Journal of Behavioral and Experimental Economics 99 (2022) 101882

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/jbee

Does risk sorting explain overpricing in experimental asset markets?

Hubert J. Kiss[a,b], László Á. Kóczy[a,c], Ágnes Pintér[e], Balázs R. Sziklai[*,a,d,*]

[a] Institute of Economics, Centre for Economic and Regional Studies (KRTK), Hungary
[b] Department of Economics, Corvinus University of Budapest, Hungary
[c] Department of Finance, Faculty of Economic and Social Sciences, Budapest University of Technology and Economics, Hungary
[d] Department of Operations Research and Actuarial Sciences, Corvinus University of Budapest, Hungary
[e] Department of Economic Analysis, Universidad Autónoma de Madrid, Spain

ARTICLE INFO

Keywords:
Asset market
Overpricing
Experiment
Risk sorting
MiFID

ABSTRACT

Sorting according to the gender or cognitive abilities of the traders has been investigated as a potential source of overpricing in asset markets. Here we study if sorting according to risk attitudes matters, motivated by the fact that filtering out risk-averse investors is practiced widely in Europe and is in line with the Markets in Financial Instruments Directive (MiFID) of the EU.

Despite the central role of risk attitude in the literature, our study is the first that sorts participants into markets by risk tolerance and tests its effect on overpricing. We show that risk sorting can explain overpricing only partially: Markets with the most risk-tolerant traders exhibit larger overpricing than markets with the most risk-averse traders. In our study, risk aversion does not correlate with gender or cognitive abilities, bringing in an additional factor to understand overpricing.

1. Introduction

In the past decades, experimental economics has proven to be a valuable tool in understanding why and how asset price bubbles form. While the precise definition is still debated (Janssen, Füllbrunn, & Weitzel, 2018), the experimental asset market literature has studied — among other questions — how traits of the traders and expectations and features of the market mechanism have affected the emergence of overpricing and price bubbles (Palan, 2013; Scherbina & Schlusche, 2014; Powell & Shestakova, 2016). We focus on *overpricing*, which we define as trading that takes place at (significantly) higher prices than the asset's fundamental value. In this sense, bubbles are a form of overpricing that result in a crash.

Several recent experimental studies indicate that the sorting of participants may affect the formation of overpricing. The gender composition may influence the tendency of markets to exhibit irrational exuberance (Eckel & Füllbrunn, 2015; Cueva & Rustichini, 2015). Bosch-Rosa, Meissner, & Bosch-Domènech (2018) report that in markets composed of subjects with better cognitive abilities, no bubbles arise. Janssen et al. (2018) show that when traders are sorted by their speculative tendencies, markets with more speculative traders lead to greater overpricing. Kocher, Lucks, & Schindler (2019) sort participants according to self-control and find that reduced self-control is conducive to overpricing.

We propose a new sorting criterion that may explain the formation of overpricing and is both i) theoretically intuitive and ii) observable in real life. The basis of our sorting is *risk tolerance*, which, according to our hypothesis, is an important factor in the emergence of overpricing. The asset that is traded in the experimental markets is inherently risky, as it yields a stochastic dividend. By definition, more risk-tolerant traders value such an asset higher, which may translate into a higher reservation price or willingness to pay. In a market populated with more risk-tolerant traders, the market clearing price may therefore be higher. Hence, sorting based on risk attitude may be a source of overpricing.

Despite the extensive literature on sorting, one may ask whether these results have any relevance to actual asset markets. Do we really see sorting? Well, the answer is mixed. Green, Jegadeesh, & Tang (2009) record a considerable gender imbalance in asset markets, yet all-male versus all-female sorting (Eckel & Füllbrunn, 2015) is not realistic, not to mention that the result vanishes if the gender information is hidden from participants (Eckel & Füllbrunn, 2017). Sorting according to cognitive skills or speculative tendencies is also hard to imagine. Sorting by risk attitude, however, occurs naturally, for two reasons. On the one hand, banks draw up the risk profile of their customers and try to

* Corresponding author at: Institute of Economics, Centre for Economic and Regional Studies (KRTK), Hungary.
E-mail addresses: kiss.hubert@krtk.hu (H.J. Kiss), koczy.laszlo@krtk.hu (L.Á. Kóczy), pinteragnes@gmail.com (Á. Pintér), sziklai.balazs@krtk.hu (B.R. Sziklai).

https://doi.org/10.1016/j.socec.2022.101882
Received 17 June 2020; Received in revised form 9 March 2022; Accepted 18 April 2022
Available online 20 April 2022

dissuade from investments beyond their risk tolerance. They do this both to protect the client and to comply with legal requirements, such as the Markets in Financial Instruments Directive (MiFID) of the EU (European Parliament, 2014, Article 25/2) that specifically asks the bank to obtain data on the investor's risk tolerance, the Australian Financial Services Reform Act, or the EU rules for insurance and reinsurance product distribution (European Parliament, 2016, Article 30/1).

Such regulations filter out risk-averse investors, leaving only sufficiently risk-tolerant retail investors active in risky asset markets. This is a clear instance of risk sorting for retail investors. On the other hand, there is ample evidence that risk attitude affects career choice. Less risk-averse individuals select more risky careers; Sapienza, Zingales, & Maestripieri (2009) find this fact for MBA students, Fossen (2012) finds the same for entrepreneurship, while Lazear & Shaw (2007) observe that particular compensation structures may lead to self selection in certain firms.

Motivated by these considerations, we formulate the hypothesis that *the risk tolerance of traders may affect the formation of market prices*. More precisely, we expect to see higher prices in markets populated by more risk-tolerant traders and this may explain, to some extent, the overpricing observed in asset markets applying the Smith, Suchanek, & Williams (1988) paradigm. To test our hypothesis, we invited 96 participants to an experiment. First, we elicited their risk and uncertainty attitudes and cognitive abilities. Further, without telling them the reason, we sorted the subjects into 12 experimental asset markets according to their risk tolerance. In the main part of the study, they traded on these markets in two rounds, with 15 periods each. To see whether market prices are higher on markets with more risk-tolerant traders, we studied bubble measures (the positive deviation from the asset's fundamental value) and expected more overpricing here. With panel regressions, we investigated how individual and market characteristics explain buy/sell orders exceeding the fundamental value.

In the rest of the paper, we review the existing literature, present the experimental design, and formally state our hypothesis (Section 3). Sections 4 and 5 contain the results and a discussion.

2. Related literature

Our literature review discusses the existing results on sorting along different dimensions as well as the findings on the role of risk attitudes in experimental asset markets.

Experience Smith et al. (1988) found that the more *experienced* traders there are in the experimental market, the fewer or smaller bubbles form. Dufwenberg, Lindqvist, & Moore (2005); van Boening, Williams, & LaMaster (1993), and others confirmed this, but more recently, Noussair & Powell (2010) and Oechssler, Schmidt, & Schnedler (2011) found no mitigating effect.

Gender Eckel & Füllbrunn (2015), using the market design of Smith et al. (1988), provided convincing support that apparently all-male markets lead to larger bubbles than apparently all-female markets. Moreover, looking at past studies, it is known that the share of male traders is correlated with mispricing. Cueva & Rustichini (2015) found no significant difference; interestingly, mixed markets exhibited less deviation from the fundamental value. Wang, Houser, Xu et al. (2017) reported a significant difference in the US but not in China, suggesting that gender-related behavioural differences in financial markets may be sensitive to culture.

Cognitive skills Bosch-Rosa et al. (2018) sorted participants by cognitive sophistication on the basis of four simple games and invited the top and bottom 30% to participate in experimental asset markets. Only the latter exhibited the well-known bubble and crash patterns – a result confirmed by Cueva & Rustichini (2015) and Breaban & Noussair (2015). Bosch-Rosa et al. (2018) also measured risk aversion and found no correlation with cognitive skills but noted that the average session risk aversion is significantly and negatively correlated with some bubble measures, which hints at the possibility that higher average risk aversion may lead to fewer/smaller bubbles. Hanaki, Akiyama, Funaki, Ishikawa et al. (2017) stated that heterogeneity in cognitive abilities leads to significantly larger mispricing than homogeneity, regardless of the skill levels. Charness & Neugebauer (2019) reported that cognitive skills are a significant determinant of individual performance (i.e., payoff), but gender or risk aversion are not. Corgnet, Hernán-González, Kujal, & Porter (2015) analysed the effect of earned versus home money and found that subjects with low cognitive skills were net purchasers of shares when the price was above fundamental value.

Speculative tendencies, self-control, overconfidence Janssen et al. (2018), Kocher et al. (2019), and Michailova & Schmidt (2016) looked at sorting according to speculative tendencies, (reduced) self-control, and overconfidence, respectively, and found that these contribute to overpricing in experimental asset markets.

Risk attitude Early papers in the experimental asset market literature have already pointed out the role of risk attitudes. Smith et al. (1988) and Porter & Smith (2008) observed a common characteristic of first-period trading: Buyers tend to be those with low share endowments, while sellers are those with relatively high share endowments. They speculated that risk-averse traders might use the early part of trading to acquire more balanced portfolios. Palan (2013), building on the findings of Porter & Smith (1995) and Miller (2002), hypothesised that risk aversion causes prices to start out low, and as subjects get acquainted with the trading mechanism, they become less risk averse. This, in turn, leads to increases in price and potential emergence of bubbles. He also offered another possible explanation. If risk-averse subjects sell their assets early and, subsequently, only participants with a higher risk appetite trade, prices may appreciate, leading to a bubble.

Fellner & Maciejovsky (2007) analysed data of four published papers (El-Sehity, Haumer, Helmenstein, Kirchler, & Maciejovsky, 2002; Kirchler & Maciejovsky, 2002; Kirchler, Maciejovsky, & Weber, 2005; Maciejovsky, Kirchler, & Schwarzenberger, 2007) to see if risk attitudes measured through binary lottery choices are systematically associated with market behaviour. They found that the more risk averse a participant is, the less active they are in the market. They also reported marked gender differences (women being more risk averse). Huber, Palan, & Zeisberger (2019) further uncovered the effect of risk perception. Subjects associate riskiness with the probability of experiencing a loss. Assets with higher average perceived riskiness are traded at significantly lower prices. Since there is only one type of asset in the experiment, the different price curves between markets are due to risk attitudes; that is, different individuals perceive the riskiness of the same asset differently.

Breaban & Noussair (2015) found that the average risk aversion of participants correlates negatively with the price level, hence leading to less mispricing. Risk aversion also affects trading behaviour, as more risk-averse subjects are more likely to sell assets and trade more on the fundamental value. However, Cueva & Rustichini (2015) found that risk aversion is not a good predictor of bubble measures. In all these studies, there is no risk sorting; therefore, no conclusion can be drawn on the effect of such (self-)selection.

The only study we are aware of that investigates the role of risk sorting in the formation of bubbles is a chapter in Dirk-Jan Janssen's PhD thesis (Janssen, 2017) using the bomb risk elicitation task (Crosetto & Filippin, 2013) to form call markets according to risk tolerance. There are low/moderate and high risk-averse markets. They report no convincing relationship between individual and market average risk aversion and aggregate market outcomes. There are important differences between the previous and our design: (i) traders in their market start with the same endowment and (ii) endowments are reinstated after each period. It has yet to be seen if these differences explain the discrepancies between their and our results.

Though not an asset market study, Füllbrunn, Janssen, & Weitzel (2019) investigate how risk sorting affects overbidding (that is tightly related to overpricing) in first price sealed bid auctions and report a significant relationship.

Table 1
Market averages of the elicited individual characteristics. Risk and uncertainty attitudes: how much money the participants bet, strategic uncertainty: how many participants in the market choose the payoff dominant option, cognitive ability: the number of correctly answered questions (out of three).

Market	Risk attitude		Uncertainty attitude		Strategic uncertainty	Cognitive abilities		Female
	Average	SD	Average	SD	(chose payoff dominant)	Average	SD	
1	1433.25	103.83	873.62	629.37	75.0%	1.87	1.64	50.0%
2	1006.12	17.73	580.37	397.82	50.0%	0.87	0.83	25.0%
3	799.37	21.78	710.00	230.77	50.0%	1.12	1.24	75.0%
4	744.37	2.50	652.12	139.69	37.5%	2.12	1.12	62.5%
5	700.00	0.00	605.62	179.59	62.5%	1.62	1.685	75.0%
6	609.87	62.38	486.12	246.80	87.5%	1.00	1.31	25.0%
7	500.00	0.00	554.87	105.92	50.0%	1.62	1.06	50.0%
8	467.50	36.57	521.37	243.96	37.5%	2.37	1.06	0.0%
9	387.50	23.14	381.25	125.18	37.5%	1.12	0.83	87.5%
10	268.75	37.20	318.75	217.02	62.5%	2.50	0.92	50.0%
11	182.75	29.68	151.50	160.10	37.5%	1.62	1.41	37.5%
12	38.75	43.23	172.87	255.26	37.5%	2.12	1.46	50.0%

3. Experimental design

We invited 96 students with a wide range of majors (less than 10% with economics or business studies) to the Corvinus University of Budapest (Hungary) to a single session. In the first part of the experiment, we elicited the participants' risk/uncertainty attitude and cognitive abilities in an incentivised way. In the second part of the experiment, they were sorted in groups according to their risk tolerance and participated in experimental asset markets, where we implemented the call market in the Smith et al. (1988) paradigm.

