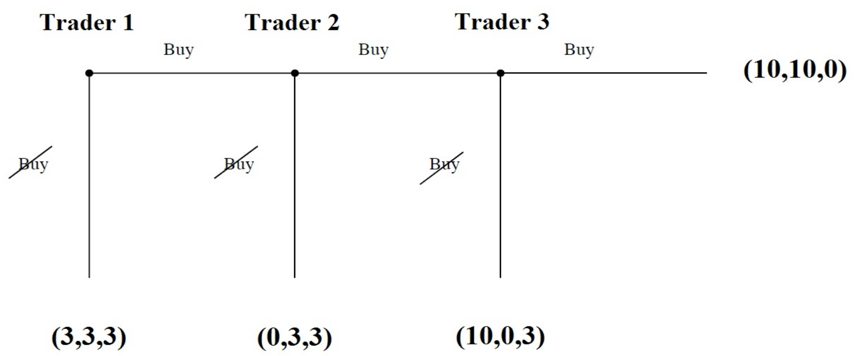
Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and uncertainty 5 (4), 297–323.

Appendix

A Instructions: SET & Comprehension Questionnaire

A.1 SET instructions

1. The Exchange Process
To play this game, the computer creates groups of three traders. Each trader is endowed with one euro which can be used to buy an asset. Your task during the game is thus to choose whether you want to buy or not the asset. This asset does not generate any dividend. If the asset price exceeds one euro, you can still buy the asset. We indeed consider that a financial partner (who is not part of the game) provides you with the additional capital and shares profits with you according to the respective capital invested. The market proceeds sequentially. The first trader is proposed to buy at a price P1. If he buys, he proposes to sell the asset to the second trader at a price which is ten times higher, P2 = 10P1. If the second trader accepts to buy, the first trader ends up the game with 10 euros. The second trader then proposes to sell the asset to the third trader at a price P3 = 10*P2 = 100*P1. If the third trader buys the asset, the second trader ends up the game with 10 euros. The third trader does not find anybody to whom he can sell the asset as he is last. Since this asset does not generate any dividend, he ends up the game with 0 euro. If you do not or cannot buy the asset – respectively because you choose not to buy or because the person before you in line does not offer you the asset – you end the game with 3 euros. This game is summarized in the following figure:



At the beginning of the game, traders do not know their position in the market sequence. Positions are randomly determined with one chance out of three for each trader to be first, second or third.

2. Proposed prices
The price P1 that is proposed to the first trader is random. This price is a power of 10 and is determined as follows:

P1	Probability that this P1 is realized
1	15 %
10	20 %
100	30 %
1.000	20 %
10.000	15 %

traders decisions are made simultaneously and privately. For example, if the first price $P_1 = 1$ has been drawn, the prices that are simultaneously proposed to the three traders are: P_1= 1 for the first trader, P_2= 10 for the second trader, andP_3

= 100 for the third trader. Identically, if the first price P_1 = 10.000 has been drawn, the prices that are simultaneously proposed to the three traders are: P_1= 10.000 for the first trader, P_2= 100. 000 for the second trader, and P_3= 1.000.000 for the third trader. The prices that are being proposed to you can give you the following information regarding your position in the market sequence:

- If you are proposed to buy at a price of 1, you are sure to be first;
- If you are proposed to buy at a price of 10, you have a 6/10 chance of being first, and a 4/10 chance of being second in the sequence;
- If you are proposed to buy at a price of 100, you have a 5/10 chance of being first, a 3/10 chance of being second and a 2/10 chance of being last in the sequence;
- If you are proposed to buy at a price of 1.000, you have a 3/10 chance of being first, a 4/10 chance of being second and a 3/10 chance of being last;
- If you are proposed to buy at a price of 10.000, you have a 2/10 chance of being first, a 3/10 chance of being second and a 5/10 chance of being last in the sequence;
- If you are proposed to buy at a price of 100.000, you have a 4/10 chance of being second and a 6/10 chance of being last in the sequence;
- If you are proposed to buy at a price of 1.000.000, you are sure to be last in the sequence.