Mainly two trading institutions are used in the asset market literature, namely, (continuous) double auction markets and call markets. Considering the long elicitation phase, we implemented call markets in the market phase. Two recent surveys, Palan (2013, Observation 27) and Powell & Shestakova (2016, Section 2.2), found no qualitative difference between the two institutions regarding outcomes. Unlike some other studies that have analysed call markets (e.g., Bosch-Rosa et al. 2018, Haruvy, Lahav, & Noussair 2007, Carlé, Lahav, Neugebauer, & Noussair 2019), we do not elicit price forecast. Hanaki, Akiyama, & Ishikawa (2018b) found that if price forecasts are elicited and subjects are paid based on both forecasting and trading, mispricing is enhanced.

The experiment was programmed and conducted with the experimental software z-Tree (Fischbacher, 2007), and for the asset market, we used a modified version of GIMS (Palan, 2015). In the experimental asset market, we implemented 12 independent call markets, each with eight traders trading 16 assets. The experiment lasted for about two hours. The outline of the experiment is as follows:

- **Part I**
  - Subjects randomly seated
  - Instructions for Part I are handed out and read.
  - Tests for risk/uncertainty elicitation and measuring cognitive abilities:
    * Gneezy-Potters task with known probabilities,
    * Stag Hunt,
    * Cognitive Reflection Test,
    * Gneezy-Potters task with unknown probabilities
  - Subjects informed about Part I earnings.
- **Part II**
  - Subjects reseated in groups of 8 according to their risk attitudes without disclosing this reason,
  - Instructions for Part II are handed out and read.
  - Brief trial of the call market mechanism.
  - Round I of the experimental asset market.
  - Round II of the experimental asset market.
- **Payment**

We now explain each step in more detail.

3.1. Eliciting individual characteristics

In the first part of the experiment, upon arrival, the participants were seated randomly in front of computers in one of the four rooms used in the experiment. The four glass-walled rooms are located on the same floor of one of the university buildings, and both parts of the experiment were carried out in the same session.

Once all the subjects were ready, the instructions for the first part of the experiment were read aloud and questions were answered privately (see Appendix A). Subjects were informed that the experiment would consist of two parts. Moreover, they learnt from the experimenter that one task from the first part would be randomly chosen and paid at the end of the experiment. The main objective of the first part of the experiment was to evaluate several individual characteristics of the subjects. In particular, we were interested in the (i) risk attitude, (ii) decisions in situations with strategic uncertainty, (iii) cognitive abilities, and (iv) choices under uncertainty.

Subjects started with completing a version of the investment game introduced by Gneezy & Potters (1997). More concretely, we used the same task to elicit risk attitudes as Sutter, Kocher, Glätzle-Rützler, & Trautmann (2013). There was a virtual bag containing 10 black and 10 red balls of which one ball would be randomly drawn. Participants were endowed with 1489 Tokens and chose one of the colours and the amount to bet on the chosen colour. We used 1489 Tokens for endowment because it is not a round number in the sense that it does not end in zero (s), so it is not so easy to make focal decisions (e.g., risking half of the endowment). If the subject correctly guessed the colour of the ball that was selected by the computer randomly with equal probability, they earned 2.5 times their bet, and otherwise, the money at risk was lost. The amount of the bet is a natural measure of risk attitude: The more a participant bets, the more risk tolerant they are.[1] Notice that risk-neutral and risk-seeking participants would bet the whole amount, so this test indeed measures the risk aversion spectrum of risk attitude. This was a prudent choice. As Table 1 shows, very few participants bet the full amount; hence, distinguishing between risk-neutral and risk-loving participants would not have yielded a new group. Henceforth, we will refer to the participants with the highest bets as the (most) risk-tolerant and the least betting participant as risk-averse, or sometimes as the least

[1] Crosetto & Filippin (2016) compare the four most widely used risk elicitation methods in experiments, among them the investment game. They conclude that there is no best method, but – similarly to Charness, Gneezy, & Imas (2013) – they point out that parsimony and simplicty as a desirable trait of a method. The investment game has these features.

Table 2
Endowment types.

Number of traders	Assets (units)	Cash (tokens)
3	1	4720
2	2	2920
3	3	1120

risk-tolerant traders.[2]

The next stage was the Stag Hunt game with a randomly chosen partner. Through this game, we attempted to capture the participants' attitudes towards strategic uncertainty that may affect behaviour in asset markets as well (see Akiyama, Hanaki, & Ishikawa 2017 and Hanaki, Akiyama, & Ishikawa 2018a). Next, the subjects were asked to solve the Cognitive Reflection Test (Frederick, 2005) to assess their cognitive abilities. At the end, in order to evaluate the attitudes of subjects regarding uncertainty, we followed Sutter et al. (2013) and used a modified version of the first task. In this case, the distribution of the two colours was unknown.

At the end of the first part of the experiment, the subjects were informed about their performance in all four tasks (in Tokens) and the randomly chosen task that would be paid at the end of the experiment. The reason for revealing their performance was to conceal that the two parts of the experiment were connected, since the subjects' behaviour could have been affected if they knew about the sorting. After the first part, we explained to the subjects that in the second part of the experiment, they would participate in another game that they would play with other participants. Finally, everyone was assigned a new room.

As mentioned before, to sort participants into experimental asset markets, we used the risk attitude measure and other elicited measures as controls in our regressions. Risk sorting took place across rooms, so we considered all 96 participants, ranked them according to their risk attitude and formed the experimental asset markets. Before starting the second part, we re-seated the participants. Traders in the same market were moved to the same room. For instance, in room A we had the 24 students with the highest risk tolerance. Within this room, the 8 participants that risked the most in the risk attitude task formed market 1, followed by the next 8 participants with the next highest risk attitude scores forming market 2, and the remaining 8 participants formed market 3. Markets were formed following the same logic in the other rooms as well. In Table 1, we show the characteristics of the markets based on the tasks in Phase 1 of the experiment.

Note that in Market 1, which is composed of the eight most risk-tolerant participants (out of the 96 traders), traders risked more than 95% of their endowment in the task that measured risk attitudes – seven out of eight participant wagered the maximum. The corresponding number in Market 12, populated by the eight most risk-averse traders, is about 2.5%. This shows that the sorting into markets based on risk attitude led to markets with substantially different average risk characteristics. However, also note that the differences between subsequent markets are not very sharp in some cases (e.g., Markets 4 and 5 or Markets 7 and 8). This suggests that even if there is a significant difference between the markets with the most risk-tolerant and risk-averse traders, there may be small or no differences between subsequent markets.

3.2. The call market

The second part of the experiment consisted of the implementation of 12 call markets, wherein participants could trade the units of a risky asset. We used the risk attitude data from the first part of the experiment to form groups of eight that exhibited similar risk attitudes. We operated four computer labs, each hosting three groups. The reorganisation process was anonymous. That is, subjects were not informed either about the identity or any characteristic of the other traders in the market. Instructions for the second part – containing the detailed description of the functioning of the call markets – were read aloud, and all questions were answered. Subjects were informed that they would trade with the same traders during the twice-repeated 15 trading periods, each lasting 90 seconds. It was also explained in the instructions that one of the two 15-period market rounds would be randomly chosen for payment at the end of the experiment. In order to ensure that subjects understood the task and got familiar with the design of the market page, they first played a practice period. At the beginning of the real market phase, traders were given a random initial endowment, that is, a combination of assets and cash. In line with the literature, we defined three endowment types for each of the 12 markets, as represented in Table 2

Subjects were informed about their own initial endowment and that the other participants might have different initial endowments, but all with the same expected value.

In each trading period, subjects could submit one buy order (i.e., a quantity and a maximum unit price *to buy*) and/or one sell order (i.e., quantity and a minimum unit price *to sell*) at most, with the only conditions being that (i) a trader's submitted selling price could not be lower than their submitted buying price, and (ii) all submitted orders must be feasible, given the actual endowment of the subject (e.g., no short-selling is allowed). The instructions clearly stated that submitting orders and trading was not compulsory (e.g., if prices were not attractive enough). Each trading period lasted 90 seconds and orders could be submitted before the time expired. At the beginning of each trading period, subjects were informed about the quantity of assets and cash at their disposal. Once a trading period was over, the market price of the asset was determined by the computer and the endowment of the subjects was updated with the realised transactions of the period.

Each asset held at the end of a trading period paid a stochastic dividend of either 0, 40, 140, or 300 Tokens with the same probability. This gave an expected dividend of 120 Tokens, which was stated clearly in the instructions and on the trading screens. Subjects were informed at the end of each period about the market price of the asset, the number of shares they sold and/or bought in the actual period, the dividend received in the actual period, and the new (updated) amount of assets and cash at their disposal for trading in the next period. The asset has a buy-back value of 0 Token at the end of period 15; hence, the fundamental value (FV) of the asset at the end of period t was simply $120(16-t)$ Tokens – the expected value of the asset. Once the first 15-period round was over, subjects were informed about their gains: the total cash held at the end of period 15 (in Tokens). Finally, the market game was repeated (without changing the composition of the markets), with the only difference being that the initial endowment of a subject could be different, as it was randomly drawn from the same distribution again.

After both market rounds were concluded, subjects were informed about their total payoff (in Tokens), which comprised the money won in the first part of the experiment (i.e., payment of one randomly chosen task), the gains of the randomly chosen market round (which turned out to be Round 1), and the show-up fee of 3000 Tokens. The final payoffs were displayed on the last screen both in Token and in Hungarian Forint (HUF), the exchange rate being 3 Tokens = 1 HUF. The average payoff was about 3750 HUF (the equivalent of about 12 EUR or 13.3 USD at that time).

3.3. Hypothesis

The experimental asset yields a stochastic dividend that is inherently risky. By definition, the more risk tolerant an individual is, the more she values such a risky investment in terms of utility. These individual effects may aggregate on the market level. If there is a market with more

[2] Our risk measure is based on a gambling task and one may wonder if it captures the risk attitudes that are relevant in asset markets. Future research should investigate if using different risk elicitation methods leads to the same findings or not.

Table 3
Pairwise correlations between individual characteristics.

	Risk tolerance	Uncertainty tolerance	Cognitive abilities	Strategic uncertainty
Risk tolerance	—			
Uncertainty tolerance	0.5165***	—		
Cognitive abilities	− 0.1104	− 0.1869*	—	
Strategic uncertainty	0.1585	0.1731*	0.0319	—
Female	0.0042	0.2125**	− 0.2022**	− 0.0822

risk-tolerant individuals than another market, we expect that the higher individual willingness to both pay and sell at a higher price translates into a higher market price relative to the fundamental value, *ceteris paribus*.

Hypothesis: *Risk attitude affects overpricing. We expect to see larger overpricing on markets populated with more risk-tolerant traders compared to markets composed of less risk-tolerant traders.*

Note that overpricing due to risk tolerance does not necessarily need to result in a crash. It simply means that during the initial trading periods, the price might climb higher in such markets, far exceeding the expected value of the asset and subsequently converge to the buy-back value more steeply.

3.4. Risk tolerance and bubble/mispricing measures

Measures that quantify the deviation from the fundamental value are generally known as bubble or mispricing measures. We believe that distinction between the two is warranted. Bubbles are related to the idea of overpricing, which implies prices *above* the fundamental value, while mispricing encompasses *any* deviation from the fundamental value. Hence, bubble measures, contrary to mispricing measures, gauge only positive deviations from the fundamental value. Note that mispricing measures take into account the negative deviations that always occur at the beginning of the trading. However, these deviations are mainly due to the fact that in these initial periods, the subjects are getting acquainted with the trading mechanism. This learning process may make the mispricing measures noisy. Since most of the studies (e.g., Bosch-Rosa et al., 2018; Cueva & Rustichini, 2015; Dufwenberg et al., 2005) report a host of mispricing/bubble measures, we do the same for the sake of completeness, but we pay more attention to bubble measures that capture the idea of overpricing better. Janssen, Füllbrunn, & Weitzel (2019) also took the same stance and focused on "specific measures that describe fundamentally unjustified positive price deviations".

We consider four mispricing measures. *Relative Deviation* ($\frac{1}{N}\sum_t (P_t - FV_t)/\overline{FV}$) averages the deviation of period price from period fundamental value relative to the mean fundamental value in the market. A large Relative Deviation indicates that prices tend to stay above fundamentals and hence signals overpricing. Similarly, Relative Deviation close to zero shows the lack of mispricing. *Relative Absolute Deviation* ($\frac{1}{N}\sum_t |P_t - FV_t|/\overline{FV}$) sums up the absolute deviation of period price from period fundamental value relative to the mean fundamental value and shows how close prices and fundamental values are to each other. The larger the value, the larger the mispricing.[3] *Geometric Deviation* ($\exp\left(\frac{1}{N}\sum_t \ln\left(\frac{P_t}{FV_t}\right)\right) - 1$) and *Geometric Absolute Deviation* ($\exp\left(\frac{1}{N}\sum_t \left|\ln\left(\frac{P_t}{FV_t}\right)\right|\right) - 1$) are similar to their relative counterparts, but instead of the arithmetic uses the geometric mean that makes the measure independent of the numeraire (Powell, 2016).

We consider the following bubble measures that, in our view, are a better expression of overpricing. *Positive Deviation* sums up the absolute per-period price deviations from the per-period fundamental value, if prices are above the fundamental value.[4] The larger the Positive Deviation, the larger the overpricing. *Boom Duration* counts the maximum number of consecutive periods above the fundamental value. A longer Boom Duration is a sign of larger overpricing. We define a new measure of our own that we call *Positive Amplitude*. It measures the maximum positive deviation from the fundamental value ($\max_t((P_t - FV_t, 0))$).[5]

Note that all measures consider the fundamental value that is the product of the remaining periods and the expected dividend per period. The use of the expected dividend makes it a risk-neutral measure. One may argue that traders with different degree of risk tolerance (generally not corresponding to risk neutrality) value the stochastic dividend in a different way, and as a consequence overpricing is conditional on this valuation. There is no natural way to compute overpricing adjusted with risk tolerance, so we use the risk-neutral fundamental value.

4. Results

4.1. Descriptive statistics

Before discussing our results, let us first look at the characteristics of our subject pool. In Table 3, we report the pairwise correlations between the individual characteristics of the participants. Unsurprisingly, risk attitude and choices under uncertainty are highly and positively correlated. Choice under uncertainty is weakly and negatively correlated with cognitive abilities and positively correlated with strategic uncertainty. Female participants tolerated significantly more uncertainty in task 4 but performed significantly worse than male subjects in the Cognitive Reflection Test. Crucially, risk tolerance did not correlate significantly with cognitive abilities nor with gender, so risk aversion could not be used to organise the results found in the previous literature. Note that Filippin & Crosetto (2016) and Niederle (2016) showed that the significance and the magnitude of gender differences in risk taking depend on the elicitation method. For instance, no gender differences are found when the bomb risk elicitation task (Crosetto & Filippin, 2013) is used and there is a significant gender difference only in less than 10% of the studies using the Holt and Laury method (Holt & Laury, 2002), see Filippin & Crosetto (2016) for details.[6] These results suggest that the lack of correlation between gender and risk tolerance is not as surprising, as most scholars would expect based on well-known surveys (Eckel & Grossman, 2008; Croson & Gneezy, 2009; Bertrand, 2011; Charness & Gneezy, 2012).

4.2. Price evolution

Figure 1 shows the evolution of the prices in phase 1. We cluster the

[3] Due to the fact that in the call market there is only one price per period, relative deviation is tightly related to another mispricing measure, average bias. Concretely, the latter is just relative deviation scaled up by the mean fundamental value in the market. By the same reason, a further often-used mispricing measure, total dispersion is equal to relative absolute deviation multiplied by the mean fundamental value.

[4] *Positive Deviation* is similar to an often used mispricing measure, *Total Dispersion* that sums up the absolute per-period price deviations from the per-period fundamental value, both if the price is below or above the fundamental value.

[5] This measure is similar to Amplitude, a measure often used to compute overpricing (Bosch-Rosa et al., 2018). It measures the difference between the maximum and minimum deviation from the fundamental value, allowing for negative deviations as well. Our measure considers only the positive deviations. There are many other measures in the literature (Stöckl, Huber, & Kirchler, 2010). Most of them are just transformations of the ones used.

[6] Horn & Kiss (2018) report no significant association between gender and risk attitudes in a different experiment carried out with university students in Hungary.

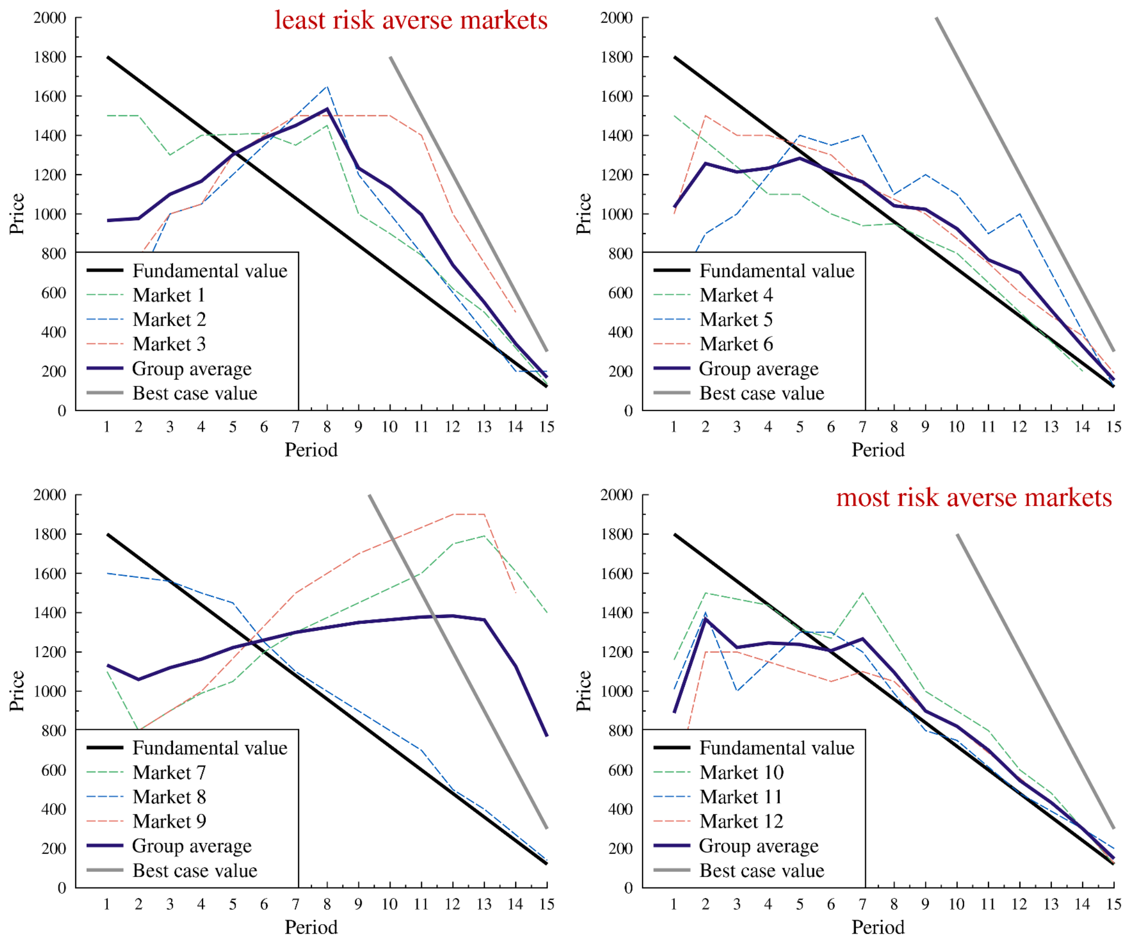

Fig. 1. Price evolution. (Top left pane: Markets 1–3 populated by the most risk-tolerant traders. Top right pane: Markets 4–6, second-most risk-tolerant set of markets. Bottom left pane: Markets 7–9, third-most risk-tolerant quartile of markets. Bottom right pane: Markets 10–12 populated by the least risk-tolerant (that is, risk-averse) traders.).

markets into groups of three and depict the average price. Grouping three markets together is natural, as these groups were seated in the same room and were supervised by the same instructor, but it is also convenient since they represent quartiles. To assess the extent of overpricing, we also plot the fundamental value.

The most apparent feature of Fig. 1 is the strange trading behaviour of Markets 7 and 9. The price evolution in Market 9 could be most aptly described as a bubble that does not end in a crash.[7] There was still ongoing trading in the last period way above the fundamental value, at a price almost five times higher than the asset's value in the best case scenario (when the participants get the highest dividend with probability 1). The trading collapsed and there were no exchanges in the last period for Market 7. We speculate that in Markets 7 and 9, something profoundly different happened than in the other groups. Thus, we analyse Markets 7 and 9 and the rest separately (see Appendix B).

Another noticeable feature is that prices start out from way below the fundamental value in all markets. This is a common phenomenon, reported in many other asset market experiments (see the price evolution figures; for instance, Bosch-Rosa et al., 2018; Cheung, Hedegaard, & Palan, 2014; Haruvy et al., 2007 or Porter & Smith, 1995). A reasonable explanation is that in the first few periods, the participants are getting acquainted with the trading mechanisms and their trading partners' behaviour. Let us remind the reader that only 10% of the participants had an academic background in economics or business. In fact, a majority of them were medical students. Understandably, even the most risk-tolerant participants would be cautious in such a new environment. This explanation is reinforced by the fact that experienced traders converge to the FV sooner; see the price evolution in Round 2 (see Fig. 2) or refer to Porter & Smith (1995).

Regarding the Hypothesis, when we consider the average price paths in the different groups of markets (and ignore Markets 7 and 9), overpricing indeed seems to be the largest in Markets 1–3, followed by Markets 4–6, and then by Markets 10–12. This supports the Hypothesis. However, when we look at the markets separately, indeed Markets 1, 2, and 3 seem to generate the largest overpricing, but for instance market 10 shows a very similar price evolution to market 1, though traders there are considerably more risk averse. To see if the Hypothesis holds, we must quantify overpricing.[8]

[7] While this seems somewhat strange, it has already been observed in the literature. For instance, in their classic study, Smith et al. (1988) find that professional and business people from the Tucson area generate a large bubble and no crash. Some of the all-female markets in Eckel & Füllbrunn (2015) also do not exhibit a crash at the end of the trading period. Moreover, Lei, Noussair, & Plott (2001) set up an environment in which speculation is impossible and even under such conditions, they document prices exceeding the maximum possible future dividend earnings.

[8] Generally (Palan, 2013; Powell & Shestakova, 2016) experience decreases mispricing. Reassuringly, we observe such tendencies when studying the price evolution in Round 2 (see Fig. 2). More precisely, in markets 1–3 we do not see a decrease in the mispricing, however in markets 4–6 and markets 10–12 mispricing diminishes and per period prices track closely the fundamental value. Markets 7 and 9 behave as strangely as they do in Round 1.

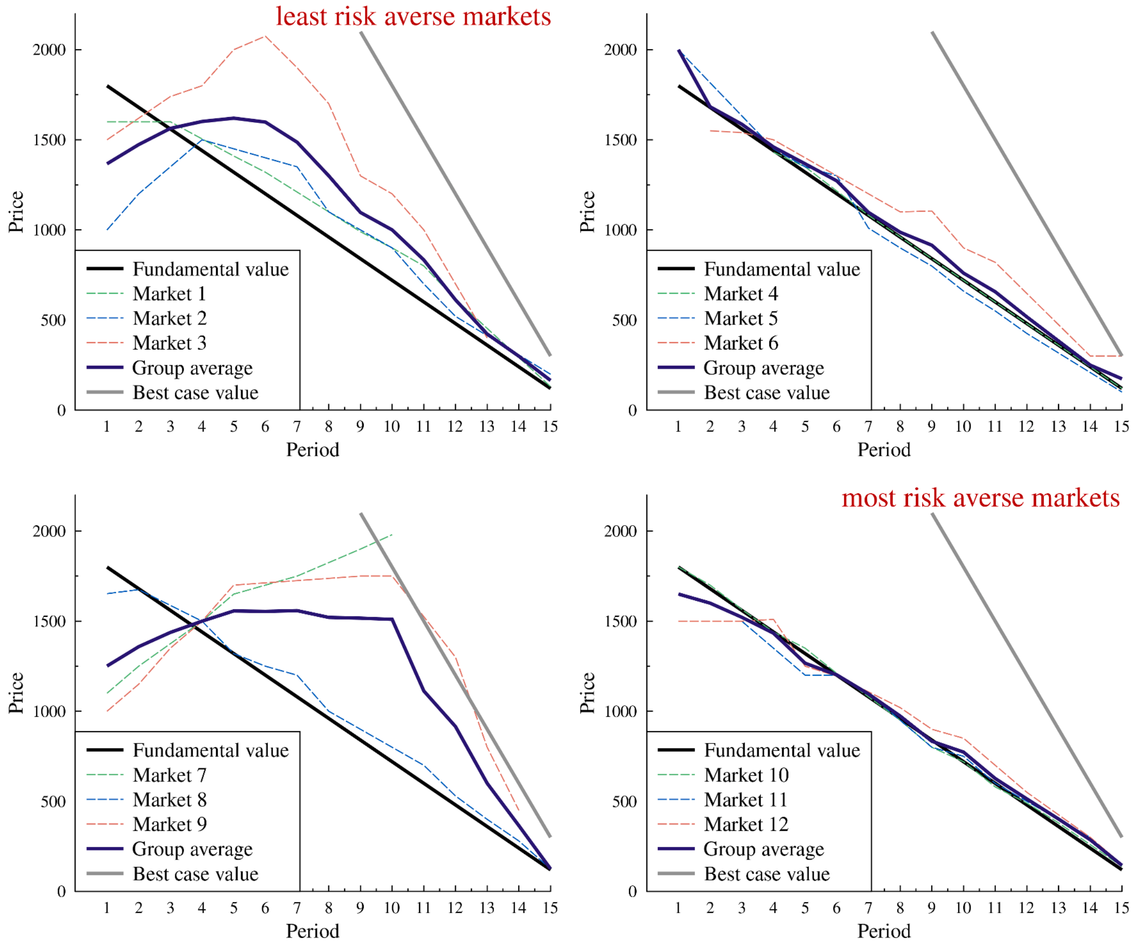

Fig. 2. Price evolution in Round 2. (Top-left pane: markets 1–3 populated by the most risk-tolerant traders. Top-right pane: Markets 4–6, second-most risk-tolerant set of markets. Bottom-left pane: Markets 7–9, third-most risk-tolerant quartile of markets. Bottom-right pane: Markets 10–12, populated by the least risk-tolerant traders.).