Please note that all your decisions are completely anonymous as we do not work with names but with numbers.

Are there any questions?

A.2 SET test questions

1) What is probability of being third in line when you have not been offered a price yet?

- Options: (with correct option in bold): 100%, 75%, 10%, **33.33%**

2) What is the probability of the first price (P_1) being 1.000?

- Options: (with correct option in bold): 0%, 15%, **20%**, 30%

3) What is the probability of the first price (P_1) being 100.000?

- Options: (with correct option in bold): **0%**, 15%, 20%, 30%

4) If you are offered a price of 1.000, what is the probability of not being last in line?

- Options: (with correct option in bold): **70%**, 40%, 10%, 30%

5) What is your profit when you are first in line and buy but the person next in line does not buy?

- Options: (with correct option in bold): **0€**, 3€, 10€

6) What is your profit if you are second in line and the person before and after you in line buy, but you do not buy?

- Options: (with correct option in bold): 0€, **3€**, 10€

7) What is your profit when you are first in line, you decide to buy and the trader next in line also buys?

- Options: (with correct option in bold): 0€, 3€, **10€**

A.3 Further SET instructions (shown on screen)

In this experiment we will ask you for every possible price (1, 10, 100, 1.000, 10.000, 100.000, 1.000.000) whether you would want to buy or not the asset if this price were offered to you in the game that was just explained. You thus basically play the game not once, but for every possible price. After you have made a decision (buy or not buy) for every possible price, there are three further steps performed by the computer to determine your final profit from this game:

- The computer will randomly pick one of the 7 possible prices, each one is equally likely. Your choice (buy or not buy) at this price will be used to determine your profit.
- Then the computer will give you a place in line, either first, second or third by using the probabilities of being first, second or third in line at the chosen price from step 1. You can find these probabilities for all possible prices in the instructions.
- The computer will couple you to two other traders to complete the trading sequence. As was explained, your profit also depends on the actions of these two other traders.

Please note: If you decide to buy for a price, we automatically assume you would also want to buy for all lower prices as these are in fact less risky. Because of this you will see a screen after you have decided to buy on which we tell you that we assume you automatically also want to buy for all lower prices. If this is indeed the case, simply click on "continue". However if you want to change your previous decision you can always go back to that decision by clicking on "change".