Table 4
Observed values of bubble and mispricing measures. The last row shows the *p*-value of the Mann-Whitney *U* test comparing Markets 1–3 with 10–12.

Market	Bubble measures			Mispricing measures			
	Positive Deviation	Boom Duration	Positive Amplitude	Relative Deviation	Relative Absolute Deviation	Geometric Deviation	Geometric Absolute Deviation
1	1795	8	490	0.081	2.682	0.137	0.229
2	2340	8	690	− 0.063	5.813	− 0.009	0.465
3	4180	7	800	0.097	7.448	0.173	0.719
Avg 1–3	2771.67	7.67	660	0.038	5.314	0.100	0.471
4	110.5	2	80	− 0.152	1.751	− 0.116	0.164
5	2750	10	520	− 0.002	5.760	0.092	0.494
6	960	5	160	− 0.018	2.229	0.093	0.243
Avg 4–6	1273.50	5.67	253.33	− 0.059	3.247	0.023	0.300
7	7180	5	1430	0.338	10.563	0.659	1.396
8	620	10	130	0.034	0.854	0.059	0.078
9	6140	3	1540	0.319	9.604	0.464	1.464
Avg 7–9	4646.67	6	1033.33	0.230	7.007	0.394	0.979
10	1272	5	420	0.039	2.186	0.089	0.196
11	420	3	120	− 0.125	2.500	− 0.038	0.211
12	330	4	96	− 0.204	2.730	− 0.135	0.294
Avg 10–12	674	4	212	− 0.097	2.472	− 0.028	0.234
p-value	0.0495	0.0463	0.0495	0.1266	0.1266	0.1266	0.1266

Table 4 shows the value of the different bubble/mispricing measures. If we ignore Markets 7–9 for a moment, we find that on average, the bubble/mispricing measures behave as expected: The average of the bubble/misprising measures decreases as the risk tolerance of the markets decreases. More precisely, the average of these measures is higher for Markets 1–3 than for Markets 4–6 or Markets 10–12. Similarly, these averages for Markets 4–6 are higher than those for Markets 10–12. Hence, in these bilateral comparisons across the averages of the groups, the directions are as expected for all the measures. Moreover, there is a complete separation between Markets 1–3 and Markets 10–12 when we

Table 5
Aggregated excess buy and sell prices. The values represent the extent the average price order exceeds the FV. The darker/lighter shading corresponds to the highest/lowest price in the period.

Period	6	7	8	9	10	11	12	13	14	15
Market					Excess buy prices					
1-3	428.57	564.44	356.67	422.50	350.69	478.57	362.86	470.00	157.75	130.00
4-6	216.00	320.00	223.33	147.14	304.20	287.50	190.00	160.63	114.00	430.00
10-12	75.25	220.00	55.00	114.83	176.40	143.33	86.67	58.86	111.67	156.67
					Excess sell prices					
1-3	436.67	490.00	753.85	740.00	736.00	817.50	754.21	605.88	543.13	438.21
4-6	576.67	575.56	600.11	396.75	450.00	510.55	514.17	383.08	270.00	203.33
10-12	349.17	353.08	880.63	249.23	190.69	236.94	220.77	225.00	215.00	196.50

focus on the bubble measures. That is, for any bubble measure, the lowest value in Markets 1–3 is larger than the largest value in Markets 10–12. This is also supported by the p-value of the Mann-Whitney U test reported in the last line, which compares the markets with the most risk-tolerant individuals (Markets 1–3) with the markets formed by the risk-averse traders (Markets 10–12).[9] However, if we carry out the same test in other relations (e.g., comparing Markets 1–3 to Markets 4–6), we do not observe statistically significant differences. Similarly, when considering mispricing measures, we fail to observe significant differences in any relations.

If we compare individual markets, the picture becomes more blurred as some markets with the least risk-tolerant traders exhibit a larger bubble measure than markets with more risk-tolerant traders. Note that there are many factors that can affect overpricing, so some inconsistency in individual market-level data is to be expected.

Overall, we get a mixed result. Although risk sorting is not a driving factor, it seems to have some effect on overpricing.

4.3. *Individual buy and sell orders*

To gain further insight, we consider each period separately. Table 5 shows the average excess buy and sell orders in each period, wherein we define an excess buy/sell order as a buy/sell order that exceeds the fundamental value. Formally, if there were $n > 0$ buy orders above fundamental value, the average excess buy order in period t is

$$B_t = \sum_{i=1}^{n} \frac{b_{i,t} - FV_t}{n_t}$$

where b_i denotes a buy order above FV_t. The average excess sell order can be calculated in a similar fashion.

The first five periods are omitted because in the early part of trading, buy and sell orders very rarely exceeded the fundamental value. In particular, in the first four periods, there were no excess buy orders in Markets 10–12. Again, we group markets together to obtain more observations.

Table 5 displays the average excess buy and sell orders in the three market groups. Each column is color coded to help the visualization of the data. The highest buy/sell orders in each period is marked with dark blue color (D), while medium and lowest prices are marked with medium (M) and light blue (L) respectively. There are six possible orders of coloring: LMD, LDM, MLD, MDL, DLM and DML. We see that one particular coloring, namely, DML is dominating in both part of Table 5). That is, Markets 1–3 generate the highest deviation from FV, Markets 4–6 take the second place, and finally, Markets 10–12 are the closest to FV. If risk tolerance had no effect on the excess buy or sell prices, the order of the market groups would vary. That is, different groups would produce the first-, second-, and third-highest prices and the colours in Table 5 would appear chaotically. Yet, there is a clear colour pattern.

If we assume that each coloring happens with equal probability, there is a $16.\overline{66}\%$ chance for one particular order. Further, if we assume that the excess buy orders are generated independently in each period, we can use the binomial distribution to calculate the probability that a

Table 6
Excess buy order in Round 1: Random-effects panel regressions with individual characteristics (first five periods excluded).

Variables	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Excess buy order				
Risk Tolerance	0.439***				0.452***
	(0.113)				(0.128)
Cognitive Abilities		– 14.38			13.35
		(37.73)			(40.13)
Female			103.5		71.65
			(88.39)		(85.52)
Strategic Uncertainty				– 97.56	– 119.5
				(79.46)	(93.72)
Assets lagged	– 35.77	– 19.46	– 17.79	– 13.66	– 29.82
	(26.65)	(12.92)	(16.44)	(17.15)	(21.06)
Cash lagged	– 0.016	– 0.005	– 0.001	– 0.002	– 0.013
	(0.0127)	(0.013)	(0.012)	(0.013)	(0.011)
Concentration	368.5	423.7	386.3	410.5	300.3
	(256.8)	(401.9)	(464.2)	(448.3)	(236.6)
Market Price lagged	0.131	0.150	0.146	0.169	0.139
	(0.191)	(0.195)	(0.202)	(0.211)	(0.162)
Dividend lagged	0.121	0.155	0.165	0.195	0.185
	(0.175)	(0.173)	(0.178)	(0.184)	(0.191)
Remaining Period	8.396	22.91	23.58	21.90	9.475
	(39.87)	(45.64)	(45.70)	(47.13)	(36.94)
Remaining Period Squared	– 1.696	– 2.765	– 2.721	– 2.669	– 1.686
	(2.625)	(2.360)	(2.386)	(2.418)	(2.514)
Constant	1.415	142.5	52.63	138.2	– 27.99
	(206.5)	(144.1)	(215.5)	(200.1)	(202.8)
Observations	107	107	107	107	107
Number of sid	59	59	59	59	59

Standard errors clustered on the market level in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

[9] Since we compare two groups with a very low sample sizes, take these significant results with a grain of salt. In fact, if we repeat the same exercise, but compare the upper 4/5 markets with the lower 4/5 markets (and ignore markets 7 and 9 that do not show the crash pattern), then we do not observe any significant differences in the bubble / mispricing measures. It is not surprising because as we widen the scope and include more markets from the middle, the differences between the groups of markets become less pronounced.

Table 7
Observed values of bubble and mispricing measures in Round 2. The last row shows the p-value of the Mann-Whitney U test comparing Markets 1–3 with 10–12.

	Bubble measures			Mispricing measures			
Market	Positive Deviation	Boom Duration	Positive Amplitude	Relative Deviation	Relative Absolute Deviation	Geometric Deviation	Geometric Absolute Deviation
1	925	4	200	0.084	1.172	0.126	0.156
2	1359	9	270	0.007	2.749	0.074	0.253
3	5035	9	875	0.448	5.557	0.414	0.462
Avg 1–3	2439.67	7.33	448.33	0.180	3.159	0.205	0.291
4	32.5	3	30	0.003	0.045	0.002	0.005
5	340	3	200	− 0.002	0.725	− 0.040	0.083
6	1105	4	265	0.111	1.307	0.253	0.280
Avg 4–6	492.5	3.33	165	0.037	0.693	0.072	0.122
7	4245	4	1260	0.406	5.599	0.355	0.650
8	645	10	120	0.037	0.831	0.064	0.077
9	3850	3	1030	0.241	5.615	0.381	0.725
Avg 7–9	2913.33	5.67	803.33	4.015	7.007	0.267	0.484
10	115	3	30	0.003	0.193	0.381	0.026
11	130	1	60	− 0.019	0.458	0.008	0.059
12	580	5	130	0.013	1.057	0.069	0.120
Avg 10–12	275	3	73.33	− 0.0009	0.569	0.152	0.068
p-value	0.0495	0.1212	0.0495	0.1266	0.0495	0.2752	0.0495

Table 8
Excess buy order in Round 2: Random-effects panel regressions with individual characteristics (first five periods excluded).

Variables	(1) Dependent variable: Excess buy order	(2)	(3)	(4)	(5)
Risk Tolerance	− 0.00818				− 0.0396
	(0.0333)				(0.0347)
Cognitive Abilities		− 16.11***			− 20.01***
		(6.144)			(6.261)
Female			5.821		2.022
			(22.91)		(26.81)
Strategic Uncertainty				21.57	27.18
				(13.78)	(19.87)
Assets lagged	− 7.478	− 7.663	− 6.980	− 8.028*	− 8.730
	(4.823)	(6.381)	(5.101)	(4.398)	(5.940)
Cash lagged	− 0.016**	− 0.014***	− 0.015**	− 0.014**	− 0.015**
	(0.006)	(0.005)	(0.007)	(0.006)	(0.006)
Concentration	− 69.75	− 149.7	− 84.75	− 64.74	− 167.5
	(199.7)	(205.2)	(228.4)	(199.0)	(204.1)
Market Price lagged	1.015***	0.973***	1.007***	1.016***	0.987***
	(0.022)	(0.019)	(0.028)	(0.023)	(0.028)
Dividend lagged	0.075	0.076	0.082	0.074	0.059
	(0.078)	(0.079)	(0.085)	(0.073)	(0.088)
Remaining Period	− 126.8***	− 123.4***	− 125.2***	− 126.5***	− 125.4***
	(21.12)	(17.58)	(23.72)	(20.87)	(21.13)
Remaining Period Squared	1.914	2.050	1.852	1.813	2.035
	(1.768)	(1.645)	(1.878)	(1.753)	(1.825)
Constant	− 103.7	− 55.58	− 113.6*	− 128.5**	− 35.42
	(67.45)	(66.68)	(66.42)	(62.66)	(76.50)
Observations	79	79	79	79	79
Number of sid	48	48	48	48	48

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

particular order is repeated at least k times. It is extremely unlikely ($\approx 7.6 \times 10^{-7}$) that the excess buy orders produce the DML pattern 9 out of 10 times. The pattern for excess sell orders is noisier but still very improbable ($\approx 2.4 \times 10^{-4}$). Even if we cannot assume independence, it is implausible that there is no relation between risk tolerance and excess buy and sell orders.

We carry out regression analyses in which the dependent variable is either the excess buy order or the excess sell order that led to transaction, in a given period.[10] That is, in each period we consider only those buy/sell orders that are above the fundamental value in the given period and are relevant for transaction. We try to understand which factors predict the difference between these buy/sell orders and the fundamental value. We control for when a buy/sell order is placed among other variables (as before, we exclude Markets 7 and 9 from this analysis). We also include the lag of market price and dividend (that is, the market price and dividend in the previous period) as a control in the regression, as these represent the most recent market experience of the participants. To account for the participants' financial position, we also consider their asset and cash holding. We further control for the concentration of assets on the market, using the Herfindahl-Hirschman index as a measure of concentration. Since we are mainly interested in the effect of time-invariant variables, we use a random-effects panel estimation. Standard errors are clustered on the market level.

On the individual level, risk and uncertainty are positively and significantly correlated; hence, in the regressions, we use only the risk tolerance measure (captured by the amount of Tokens placed as bet, ranging from 0 to 1489). Cognitive abilities correlate negatively in a significant way with being female. As both these measures have been found important in the literature, we will use both of them in separate regressions. Hence, our individual characteristics are *risk tolerance* (the variable used to form the groups), *cognitive abilities* that are measured by the results of the Cognitive Reflection Test, a dummy variable that is 1 if a participant chooses the risky option in the Stag Hunt game (*strategic uncertainty*), and a dummy for being *female*.