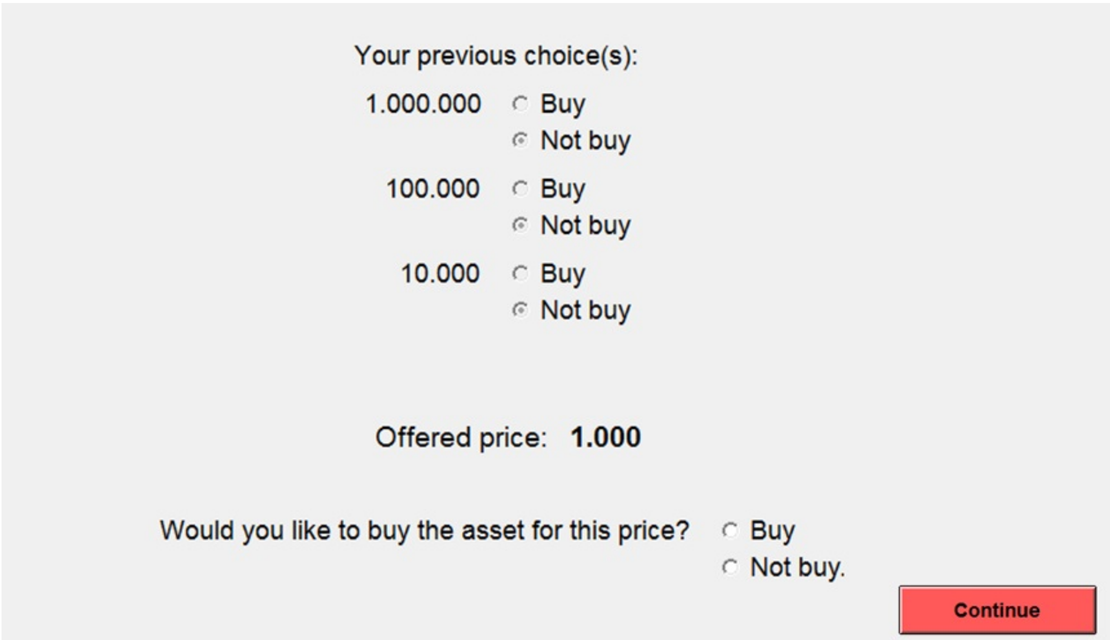


Figure A.1: Screenshot of the SET decision environment.

A.4 Belief elicitation task instructions (shown on screen)

You have just played a game where you had to decide for 7 different prices whether or not you wanted to buy the asset. Could you indicate below for which price you think the other participants STARTED to buy? Please do so by assigning the number of participants who you think STARTED buying at a particular price and then pressing the "assign" button. For example: if you think 12 participants started buying at a price of 1000 (which of course means they also bought for all lower prices) you fill in 12 next the the price of 1000 and press assign. If you think some people never bought the asset, you should assign them to the "never" category. Make sure you assign ALL other participants to a category (you can check this on the right side of your screen). You can always change your choices by typing a different number and pressing on the "assign" button once more. Once you have assigned all the other participants, please click the "continue" button.You will earn 3 euros if you predict the prices at which the others STARTED buying correctly for more than 90% of the participants, 2 euros if you predict them correctly for between 75%-90% of the participants and 1 euro if you predict them correctly for between 50%-75% of the participants. REMINDER: You yourself started buying at a price of : <insert price at which a subject started buying in the SET>

Figure A.2: Screenshot of the belief elicitation task after the SET.

B Instructions: SSW Asset Market

1. General instructions

This is an experiment in the economics of market decision making. If you follow the instructions and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The experiment will consist of a sequence of trading periods in which you will have the opportunity to buy and sell shares. Money in this experiment is expressed in francs (300 francs = 1 euro).

2. How to use the computerized market

The goods that can be bought and sold in the market are called Shares. On the top panel of your computer screen you can see the Money you have available to buy shares and the number of shares you currently have.

If you would like to offer to **sell a share**, use the text area entitled "Enter Sell price". In that text area you can enter the price at which you are offering to sell a share, and then select "Submit Sell Price". Please do so now. You will notice that around 30 numbers, one submitted by each participant, now appear in the column entitled "Sell Price". The lowest sell price will always be on the top of that list and will be highlighted. If you press "BUY", you will buy one share for the lowest current sell price. You can also highlight one of the other prices if you wish to buy at a price other than the lowest. Please try to purchase a share now by highlighting a price and selecting "BUY". Since each of you had put a share for sale and attempted to buy a share, if all were successful, you all have the same number of shares you started out with. This is because you bought one share and you sold one share.

If you would like to offer to **buy a share**, use the text area entitled "Enter Buy price". In that text area you can enter the price at which you are offering to buy a share, and then select "Submit Buy Price". Please do so now. You will notice that again around 30 numbers, one submitted by each participant, now appear in the column entitled "Buy Price". The highest price will always be on the top of that list and will be highlighted. If you press "SELL", you will sell one share for the highest current buy price. You can also highlight one of the other prices if you wish to sell at a price other than the highest. Please sell a share now by highlighting a price and selecting "SELL". Since each of you had put a share for purchase and attempted to sell a share, if all were successful, you all have the same number of shares you started out with. This is because you sold one share and you bought one share.

There are 2 ways to sell a share: Choose a buy price and press "SELL" or submit a Sell offer yourself.
There are 2 ways to buy a share: Choose a sell price and press "BUY" or submit a buy offer yourself.

When you buy a share, your Money decreases by the price of the purchase, but your number of shares increase by one. When you sell a share, your Money increases by the price of the sale, but your number of shares decrease by one. Purchase prices are displayed in the middle section of your screen and are ranked by price. You will now have a practice period. Your actions in the practice period do not count toward your earnings and do not influence your position later in the experiment. The goal of the practice period is only to master the use of the interface. Please be sure that you have successfully submitted buy prices and sell prices. Also be sure that you have accepted both buy and sell prices. You are free to ask questions, by raising your hand during the practice period.

3. Specific instructions for this experiment

The experiment will consist of 15 trading periods, you will receive 2500 francs in money as well as two shares at the beginning of the experiment. In each period. Each period lasts for 180 seconds, in which you may buy and sell shares. Shares are assets with a life of 15 periods, and your inventory of shares carries over from one trading period to the next. You may receive dividends for each share in your inventory at the end of each of the 15 trading periods.

At the end of each trading period, including period 15 the computer randomly draws a dividend for the period. Each period, each share you hold at the end of the period:

- earns you a dividend of 0 francs with a probability of 25%
- earns you a dividend of 8 francs with a probability of 25%
- earns you a dividend of 28 francs with a probability of 25%
- earns you a dividend of 60 francs with a probability of 25%

Each of the four numbers is equally likely. The average expected dividend in each period is 24. The dividend is added to your cash balance automatically. After the last dividend is paid at the end of period 15, there will be no further earnings possible from shares.

4. Average Holding Value Table
You can use the following table to help you make decisions:

Ending Period	Current Period	Number of Holding Periods	×	Average Dividend per Period	=	Average Value per Share in Inventory
15	1	15	×	24	=	360
15	2	14	×	24	=	336
15	3	13	×	24	=	312
15	4	12	×	24	=	288
15	5	11	×	24	=	264
15	6	10	×	24	=	240
15	7	9	×	24	=	216
15	8	8	×	24	=	192
15	9	7	×	24	=	168
15	10	6	×	24	=	144
15	11	5	×	24	=	120
15	12	4	×	24	=	96
15	13	3	×	24	=	72
15	14	2	×	24	=	48
15	15	1	×	24	=	24

There are 5 columns in the table. The first column, labeled Ending Period, indicates the last trading period of the experiment. The second column, labeled Current Period, indicates the period during which the average holding value is being calculated. The third column gives the number of holding periods from the period in the second column until the end of the experiment. The fourth column, labeled Average Dividend per Period, gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled Average Holding Value Per Unit of Inventory, gives the average value for each unit held in your inventory from now until the end of the experiment. That is, for each unit you hold in your inventory for the remainder of the experiment, you will earn on average the amount listed in column 5.

Suppose for example that there are 7 periods remaining. Since the dividend on a Share has a 25% chance of being 0, a 25% chance of being 8, a 25% chance of being 28 and a 25% chance of being 60 in any period, the dividend is on average 24 per period for each Share. If you hold a Share for 7 periods, the total dividend for the Share over the 7 periods is on average 7*24 = 168. Therefore, the total value of holding a Share over the 7 periods is on average 168.

5. Making predictions
In addition to the money you earn from dividends and trading, you can make money by accurately forecasting the average trading price for the next period. You will indicate your forecasts before each period begins on the computer screen. The money you receive from your forecasts will be calculated in the following manner :

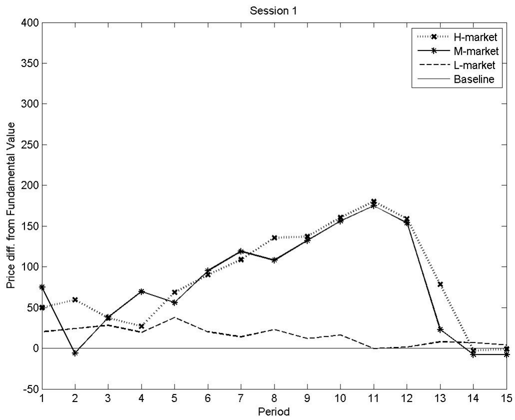
Accuracy	Your Earnings
Within 10% of actual average price	50 francs
Within 25% of actual average price	20 francs
Within 50% of actual average price	10 francs