Table 6 summarises the findings of the panel regression regarding excess buy orders. Column (1) indicates that markets populated by traders with a high elicited risk tolerance exhibit higher excess buy orders. Column (2) replicates the idea of the literature that individuals with better cognitive abilities act less in a way that fuels bubbles. In our case, this is equivalent to submitting lower excess buy orders, though the effect is not significant. Column (3) shows that women tend to submit higher excess buy orders that eventually lead to transaction, but the

[10] Hence, in period t, we drop all buy orders that are equal to or below the fundamental value and focus on the excess buy orders, defined as $b_{i,t} - FV_t$, where $b_{i,t}$ denotes a buy order placed by trader i in period t. Excess sell orders are determined similarly. Moreover, we restrict our attention to those buy and sell orders that were conducive to transaction.

coefficient is not significant. Column (4) reports no role of strategic uncertainty to understand the magnitude of excess buy orders.[11] If we introduce all variables in the same regression (Column (5)), risk attitudes still remain a very significant predictor in the expected way of the magnitude of the excess buy orders. We see the same result if we include the first five periods; see Appendix D.

In Table 6, we used individual characteristics. Therefore, for instance, we explored the association between individual risk tolerance and individual excess buy order. However, our research question concerns risk sorting, so we carry out the same exercise, but we replace individual characteristics with market-level means and standard deviations. Thus, we relate an individual's excess buy order leading to transaction to the average and standard deviation of risk tolerance (for the other elicited characteristics) to see if markets with a larger average risk tolerance produce larger excess buy orders. We have placed the output table (Table A5) in Appendix E. We find that the market-level average of risk tolerance keeps being significant at the 5% even if we add all the market-level averages and standard deviations of the elicited characteristics. This suggests that markets with a higher average risk tolerance (a consequence of risk sorting) produce larger excess buy orders that lead to transaction.

Despite the promising colour pattern in Table 5, we find no significant effect of risk tolerance for excess sell orders (that lead to transactions) when considering individual or market-level characteristics (see Tables A6 and A7 in Appendix F). This is most probably because in periods 6–8, markets populated with less risk-tolerant traders produced unusually high excess sell orders. Moreover, we have considerably less observations in the regressions on sell orders that also affects whether coefficients are significant or not.

Overall, we find some evidence that supports the Hypothesis. Excess buy orders seem to behave as we expected. We find no significant evidence for excess sell orders. Whether this is a statistical glitch or a truly different behaviour on the traders' side cannot be determined from the data.[12]

4.4. Round 2

In this section we briefly study how traders behaved in Round 2. Fig. 2 shows price evolution in Round 2. The most remarkable feature of Fig. 2 relative to Fig. 1 is that bubbles disappear in markets 4–6 and 10–12, while they remain in markets 1–3. Markets 7–9 behave as erratically as in Round 1.

Table 7 is analogous to Table 4, but uses observations from Round 2. When regarding bubble measures, in most markets we observe a decrease, while for mispricing measures we do not see a clear tendency.[13] When comparing markets 1–3 and 10–12 in Round 2, similarly to Round 1, we observe a significant difference in two of the bubble measures (positive deviation and positive amplitude). The last bubble measure (boom duration) ceases to show a significant difference, in contrast to Round 1. While in Round 1 there was no significant difference in the mispricing measures, in Round 2 we document that relative and geometric absolute deviations are significantly larger in markets 1–3. Overall, when comparing the extreme quartiles, the differences in bubble and mispricing measures did not disappear in Round 2.

Turning to the regression analysis, in contrast to Round 1 (see Table 6), we do not observe a significant positive relationship between risk tolerance and excess buy orders that lead to transaction in Round 2 (see Table 8). Probably, the association vanished due to the experience that traders gained in Round 1.

Regarding excess sell orders, we find qualitatively the same as in Round 1 (see Tables G.2 and G.3 in Appendix G). Risk tolerance does not correlate with excess sell orders neither when considering the individual or the market level.

5. Discussion

Figures 1 and 2, and Tables 4 and 5 provide some evidence in support of the Hypothesis. Clearly, traders on different extremes of the risk tolerance scale behave differently. If overpricing were independent of risk attitude, it would appear inconsistently, but (save Markets 7 and 9) there is a clear decreasing pattern. Our explanation is not only the most likely but also the most intuitive. Risk-tolerant participants value the asset more; thus, they are willing to pay a higher price for it. Markets 7 and 9 produced real price bubbles but the underlying cause is different and unrelated to the treatment. The pattern is noisy as there are other factors affecting overpricing besides risk sorting.

Table 5 shows that excess buy orders depend linearly on risk tolerance, partly supporting the Hypothesis, but the same does not hold for excess sell orders. The sudden rise in excess sell order in Markets 10–12 in the middle part of trading might have happened by chance. Another interesting explanation is that excess buy and sell orders work differently. Individuals with different risk attitudes may consider selling an altogether different animal than buying, and place excess sell orders at different periods of time. There is also a marked difference between the number of buy and sell orders.

Risk attitudes can indirectly induce overpricing in yet another way. The instructions stated clearly that each dividend occurs with equal probability, so any participant could compute the probability of the realisation of any sequence of dividends. Some participants may have exhibited exuberant optimism and expected to receive larger dividends, yielding a higher FV of the asset. If optimism associates positively with risk tolerance, the Hypothesis may hold.[14]

Overpricing might emerge because participants value the risky asset more. Their risk attitudes may express their preferences: They like the thrill of throwing the dice. However, risk-tolerant behaviour can also be a symptom, a result of a belief or deeper sentiment (e.g., optimism). In the first case, participants calculate the same expected value, that is, the same FV as everybody else, but derived greater utility from holding the asset. In the second case, they sought to hold the asset because they calculated a higher FV.[15]

The fact that in the second round, overpricing remains in some markets while it disappears in others, can also be explained by the two types of risk-tolerant traders. Those whose risk-tolerant behaviour was fuelled by optimism may have realised that they were not so lucky after all, and they may have approached the trading for the second time with more caution. Those whose risk tolerance was a preference-based behaviour were only consistent when repeatedly behaved in a way

[11] In contrast, Akiyama et al. (2017) devised a call market experiment to examine the effect of strategic uncertainty on mispricing. They organised two treatments, one with six humans and one with one human and five computers. They elicited subjects' expectations about future prices and found that half the median initial forecast deviation is due strategic uncertainty.

[12] Findings are qualitatively identical, if instead of risk tolerance we use the uncertainty tolerance measure.

[13] We also compare markets in the same quartile across rounds. That is, we investigate if the bubble and mispricing measures in markets 1–3 / 4–6 / 7–9 and 10–12 were different in the two rounds. The Mann-Whitney test shows no significant differences in most cases, the exceptions being markets 4–6 when considering relative deviation and relative absolute deviation, and markets 10–12 when considering relative absolute deviation and geometric absolute deviation. In all these cases, there is a significant decrease at 5% in the corresponding measures.

[14] We did not measure optimism or any other potential confounder, so we cannot exclude the possibility that our findings are due to them.

[15] Note that Dickinson (2009) reported risk-averse yet optimistic subjects in a bargaining game and showed that the minimally acceptable settlement value from a risk-loving but unbiased-belief bargainer is empirically indistinguishable from what one could get with risk-neutrality and optimistically biased beliefs.

that led to overpricing the asset in the second round. Nevertheless, this is only speculation that we cannot confirm by looking at the data. The relation of optimism and overpricing is an interesting future research question, especially as optimism might be the confounding factor of overconfidence, which is also a known factor in overpricing.

According to our interpretation of the results, not every overpricing is a bubble. Markets 7 and 9 produced real bubbles, where the price overstepped even the asset's highest potential value, while the overpricing in Markets 1–3 could be explained with rational choice models without assuming any speculative behaviour on the traders' part.

Finally, a larger sample size would have made it easier to separate the effect from the noise. Sadly, with 96 participant, we were already at the end of our lab's capacity. In hindsight, we should have opted for more market groups even at the cost of re-running the experiment at a different time. Still, we believe that these results will serve as an important reference point to determine the role of risk attitudes in overpricing.

6. Conclusion

Recent studies use sorting along some individual characteristics to study the emergence of overpricing in experimental asset markets. Motivated by current practices as well as guidelines such as the MiFID, we considered risk tolerance and investigated the effect of sorting on overpricing in a laboratory experiment.

Unfortunately, we cannot rule out such an effect. In other words, practices aimed at protecting risk-averse investors from intolerable losses may, at the same time, contribute to the emergence of financial bubbles. We find some evidence that markets with the most risk-tolerant traders exhibit larger overpricing than those with the least risk-tolerant ones. The effect is linear if we consider excess buy orders (i.e., price orders that exceed the fundamental value of the assets). Excess sell orders show a linear pattern only in the late periods of trading, but not overall. We observe different forms of overpricing, of which price bubbles are only one. Based on risk attitudes, we offer an explanation regarding how rational agents may trade at significantly higher prices than the fundamental value of the asset, and why such a trade does not necessarily result in a crash.

We do not claim that differences in risk aversion alone cause the differences in overpricing, as there may be other confounding factors. In an experimental environment, we may neutralise several interfering aspects, but the interaction of several traders creates a plethora of situations wherein the same trader may act differently. For instance, a single confused trader (recall that risk aversion and cognitive skills do not correlate) may drive the market to unexpected directions, just as in real life. Further, the belief that future dividends correlate with risk aversion and more risk-tolerant traders are also more optimistic about future dividend may be the factors of optimism that drive the results. More research is needed to unearth the causal mechanisms.

On the other hand, risk tolerance may be an organising principle behind some of the previous sorting results. Gender and cognitive abilities often relate to each other. Male participants often perform better in cognitive tasks (Frederick, 2005; Branas-Garza, Kujal, & Lenkei, 2019), although these results may be due to the nature of the cognitive tests (Holt, Porzio, & Song, 2017) and alternative measures display no significant difference between male and female participants (Frederick, 2005). Hence, according to Bosch-Rosa et al. (2018), males could be expected to generate fewer and smaller bubbles, contradicting the findings of Eckel & Füllbrunn (2015). A possible way out of this conundrum is the association of these factors with risk aversion. Eckel & Grossman (2008), Croson & Gneezy (2009), Dohmen et al. (2011), Bertrand (2011), Charness & Gneezy (2012) and others reported that females are more risk averse than males, while Burks, Carpenter, Goette, & Rustichini (2009), Dohmen, Falk, Huffman, & Sunde (2010), Benjamin, Brown, & Shapiro (2013), Dohmen, Falk, Huffman, & Sunde (2018) found that cognitive abilities are negatively related to risk aversion.[16] Therefore, risk aversion emerges as a potential factor to explain the mechanisms behind the effects of gender and cognitive abilities. In fact, both Eckel & Füllbrunn (2015) and Bosch-Rosa et al. (2018) pointed out the importance of risk aversion.

Acknowledgment

This research was supported by the SME under research project ECO2014-52372; and by the Hungarian National Research, Development and Innovation Office, grant numbers K119930 (Sziklai), K119683 (Kiss), and K109354, K128573 (Kóczy). Balázs R. Sziklai is the grantee of the János Bolyai Research Scholarship of the Hungarian Academy of Sciences and the New National Excellence Program Bolyai+ scholarship of the Ministry for Innovation and Technology. Hubert János Kiss acknowledges the financial support by the Hungarian Academy of Sciences, Momentum Grant No. LP2021-2.

Appendix A. Instructions

Dear Participant,

Thank you for participating in this experiment! Participation is VOLUNTARY and ANONYMOUS, that is, none of the participants will ever get any information about your decisions or earnings. We treat all information that we gather during the experiment confidentially.

Please follow the instructions carefully. Always keep the identifier that you received at the entrance with you, as you need it during the experiment and to get your earnings at the end. Should you have questions, raise your hand and we will attend to you. During the experiment, it is forbidden to speak or communicate in any other way with the other participants. If you do not comply with that rule, you will be excluded from the experiment. Please switch off your mobile phone.

The course of the experiment

1.a Tasks
1.b Trial period
1.c Questionnaire
— Reassignment to other computer—
2 Trading game
3 Payment of earnings

You receive 1000 HUFs for participating in this experiment, and for your performance in 1.a and 2, you are entitled to additional earnings. During the experiment, the experimental currency is called *petak*; we register all your transactions in this currency. We pay all the petaks that you earn at the end of the experiment in cash at the following exchange rate: **3 petaks = 1 HUF**.

Part 1

In part 1.a, you see will four tasks and the answers you give in those tasks may earn you money. Note that the questions you see in these tasks

[16] It should be noted that the literature is ambiguous. Andersson, Holm, Tyran, & Wengström (2016) claimed that commonly used measures of risk aversion may mechanically generate a spurious correlation between risk aversion and cognitive ability, so one should be careful when observing a significant association between these two variables.

often have no objectively correct answers. At the end of the experiment, we will choose one of the tasks randomly to calculate your earnings. Your earnings in part 1 are determined by the answer that you have given in that task.

In part 1.b, we will go through how the trading game works, and then, you will play a trial period. The trial period will be followed by a short questionnaire (1.c). Further, we will regroup you and you may have to change rooms.