6. Your earnings

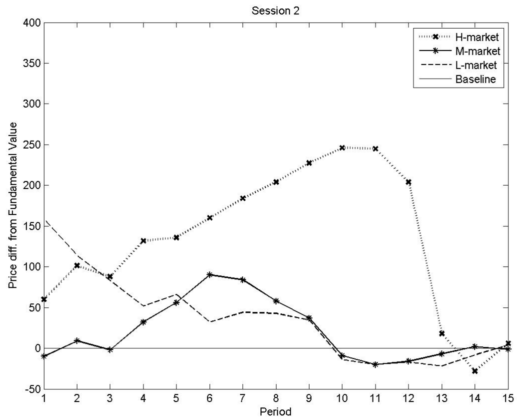
Your earnings for this part of the experiment will equal the amount of cash that you have at the end of period 15, after the last dividend has been paid, plus the money you made with your price predictions. The amount of cash you will have is equal to:

Money you have at the beginning of the experiment + Dividends you receive + Money received from sales of shares - Money spent on purchases of shares + Earnings from all price predictions

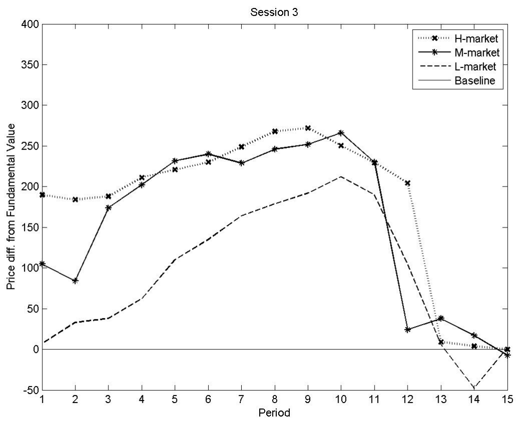
C Additional figures



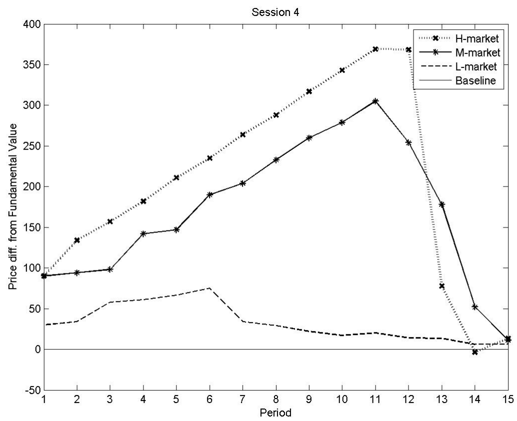
(a) Price paths for session 1.



(b) Price paths for session 2.



(c) Price paths for session 3.



(d) Price paths for session 4.

Figure A.3: Price paths

D Additional tables

Table A.1: Subject pool descriptives.

Variable	Mean	Median	Min	Max	Std. dev.
Age	20.85	20	18	28	2.24
Female	46.61%	-	-	-	-
Foreign	11.97%	-	-	-	-
Economics	93.16%	-	-	-	-
Risk attitude (Holt & Laury)	5.73	6	3	10	1.55
General Risk	6.49	7	1	11	1.98
CRT-score	1.66	2	0	3	1.06

***Notes*:** N=117. 'Economics' stands for the percentage of economics students in our population. 'Risk attitude (Holt & Laury)' represents the number of the row where a subject first switched from lottery A to lottery B (see appendix section E). 'General risk' indicates the answer on a Likert scale from 1 to 11 given to the question "In general, are you willing to take risks?" from Bonin et al. (2007) (the higher the score the higher the willingness to take risks). 'CRT score' indicates the number of questions correctly answered in the CRT test from Frederick (2005).