Part 2

In part 2, you will play the trading game in groups of eight. In the trading game, you may sell and buy securities. If you make good decisions, you may earn a substantial amount of money. This part of the experiment consists of two rounds that are independent, and in each round, there will be 15 periods. You will receive more information about the trading game before the trial period.

Market and Trading

You will trade on a market with seven other participants. Throughout the experiment, the markets will not not change, that is, you will trade with the same participants.

The experiment consists of two independent rounds, and in each round, you can trade for 15 periods. At the beginning of each round, the participants will be endowed with a certain amount of ECU (experimental currency) and some assets. The amount of ECUs and the number of assets may vary among participants, but the expected value of the bundle of ECUs and assets you receive will be the same for all participants.

Assets expire after 15 periods; that is, at the end of the round, they are worthless. If you buy an asset, you will own the asset starting from the period you buy it until you sell it. After each period (including the last one, i.e., the 15th period), each asset will yield 0, 40, 140, or 300 ECUs. The probability of each dividend is 25%. This means that the average dividend in each period is 120 ECUs. The dividend will be added to your account automatically after each period. After the dividends are distributed at the end of the 15th period, the market will close and the assets will cease to exist.

We attach a table named "Average value of holding an asset," which can help you in deciding whether to buy or sell. The table shows how much dividend you can expect, on average, if you keep the asset till the end of the round. We have calculated this value by taking the remaining number of periods and multiplying it by 120, the average dividend in each period.

If you want to buy an asset, you can place a buy order to do so. A buy order consists of the number of assets you want to buy and the highest price you are willing to pay for each asset. It is important to note that you will buy each asset for the same price.

If you want to sell an asset, you can place a sell order to do so. Similarly to the buy order, a sell order consists of the number of assets you want to sell and the lowest price for which you are willing to sell each asset. As in the previous case, each asset will be sold for the same price.

It is important to note that you can place only one sell order in each period; that is, you can only sell your assets for one price. You can sell more than one asset for this price (but only as many as you own). Similarly, you can place only one buy order, but for this price, you can buy more than one asset (provided you have enough ECUs). You can place both a buy and a sell order in one period, but here, the buying price must be lower than the selling price. In all cases, prices refer to the per-asset prices. You are not obliged to trade. If you think that neither selling nor buying an asset is worth it, you do not need to initiate any transaction.

In each period, you have 90 seconds to place buy and sell orders, which you can do on the bottom-right corner on the trading screen with a yellow background (see Fig. A.3.). If you click on the 'Place buy order' button (B2), your order in the purple container (A1) will be transferred into the order book on the left (C3). Your order is then marked as sent, but you can cancel it until the end of the period. The sell order works in a similar fashion. If you have already decided on what orders to place and have transferred these to the order book, you have two options. You can either wait for the remaining time to run out or click the 'Send order' button (D4), after which you cannot trade any more in the given period.

Determining the Trading Price

The trading software compiles the buy and sell orders and determines the trading price on which the assets are exchanged. Under the calculated price, the maximum amount of asset exchange will take place. It is possible that there is more than one such price. In the following example, we demonstrate how the trading price gets chosen.

It is important to note that if your buy order is lower than the calculated trading price, you will not buy any assets. Sometimes it can happen that even though your buy order is higher than the trading price, you still do not manage to buy any assets. This occurs because there is an over-demand, and it is impossible to satisfy all claims. In such cases, transactions happen in the order that the buy orders were placed. Similarly, if you have given a higher sell order than the trading price, you will not sell any assets. In case of oversupply, it can happen that you have given a sell order that is lower than the trading price, but you still do not sell any assets because the others placed orders before you.

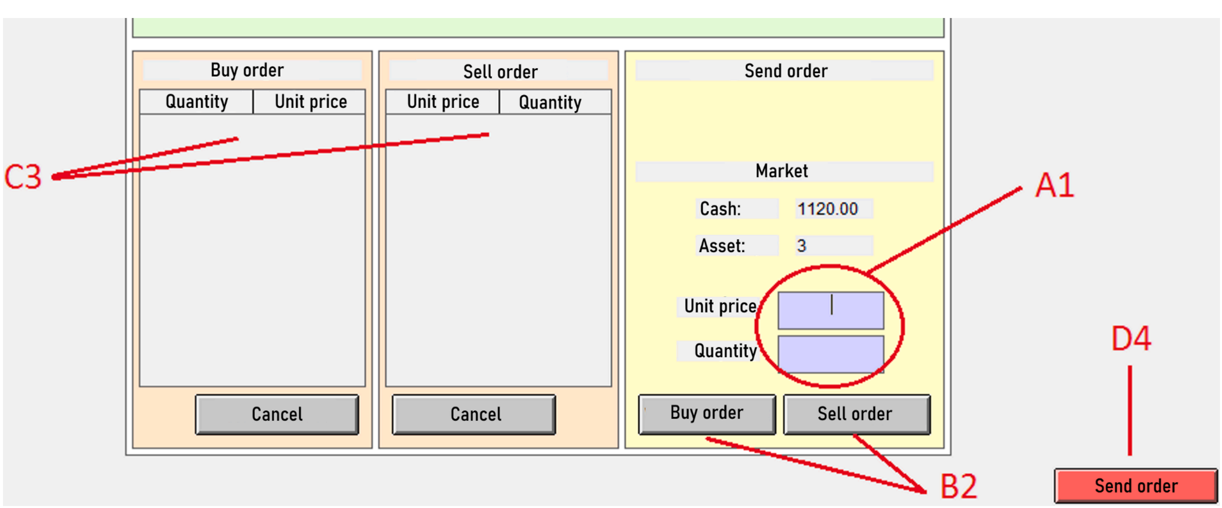

Fig. A.3. The trading screen (with labels translated for convenience).

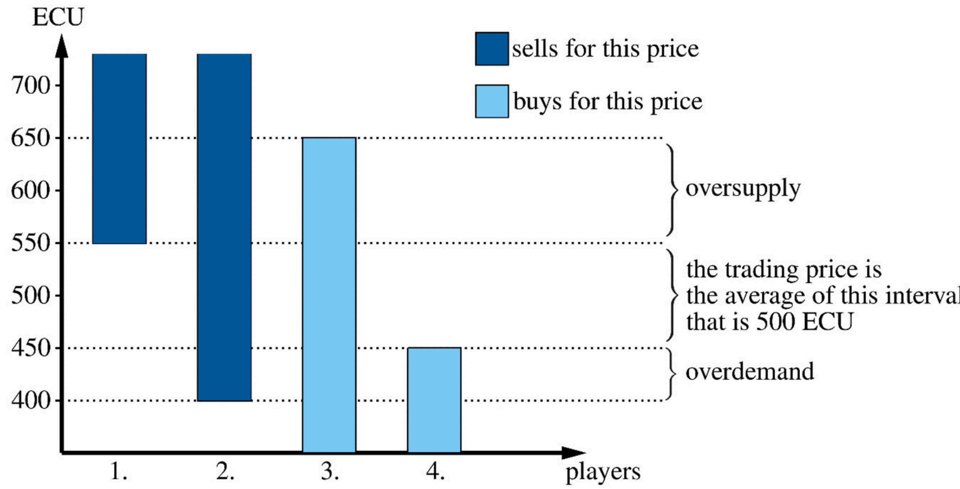

Fig. A.4. Example (with labels translated for convenience).

Example

As we can see in Fig. A.4, both Players 3 and 4 would buy below 400 ECUs, but neither Player 1 nor Player 2 is willing to sell. In this case, the demand is greater than the supply: There is excess demand. Prices below 400 ECUs do not lead to transactions. For prices between 400 and 450 ECUs, both Player 3 and 4 are still willing to buy and Player 2 is willing to sell their asset. As there are more buyers than sellers, there is still excess demand. Similarly, above 550 ECUs, both Players 1 and 2 are willing to sell their assets, but only Player 3 is willing to buy. Two sellers face only one buyer; thus, there is excess supply. Above 650 ECUs, the events worsen as there are no buyers although there are two sellers.

Between 450 and 550 ECUs, Player 2 is willing to sell their asset and Player 3 is willing to buy for this price. This price is too high for Player 4 (who would like to buy) and too low for Player 1 (who would like to sell). That is, for such prices, there is only one buyer and one seller, so there is no excess demand or supply. In such a case, the trading price is the average of 450 and 550 ECUs, that is, 500 ECUs.

If oversupply drives the market, buyers are in a better position. Thus, the smallest trading price will be realised. If there is dominantly an over-demand on the market, sellers are in a better position. Hence, the highest possible price will prevail. If there is both oversupply and over-demand, the trading price is set as the average of the highest and lowest possible prices.

To understand the decision mechanism better, there will be a trial period wherein you can place buy and sell orders, before entering the real market. For these decisions, you will not receive any payment. In the trial period, you will receive a different amount of ECUs and assets than in the real rounds, and in addition, after the end of the trial period, you will not see the trading price. Instead, you will see what transactions took place under the different buy and sell orders.

The trial period is followed by a short query, after which you will be assigned to a computer in one of the labs for part 2 of the experiment. Please do not wander off too far during the break when you are reassigned.

Payments

Your final payment consists of three parts:

- One thousand HUF for participating in the experiment
- The money you earn in one of the four questions (chosen randomly) in part 1 of the experiment
- Your balance after the 15th period in one of the rounds (chosen randomly) in part 2 of the experiment

As we mentioned earlier, we keep your balance in ECUs and pay you with the exchange rate of 3 ECU = 1 HUF at the end of the experiment.

If you have any further question, please indicate them now!

Appendix B. Interpretation of the data of Markets 7 and 9

We have seen some convincing statistics that suggest that risk sorting and overpricing are related. However, the evidence is clouded by the strange trading behaviour in Markets 7 and 9. Therefore, let us address the question of what happens in these two markets.

Significant overpricing is displayed in the first three markets as well as in Markets 7 and 9. However, in the first three markets, prices never exceeded the asset's highest potential value. This indicates that the reasons for overpricing are different in Markets 7 and 9. Henceforth, let us refer to the events in these two markets as 'bubbles'. The cause of bubbles may be speculation or 'trading fever', as well as confusion or misinterpretation of the trading mechanics, although the latter is less likely. In the second round of the experiment, the bubble is repeated in both markets despite the clear first-hand experience that the asset is worthless after the last period.

Markets 7 and 9 and the first three markets differ in other aspects as well. Let us start with the obvious: by design, they are composed of traders of different risk attitudes. It is unlikely that risk tolerance is the cause of bubbles, as Market 8, which is the closest to Markets 7 and 9 in this aspect, is the polar opposite in terms of price evolution.

Table A1
Asset concentration measured by the Herfindahl-Hirschman index and buy/sell ratios. Highest and smallest values in the rows are highlighted by dark and light blue, respectively.

Market:	1	2	3	4	5	6	7	8	9	10	11	12
Asset conc. (%)	21.3	25.0	18.4	18.6	19.6	22.7	29.3	17.4	21.6	21.3	20.0	24.3
Buy/sell orders	1.0	1.3	1.1	1.5	1.2	1.4	1.4	1.3	1.6	1.4	1.3	1.5
Buy/sell volume	1.0	1.9	1.2	1.8	1.3	2.1	1.5	2.3	1.9	1.7	2.0	1.8

These markets are also dissimilar in trading behaviour (Table A1). Members of Markets 7 and 9 placed many more buy orders relative to sell orders than participants of the first three markets. In fact, they are on the opposite extremes. The same is true for the buy/sell volume. Asset concentration is high for both Markets 7 and 9, but it varies for the first three markets.

Beside risk attitude, the literature lists half a dozen factors that may contribute to overpricing from the traders' cognitive abilities or speculative tendencies to the concentration assets. Some of these factors are indeed present in Markets 7 and 9. In fact, Market 7 has the highest asset concentration among all markets, whilst Market 9 consists of participants with low cognitive abilities. Is it far fetched to believe that bubbles in these cases are triggered by some other factor, independent of risk attitude? As soon as we remove Markets 7 and 9, the data start making sense. Had we opted for the design of Bosch-Rosa et al. (2018) and performed the experiment only at the extremes, we would have a clear-cut picture.

Appendix C. Market-level correlation between bubble/mispricing measures and individual characteristics

Tables A2 and A3.

Table A2
Pairwise correlation between market-level bubble measures and market-level individual characteristics (all markets).

		Bubble measures			Mispricing measures		
		Positive Deviation	Boom Duration	Positive Amplitude	Average Bias	Total Dispersion	Amplitude
Risk	(mean)	0.0852	0.4717	0.1020	0.1267	0.0512	– 0.0851
Risk	(Std.dev.)	– 0.3517	0.1354	– 0.3031	– 0.0986	– 0.4647	– 0.4015
Uncertainty	(mean)	0.2183	0.5014*	0.1819	0.2716	0.1482	– 0.0507
Uncertainty	(Std.dev.)	– 0.2650	0.4568	– 0.1997	– 0.1547	– 0.3045	– 0.2797
Share of risky choice in stag hunt		– 0.0526	0.3077	– 0.0870	0.0883	– 0.1349	– 0.1081
Cognitive	(mean)	– 0.4544	– 0.0101	– 0.4533	– 0.2594	– 0.5623*	– 0.5904**
Cognitive	(Std.dev.)	– 0.3176	0.2481	– 0.4218	– 0.3552	– 0.2889	– 0.2730
Share of female		0.4955	– 0.3069	0.5056*	0.3220	0.5582*	0.5798**

Table A3
Pairwise correlation between market-level bubble measures and market-level individual characteristics (ignoring Markets 7 and 9).