Table A.2: Bubble measures for all markets. S1-L stands for session 1 market L.

MARKET	SET-Score	Turnover	Amplitude	Norm. dev.	Tot. disp.	Avg. bias	APD	PD	RAD	RD	RPAD
S1-L	2.50	3.9	0.107	67.2	235.5	15.6	11.8	11.7	0.082	0.081	0.088
S1-M	4.00	6.1	1.442	471.8	1577.5	102.2	98.6	95.8	0.548	0.532	0.702
S1-H	4.67	6.0	0.508	485.5	1295.5	85.8	64.8	64.4	0.450	0.447	0.577
S2-L	2.50	3.5	0.503	227.5	712.5	36.7	35.6	27.5	0.247	0.191	0.222
S2-M	3.00	2.8	0.306	85.2	433.5	20.2	21.7	15.1	0.151	0.105	0.151
S2-H	4.20	10.7	0.761	1503.3	2040.0	132.3	102.0	99.2	0.708	0.689	0.841
S3-L	2.00	3.4	0.611	209.9	1442.0	95.1	72.1	71.3	0.501	0.495	0.583
S3-M	3.70	7.4	0.760	1129.2	2346.0	155.4	117.3	116.6	0.815	0.809	0.848
S3-H	4.20	11.2	0.756	2153.1	2710.5	180.7	135.5	135.5	0.941	0.941	0.958
S4-L	2.50	6.4	0.192	194.6	486.0	32.4	24.3	24.3	0.169	0.169	0.172
S4-M	3.80	4.5	0.817	736.9	2537.0	169.1	126.9	126.9	0.881	0.881	1.169
S4-H	4.20	8.4	1.035	1700.0	3053.5	203.1	152.7	152.3	1.060	1.058	1.279
Avg.-L	2.38	4.3	0.272	221.0	761.7	48.2	38.1	36.2	0.295	0.251	0.281
Avg.-M	3.63	6.1	0.416	420.1	1282.0	84.7	64.1	63.5	0.445	0.441	0.481
Avg.-H	4.32	9.1	0.633	1252.6	2012.0	132.9	100.6	99.7	0.699	0.692	0.786

***Notes*:** N=117. The bubble measures defined are as: $Turnover = \sum_{t=1}^{15} \frac{\#\, of\, Trades_t}{TSU}$; $Amplitude = \frac{max_t\,(P_t - FV_t)}{FV_1} - \frac{min_t\,(P_t - FV_t)}{FV_1}$; $Normalized\, deviation = \sum_{t=1}^{15} \frac{(|P_t - FV_t|)(\#\, of\, Trades_t)}{TSU}$; $Total\, Dispersion = \sum_{t=1}^{15} \mid median\,(P_t) - FV_t \mid$; $Average\, Bias = \frac{1}{15} \sum_{t=1}^{15} (median\,(P_t) - FV_t)$; $APD = \frac{1}{TSU} \sum_{t=1}^{15} \mid P_t - FV_t \mid$; $PD = \frac{1}{TSU} \sum_{t=1}^{15} (P_t - FV_t)$; $RAD = \frac{1}{15} \sum_{t=1}^{15} \frac{|P_t - FV_t|}{mean\,(FV)}$; $RD = \frac{1}{T} \sum_{t=1}^{15} \frac{(P_t - FV_t)}{mean\,(FV)}$; $RPAD = \frac{1}{15} \sum_{t=1}^{15} \frac{|P_t - FV_t|}{FV_t}$. Total stock of units (TSU) is equal to the number of stock per subject times the number of subject in a market. Each separate market consisted of on average 10 participants.

Table A.3: Results of the Mann Whitney U test for differences in the SET scores and the Wilcoxon test for both differences in the RAD and RD values for selected markets.