		Bubble measures			Mispricing measures		
		Positive Deviation	Boom Duration	Positive Amplitude	Average Bias	Total Dispersion	Amplitude
Risk	(mean)	0.4861	0.4396	0.5663*	0.5185	0.3332	0.0795
Risk	(Std.dev.)	– 0.1371	0.0713	– 0.0766	0.3294	– 0.3616	– 0.2965
Uncertainty	(mean)	0.5357	0.4913	0.5344	0.6051*	0.3312	0.0253
Uncertainty	(Std.dev.)	0.2131	0.3881	0.3764	0.3892	0.0570	0.0274
Share of risky choice in stag hunt		0.2768	0.2333	0.2696	0.5287	0.0721	0.1126
Cognitive	(mean)	– 0.5464	– 0.1332	– 0.4979	– 0.1097	– 0.6638**	– 0.6018*
Cognitive	(Std.dev.)	0.0815	0.1051	– 0.0897	– 0.0020	0.0827	0.0833
Share of female		0.4691	– 0.1702	0.3895	0.0363	0.5379	0.4671

Appendix D. Excess buy order: Robustness check

Here, we reproduce Table 6, but we do not exclude the first five periods. Although the coefficients change somewhat, qualitatively, we observe the same findings. Risk tolerance remains a significant predictor of excess buy order (Table A4).

Table A4
Excess buy order in Round 1: Random-effects panel regressions with individual characteristics (first five periods included).

Variables	(1)	(2)	(3)	(4)	(5)
			Dependent variable: Excess buy order		
Risk Tolerance	0.432***				0.442***
	(0.119)				(0.137)
Cognitive Abilities		– 19.25			3.522
		(36.66)			(39.96)
Female			93.31		56.77
			(89.68)		(89.15)
Strategic Uncertainty				– 86.97	– 108.2
				(76.24)	(90.89)
Assets lagged	– 37.31*	– 24.25**	– 22.86*	– 19.21	– 33.85**
	(19.52)	(11.09)	(12.85)	(14.34)	(15.42)
Cash lagged	– 0.015	– 0.005	– 0.003	– 0.002	– 0.014
	(0.0114)	(0.013)	(0.012)	(0.013)	(0.011)
Concentration	273.9	282.8	279.8	299.5	252.6
	(255.6)	(354.6)	(423.2)	(407.1)	(241.3)
Market Price lagged	0.128	0.138	0.138	0.155	0.130
	(0.166)	(0.169)	(0.177)	(0.183)	(0.138)
Dividend lagged	0.053	0.063	0.088	0.099	0.103
	(0.210)	(0.219)	(0.235)	(0.234)	(0.218)
Remaining Period	13.66	19.81	18.67	18.70	13.23
	(40.96)	(49.55)	(51.02)	(51.10)	(36.92)
Remaining Period Squared	– 2.389	– 2.457	– 2.302	– 2.373	– 2.226
	(2.486)	(2.988)	(3.055)	(3.017)	(2.294)
Constant	21.75	207.8	114.3	188.2	22.02
	(198.4)	(150.7)	(210.5)	(188.9)	(192.4)
Observations	121	121	121	121	121
Number of sid	61	61	61	61	61

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Appendix E. Excess buy order: Market-level variable

Here, we run the same regression as in Table 6, but instead of the individual characteristics, we use the market-level average and standard deviation of the given characteristic (Table A5).

Table A5
Excess buy order in Round 1: Random-effects panel regressions with market-level characteristics (first five periods excluded).

Variables	(1)	(2)	(3)	(4)	(5)
			Dependent variable: Excess buy order		
Risk Average	0.419***				0.269**
	(0.127)				(0.116)
Risk St.Dev.	0.095				3.572*
	(1.838)				(2.027)
Cognitive Average		– 186.7*			– 151.0
		(103.1)			(98.25)
Cognitive St.Dev.		286.0*			– 54.47
		(149.3)			(152.6)
Share of Females			66.34**		81.60**
			(29.27)		(40.03)
Str. Unc. Average				392.1	– 410.9
				(449.9)	(264.6)
Assets lagged	– 34.09	– 23.62	– 21.10	– 25.66	– 35.35*
	(24.80)	(18.94)	(13.25)	(22.97)	(19.99)
Cash lagged	– 0.015	– 0.015	– 0.004	– 0.009	– 0.022**
	(0.013)	(0.010)	(0.008)	(0.015)	(0.009)
Concentration	390.5	456.5	163.4	536.1	1.605
	(304.8)	(396.2)	(569.4)	(398.5)	(463.2)
Market Price lagged	0.129	0.086	0.114	0.156	0.061
	(0.195)	(0.185)	(0.191)	(0.212)	(0.161)
Dividend lagged	0.129	0.053	0.094	0.125	– 0.026
	(0.168)	(0.133)	(0.153)	(0.177)	(0.148)
Remaining Period	10.80	42.99	25.50	25.01	22.90
	(41.82)	(42.18)	(47.92)	(44.04)	(39.30)
Remaining Period Squared	– 1.871	– 4.458**	– 2.417	– 3.311	– 2.339
	(2.592)	(1.990)	(2.826)	(2.218)	(2.422)
Constant	– 6.982	157.1	– 49.29	– 76.84	372.4
	(215.5)	(271.0)	(169.2)	(267.7)	(353.4)
Observations	107	107	107	107	107
Number of sid	59	59	59	59	59

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Appendix F. Excess sell orders

Table A6
Excess sell order in Round 1: Random-effects panel regressions with individual characteristics (first five periods excluded).

Variables	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Excess sell order				
Risk Tolerance	0.184*				0.124
	(0.111)				(0.116)
Cognitive Abilities		– 15.31			– 6.961
		(49.20)			(60.84)
Female			65.11		54.85
			(100.3)		(84.21)
Strategic Uncertainty				158.7	135.3
				(129.4)	(130.3)
Assets lagged	2.380	4.596	9.825	– 6.382	7.997
	(41.59)	(38.80)	(40.82)	(46.61)	(44.35)
Cash lagged	0.059***	0.055***	0.055***	0.060***	0.066***
	(0.018)	(0.015)	(0.016)	(0.018)	(0.019)
Concentration	178.7	162.2	141.8	82.17	– 16.76
	(269.3)	(236.7)	(323.8)	(301.4)	(231.7)
Market Price lagged	0.121	0.156	0.143	0.119	0.075
	(0.170)	(0.164)	(0.166)	(0.181)	(0.178)
Dividend lagged	– 0.303	– 0.376	– 0.383	– 0.376*	– 0.383
	(0.323)	(0.307)	(0.318)	(0.224)	(0.306)
Remaining Period	292.6***	300.8***	298.1***	286.4***	285.3**
	(98.65)	(98.03)	(93.93)	(106.3)	(114.7)
Remaining Period Squared	– 25.55***	– 26.99***	– 27.12***	– 25.39***	– 25.26**
	(9.793)	(9.124)	(9.059)	(9.392)	(11.19)
Constant	– 966.6***	– 827.1***	– 855.0***	– 824.1***	– 915.3***
	(251.4)	(218.3)	(215.0)	(246.5)	(249.8)
Observations	32	32	32	32	32
Number of sid	23	23	23	23	23

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A7
Excess sell order in Round 1: Random-effects panel regressions with market-level characteristics (first five periods excluded).

Variables	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Excess sell order				
Risk Average	0.141				– 0.0812
	(0.0993)				(0.117)
Risk St.Dev.	0.804				0.383
	(1.508)				(1.596)
Cognitive Average		– 257.6***			– 241.8***
		(82.17)			(46.92)
Cognitive St.Dev.		143.5			58.73
		(126.6)			(157.7)
Share of Females			1.797		1.906
			(27.57)		(32.92)
Str. Unc. Average				628.2***	517.9**
				(214.2)	(242.4)
Assets lagged	3.272	– 23.08	1.254	– 0.764	– 20.36
	(44.83)	(26.44)	(42.91)	(38.30)	(35.41)
Cash lagged	0.060***	0.037**	0.054***	0.045***	0.033
	(0.019)	(0.015)	(0.020)	(0.011)	(0.020)
Concentration	171.4	– 49.55	177.7	49.23	– 194.8
	(272.0)	(220.8)	(314.4)	(243.5)	(214.3)
Market Price lagged	0.141	0.116	0.153	0.232**	0.171
	(0.161)	(0.119)	(0.171)	(0.114)	(0.122)
Dividend lagged	– 0.303	– 0.556***	– 0.362	– 0.447	– 0.614**
	(0.343)	(0.155)	(0.311)	(0.280)	(0.257)
Remaining Period	291.7***	333.8***	300.6***	335.2***	358.2***
	(105.6)	(95.57)	(95.24)	(106.0)	(130.0)
Remaining Period Squared	– 25.53**	– 30.23***	– 27.01***	– 30.22***	– 32.78***
	(10.27)	(9.187)	(9.106)	(9.249)	(11.90)
Constant	– 983.3***	– 425.0	– 838.4***	– 1257***	– 644.9
	(285.7)	(466.3)	(225.2)	(250.8)	(540.1)
Observations	32	32	32	32	32
Number of sid	23	23	23	23	23

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Appendix G. Round-2 panel regressions

G1. Excess buy order in Round 2 - market level

Table A8

Table A8
Excess buy order in Round 2: Random-effects panel regressions with market-level characteristics in Round 2 (first five periods excluded).

Variables	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Excess buy order				
Risk Average	– 0.000923				– 0.00533
	(0.0426)				(0.0306)
Risk St.Dev.	– 0.265				– 0.155
	(0.512)				(0.337)
Cognitive Average		– 22.16			– 20.97
		(15.46)			(26.56)
Cognitive St. Dev.		108.3***			88.05***
		(28.77)			(23.75)
Share of Females			13.20**		4.537
			(6.713)		(5.010)
Str. Unc. Average				93.03	18.80
				(64.76)	(69.40)
Assets lagged	– 6.627	– 4.212	– 5.399	– 7.139	– 3.674
	(4.172)	(4.431)	(4.772)	(4.855)	(4.693)
Cash lagged	– 0.0146**	– 0.00964	– 0.0105	– 0.0138**	– 0.00856
	(0.00731)	(0.00718)	(0.00710)	(0.00570)	(0.00864)
Concentration	– 59.70	– 264.7	– 230.1	– 81.09	– 287.5
	(203.5)	(178.3)	(199.2)	(198.7)	(212.6)

(continued on next page)

Table A8 (*continued*)

Variables	(1) Dependent variable: Excess buy order	(2)	(3)	(4)	(5)
Market Price lagged	1.007***	0.941***	0.948***	0.996***	0.925***
	(0.0301)	(0.0515)	(0.0451)	(0.0289)	(0.0692)
Dividend lagged	0.0826	0.0710	0.119	0.0958	0.0910
	(0.0889)	(0.0888)	(0.0958)	(0.0836)	(0.104)
Remaining Period	– 124.9***	– 108.9***	– 113.1***	– 122.7***	– 105.9***
	(24.67)	(30.53)	(29.18)	(23.25)	(34.45)
Remaining Period Squared	1.804	1.271	1.373	1.753	1.126
	(1.938)	(2.289)	(2.231)	(1.893)	(2.549)
Constant	– 108.4	– 203.4*	– 145.8	– 165.2**	– 196.7
	(75.14)	(110.6)	(90.37)	(79.37)	(155.9)
Observations	79	79	79	79	79
Number of sid	48	48	48	48	48

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

G2. *Excess sell order in Round 2 - individual level*

Table A9

Table A9
Excess sell order in Round 2: Random-effects panel regressions with individual characteristics in Round 2 (first five periods excluded).

Variables	(1) Dependent variable: Excess sell order	(2)	(3)	(4)	(5)
Risk Tolerance	0.0352				0.0617
	(0.136)				(0.209)
Cognitive Abilities		16.33			17.89
		(32.60)			(32.68)
Female			– 24.01		– 10.34
			(86.01)		(123.9)
Strategic Uncertainty				– 15.25	– 24.16
				(88.82)	(126.8)
Assets lagged	– 21.16	– 30.07	– 23.89	– 22.19	– 29.42
	(57.78)	(63.15)	(61.12)	(60.21)	(85.75)
Cash lagged	– 0.0867	– 0.0958	– 0.0882	– 0.0881	– 0.0983
	(0.107)	(0.110)	(0.111)	(0.108)	(0.133)
Concentration	– 1661	– 1673	– 1622	– 1668	– 1781
	(1724)	(1741)	(1726)	(1706)	(1819)
Market Price lagged	– 0.00528	– 0.0161	0.00584	– 0.00627	– 0.0414
	(0.495)	(0.493)	(0.493)	(0.498)	(0.536)
Dividend lagged	– 0.126	– 0.106	– 0.124	– 0.124	– 0.100
	(0.223)	(0.230)	(0.232)	(0.236)	(0.294)
Remaining Period	– 72.66	– 84.06	– 77.17	– 74.18	– 82.70
	(68.84)	(74.04)	(74.34)	(72.48)	(106.3)
Remaining Period Squared	2.878	3.526	3.076	2.955	3.551
	(6.063)	(6.275)	(6.412)	(6.318)	(8.363)
Constant	1,289	1,411	1,336	1,339	1,430
	(1679)	(1672)	(1731)	(1653)	(2079)
Observations	32	32	32	32	32
Number of sid	23	23	23	23	23

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

G3. *Excess sell order in Round 2 - market level*

Table A10

Table A10
Excess buy order in Round 2: Random-effects panel regressions with market-level characteristics in Round 2 (first five periods excluded).