MARKET	SET-score	RAD	RD
S1: L vs. M	0.001	0.002	0.006
S1: M vs. H	0.059	0.648	0.231
S1: H vs. L	0.000	0.001	0.002
S2: L vs. M	0.063	0.117	0.753
S2: M vs. H	0.000	0.001	0.001
S2: H vs. L	0.000	0.009	0.011
S3: L vs. M	0.000	0.006	0.005
S3: M vs. H	0.105	0.221	0.173
S3: H vs. L	0.000	0.002	0.001
S4: L vs. M	0.000	0.001	0.001
S4: M vs. H	0.051	0.030	0.035
S4: H vs. L	0.000	0.001	0.001
Avg: L vs. M	0.000	0.001	0.001
Avg: M vs. H	0.000	0.002	0.002
Avg: H vs. L	0.000	0.001	0.001

***Notes*:** N=117. S1-L stands for session 1 market L. Each separate market consisted of, on average, 10 participants.

E Risk attitudes and CRT

Risk attitude elicitation instructions (based on Holt and Laury, 2002)

On the left side of the screen you see 10 lines with two lotteries per line: "Lottery A" and "Lottery B". Both lotteries have two potential outcomes. For every one of the 10 lines, either choose lottery A or lottery B, depending on which lottery you would rather participate in. Once you have filled in you choice for all 10 lines, please click on the "Continue" button. Out of the lines will be chosen at random and you will participate automatically in the lottery you chose at that line (either A or B). You will receive the amount of money that will follow from the outcome of your chosen lottery.

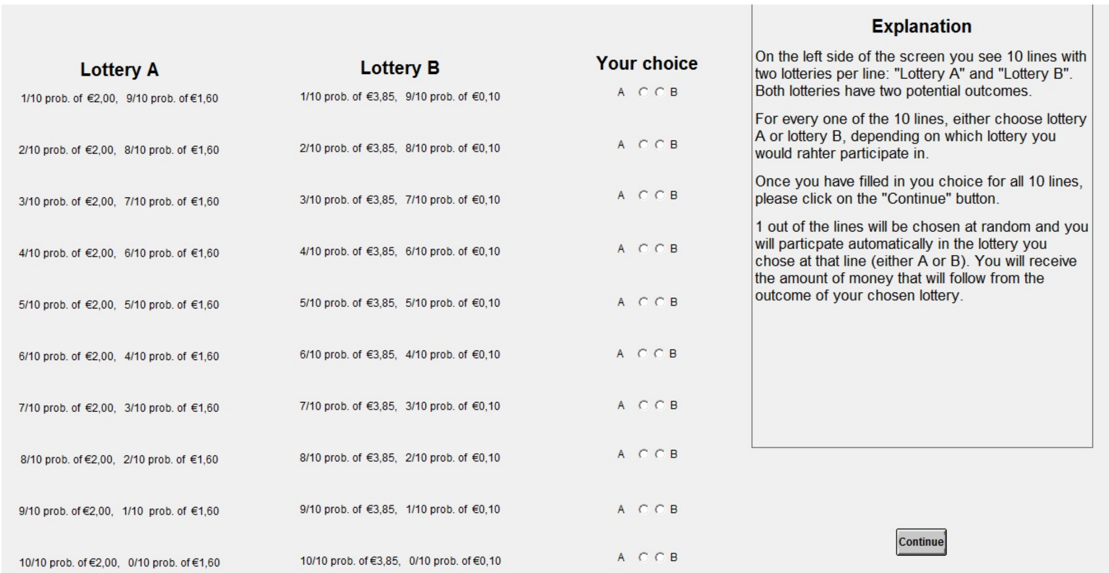


Figure A.4: Screenshot of the Holt & Laury task.

CRT instructions (Frederick, 2005)

Please answer the following three questions. You will receive 1.5 euro per correct answer and you have 3 minutes to answer the questions.

- A bat and a ball cost \$1.10 in total. The bat costs \$1 more than the ball. How much (in whole cents) does the ball cost?
- If it takes five machines five minutes to make five bottles, how long (in minutes) would it take 100 machines to make 100 bottles?
- In a lake, there is an oil stain. Every day, the stain doubles in size. If it takes 48 days for the stain to cover the entire lake, how long (in days) would it take for the stain to cover half the lake?

F Beliefs and calculation of optimal prices

1. Calculation of optimal buying prices

We assume an expected utility framework with risk neutrality, which is a conservative assumption in our setting (see further below), and compute the individually optimal buying price as follows. For each subject we first determine for each possible buying price i ($with\, i = 1,\, denoting\, P = 1,\, i = 2,\, denoting\, P = 10, ...i = 7\, denoting\, P = 1,000,000$) the probability of someone buying both before and after a subject n, denoted by $Pr(b_{i,n})$ and $Pr(a_{i,n})$ respectively, given that subject's beliefs about the buying decisions of his $N-1$ fellow participants in a session (taking into account the probabilities of being 1st, 2nd and 3rd at that particular price). For instance, to determine the probability of someone buying after subject n at a price of $P = 100$, we first divide the amount of traders believed by subject n to buy at prices higher than $P = 100$ by N and subsequently multiply this number with the probability *not* to be last at this price (which equals 0.8 at $P = 100$). We then calculate the expected earnings from buying at price i for subject n, $E(E_{i,n})$, as:
$E(E_{i,n}) = 10\, Pr(b_{i,n}) Pr(a_{i,n}) + 3(1 - Pr(b_{i,n}))$. The earnings at each possible buying price i are equal to $E(E_{i,n})$ when subject n buys and equal to 3 when the subject does not buy. Finally, because buying at some price i automatically implies buying at all prices$< i$, the total expected earnings for subject n, denoted $E(TE_{i,n})$, when starting to buy at some price i are equal to: $E(TE_{i,n}) = \sum_1^i \frac{1}{7} E(E_{i,n}) + \sum_{i+1}^7 \frac{3}{7}$. The price i at which $E(TE_{i,n})$ reaches its maximum defines the optimal buying price.

2. Optimal vs. actual buying price

Table A.4 shows the percentage of subjects that bought at a particular number of steps too early/late compared to their optimal buying price (as calculated above) as well as the average ratio of earnings to optimal earnings and the average buy premium (defined as the actual earnings minus 3 euros) for those subjects. 84.6 percent of subjects buy at most one step away from their optimal buying price, with the ratio of actual earnings to optimal earnings close to 1 for all subjects, showing a decreasing trend with the number of steps a subjects is deviating from the optimal buy price. The average buy premium shows the same trend, which is even more pronounced. Note that all calculations regarding the optimal buying price were made under the assumption of risk neutrality and are thus relatively conservative compared to methods using probability weighting such as cumulative prospect theory Tversky and Kahneman (1992). As probability weighting would increase especially low probabilities $Pr(b_{i,n})$ and $Pr(a_{i,n})$ at which $E(E_{i,n})$ is not high enough to satisfy a trader's IRC, probability weighting would increase $E(E_{i,n})$ to the point where the IRC is satisfied, increasing the percentage of optimal decisions.

Table A.4: Optimal vs. actual buy price.

# of steps from optimal buying price	-1	0	1	2	3	4
subjects (%)	5.12	23.93	55.56	9.40	5.13	0.85
Avg. earnings/optimal earnings	0.93	1	0.96	0.91	0.85	0.86
Avg. buy premium (€)	1.05	1.71	1.68	0.82	0.04	-0.04

Notes: N=117. The number of steps from the optimum in the above table is defined as the number of steps that a subject's buy price deviates from the optimal buying price, i.e. the actual SET-score minus the optimal SET score. All earnings (both at the optimal and at the actual buy price) are calculated as explained in this appendix. The buy premium is defined as the actual earnings minus 3 euros. Hence, a negative premium indicates that, on average, subjects should not have bought at their indicated price, given their beliefs.