Variables	(1) Dependent variable: Excess sell order	(2)	(3)	(4)	(5)
Risk Average	0.0909				– 0.206
	(0.123)				(0.138)
Risk St.Dev.	– 1.713				3.132**
	(1.828)				(1.420)
Cognitive Average		– 238.4**			– 57.59
		(116.1)			(132.0)
Cognitive St.Dev.		10.62			– 538.0*
		(188.6)			(319.7)
Share of Females			41.38		88.82**
			(32.56)		(45.12)
Str. Unc. Average				88.97	112.8
				(264.9)	(324.7)
Assets lagged	– 17.39	– 36.77	– 16.80	– 24.71	– 1.385
	(56.94)	(69.02)	(55.99)	(62.04)	(42.54)
Cash lagged	– 0.0902	– 0.123	– 0.0889	– 0.0901	– 0.0520
	(0.104)	(0.124)	(0.0986)	(0.111)	(0.0883)
Concentration	– 1902	– 2438	– 1879	– 1660	– 1195
	(1728)	(1933)	(1686)	(1743)	(1550)
Market Price lagged	– 0.0561	– 0.208	– 0.0755	– 0.0108	0.106
	(0.495)	(0.569)	(0.462)	(0.510)	(0.428)
Dividend lagged	– 0.118	– 0.0258	– 0.116	– 0.117	– 0.178
	(0.218)	(0.277)	(0.200)	(0.240)	(0.142)
Remaining Period	– 68.31	– 98.28	– 61.85	– 77.14	– 59.13
	(69.26)	(83.30)	(70.32)	(73.72)	(51.06)
Remaining Period Squared	2.877	5.513	2.607	3.167	2.319
	(5.913)	(7.252)	(5.740)	(6.445)	(4.838)
Constant	1394	2294	1244	1312	1261
	(1645)	(2187)	(1589)	(1618)	(1555)
Observations	32	32	32	32	32
Number of sid	23	23	23	23	23

Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

References

Akiyama, E., Hanaki, N., & Ishikawa, R. (2017). It is not just confusion! Strategic uncertainty in an experimental asset market. *The Economic Journal, 127*(605), F563–F580.

Andersson, O., Holm, H. J., Tyran, J.-R., & Wengström, E. (2016). Risk aversion relates to cognitive ability: Preferences or noise? *Journal of the European Economic Association, 14*(5), 1129–1154. https://doi.org/10.1111/jeea.12179

Benjamin, D. J., Brown, S. A., & Shapiro, J. M. (2013). Who is 'behavioral'? Cognitive ability and anomalous preferences. *Journal of the European Economic Association, 11*(6), 1231–1255. https://doi.org/10.1111/jeea.12055

Bertrand, M. (2011). New perspectives on gender, *vol. 4. Handbook of labor economics* (pp. 1543–1590). Elsevier.

van Boening, M. V., Williams, A. W., & LaMaster, S. (1993). Price bubbles and crashes in experimental call markets. *Economics Letters, 41*(2), 179–185.

Bosch-Rosa, C., Meissner, T., & Bosch-Domènech, A. (2018). Cognitive bubbles. *Experimental Economics, 21*(1), 132–153.

Branas-Garza, P., Kujal, P., & Lenkei, B. (2019). Cognitive reflection test: Whom, how, when. *Journal of Behavioral and Experimental Economics, 82*, 101455.

Breaban, A., & Noussair, C. N. (2015). Trader characteristics and fundamental value trajectories in an asset market experiment. *Journal of Behavioral and Experimental Finance, 8*, 1–17.

Burks, S. V., Carpenter, J. P., Goette, L., & Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences, 106*(19), 7745–7750.

Carlé, T. A., Lahav, Y., Neugebauer, T., & Noussair, C. N. (2019). Heterogeneity of beliefs and trade in experimental asset markets. *Journal of Financial and Quantitative Analysis, 54*(1), 215–245. https://doi.org/10.1017/S0022109018000571

Charness, G., & Gneezy, U. (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behavior & Organization, 83*(1), 50–58.

Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization, 87*, 43–51.

Charness, G., & Neugebauer, T. (2019). A test of the Modigliani-Miller invariance theorem and arbitrage in experimental asset markets. *The Journal of Finance, 74*(1), 493–529.

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.

Corgnet, B., Hernán-González, R., Kujal, P., & Porter, D. (2015). The effect of earned versus house money on price bubble formation in experimental asset markets*. *Review of Finance, 19*(4), 1455–1488.

Crosetto, P., & Filippin, A. (2013). The "bomb" risk elicitation task. *Journal of Risk and Uncertainty, 47*(1), 31–65.

Crosetto, P., & Filippin, A. (2016). A theoretical and experimental appraisal of four risk elicitation methods. *Experimental Economics, 19*(3), 613–641.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature, 47*(2), 448–474. http://www.aeaweb.org/articles?id=10.1257/jel.47.2.448.

Cueva, C., & Rustichini, A. (2015). Is financial instability male-driven? Gender and cognitive skills in experimental asset markets. *Journal of Economic Behavior & Organization, 119*, 330–344. http://www.sciencedirect.com/science/article/pii/S0167268115002309.

Dickinson, D. L. (2009). The effects of beliefs versus risk attitude on bargaining outcomes. *Theory and Decision, 66*, 69–101.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *American Economic Review, 100*(3), 1238–1260. http://www.aeaweb.org/articles?id=10.1257/aer.100.3.1238.

Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2018). On the relationship between cognitive ability and risk preference. *Journal of Economic Perspectives, 32*(2), 115–134.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association, 9*(3), 522–550.

Dufwenberg, M., Lindqvist, T., & Moore, E. (2005). Bubbles and experience: An experiment. *American Economic Review, 95*(5), 1731–1737.

Eckel, C. C., & Füllbrunn, S. C. (2015). Thar SHE blows? Gender, competition, and bubbles in experimental asset markets. *American Economic Review, 105*(2), 906–920.

Eckel, C. C., & Füllbrunn, S. C. (2017). Hidden vs. known gender effects in experimental asset markets. *Economics Letters, 156*, 7–9.

Eckel, C. C., & Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. In C. Plott, & V. Smith (Eds.), *Handbook of experimental economics results* (pp. 1061–1073). New York: Elsevier.

El-Sehity, T., Haumer, H., Helmenstein, C., Kirchler, E., & Maciejovsky, B. (2002). Hindsight bias and individual risk attitude within the context of experimental asset markets. *Journal of Psychology and Financial Markets, 3*(4), 227–235.

Fellner, G., & Maciejovsky, B. (2007). Risk attitude and market behavior: Evidence from experimental asset markets. *Journal of Economic Psychology, 28*(3), 338–350. http://www.sciencedirect.com/science/article/pii/S0167487007000086.

Filippin, A., & Crosetto, P. (2016). A reconsideration of gender differences in risk attitudes. *Management Science, 62*(11), 3138–3160.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics, 10*(2), 171–178. https://doi.org/10.1007/s10683-006-9159-4

Fossen, F. (2012). Risk attitudes and private business equity. In D. Cummings (Ed.), *The Oxford handbook of entrepreneurial finance*. New York: Oxford University Press.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives, 19*(4), 25–42.

Füllbrunn, S., Janssen, D.-J., & Weitzel, U. (2019). Risk aversion and overbidding in first price sealed bid auctions: New experimental evidence. *Economic Inquiry, 57*(1), 631–647.

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics, 112*(2), 631–645.

Green, C., Jegadeesh, N., & Tang, Y. (2009). Gender and job performance: Evidence from wall street. *Financial Analysts Journal, 65*(6), 65–78.

Hanaki, N., Akiyama, E., Funaki, Y., Ishikawa, R., et al. (2017). Diversity in cognitive ability enlarges mispricing in experimental asset markets. *Technical Report*. Groupe de REcherche en Droit, Economie, Gestion (GREDEG CNRS), University of Nice Sophia Antipolis.

Hanaki, N., Akiyama, E., & Ishikawa, R. (2018a). Behavioral uncertainty and the dynamics of traders' confidence in their price forecasts. *Journal of Economic Dynamics and Control, 88*, 121–136.

Hanaki, N., Akiyama, E., & Ishikawa, R. (2018b). Effects of different ways of incentivizing price forecasts on market dynamics and individual decisions in asset market experiments. *Journal of Economic Dynamics and Control, 88*, 51–69.

Haruvy, E., Lahav, Y., & Noussair, C. N. (2007). Traders' expectations in asset markets: Experimental evidence. *American Economic Review, 97*(5), 1901–1920. http://www.aeaweb.org/articles?id=10.1257/aer.97.5.1901.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review, 92*(5), 1644–1655.

Holt, C. A., Porzio, M., & Song, M. Y. (2017). Price bubbles, gender, and expectations in experimental asset markets. *European Economic Review, 100*, 72–94.

Horn, D., & Kiss, H. J. (2018). Which preferences associate with school performance? – Lessons from an exploratory study with university students. *PloS one, 13*(2), e0190163.

Huber, J., Palan, S., & Zeisberger, S. (2019). Does investor risk perception drive asset prices in markets? Experimental evidence. *Journal of Banking & Finance, 108*, 105635.

Janssen, D.-J., Füllbrunn, S., & Weitzel, U. (2018). Individual speculative behavior and overpricing in experimental asset markets. *Experimental Economics*, 1–23.

Janssen, D.-J., Füllbrunn, S., & Weitzel, U. (2019). Individual speculative behavior and overpricing in experimental asset markets. *Experimental Economics, 22*(3), 653–675.

Janssen, D. T. (2017). *Birds of a feather: Price dynamics and trading behavior in composed markets*. [Sl: sn]. Ph.D. thesis.

Kirchler, E., & Maciejovsky, B. (2002). Simultaneous over- and underconfidence: Evidence from experimental asset markets. *Journal of Risk and Uncertainty, 25*(1), 65–85. https://doi.org/10.1023/A:1016319430881

Kirchler, E., Maciejovsky, B., & Weber, M. (2005). Framing effects, selective information, and market behavior: An experimental analysis. *Journal of Behavioral Finance, 6*(2), 90–100.

Kocher, M. G., Lucks, K. E., & Schindler, D. (2019). Unleashing animal spirits: Self-control and overpricing in experimental asset markets. *The Review of Financial Studies, 32*(6), 2149–2178. https://doi.org/10.1093/rfs/hhy109

Lazear, E. P., & Shaw, K. L. (2007). Personnel economics: The economist's view of human resources. *Working Paper 13653*. National Bureau of Economic Research. http://www.nber.org/papers/w13653.

Lei, V., Noussair, C. N., & Plott, C. R. (2001). Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality. *Econometrica, 69*(4), 831–859. http://www.jstor.org/stable/2692246.

Maciejovsky, B., Kirchler, E., & Schwarzenberger, H. (2007). Misperception of chance and loss repair: On the dynamics of tax compliance. *Journal of Economic Psychology, 28*(6), 678–691. http://www.sciencedirect.com/science/article/pii/S0167487007000128.

Michailova, J., & Schmidt, U. (2016). Overconfidence and bubbles in experimental asset markets. *Journal of Behavioral Finance, 17*(3), 280–292.

Miller, R. M. (2002). Can markets learn to avoid bubbles? *Journal of Psychology and Financial Markets, 3*(1), 44–52.

Niederle, M. (2016). Gender*, vol. 2. Handbook of experimental economics* (pp. 481–553). Princeton University Press.

Noussair, C. N., & Powell, O. (2010). Peaks and valleys: Price discovery in experimental asset markets with non-monotonic fundamentals. *Journal of Economic Studies, 37*(2), 152–180. https://doi.org/10.1108/01443581011043564

Oechssler, J., Schmidt, C., & Schnedler, W. (2011). On the ingredients for bubble formation: Informed traders and communication. *Journal of Economic Dynamics and Control, 35*(11), 1831–1851. https://doi.org/10.1016/j.jedc.2011.05.009

Palan, S. (2013). A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys, 27*(3), 570–588. https://doi.org/10.1111/joes.12023

Palan, S. (2015). Gims-software for asset market experiments. *Journal of Behavioral and Experimental Finance, 5*, 1–14. http://www.sciencedirect.com/science/article/pii/S2214635015000039.

Parliament, E. (2014). On markets in financial instruments and amending directive 2002/92/EC and directive 2011/61/EU. *EP Directive 2014/65/EU*. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32014L0065.

Parliament, E. (2016). On insurance distribution. *EP Directive 2016/97/EU*.

Porter, D. P., & Smith, V. L. (1995). Futures contracting and dividend uncertainty in experimental asset markets. *The Journal of Business, 68*(4), 509–541. href="http://www.jstor.org/stable/2353144.

Porter, D. P., & Smith, V. L. (2008). Price bubbles. In C. Plott, & V. Smith (Eds.), *Handbook of experimental economics results* (pp. 247–255). Amsterdam: North Holland.

Powell, O. (2016). Numeraire independence and the measurement of mispricing in experimental asset markets. *Journal of Behavioral and Experimental Finance, 9*, 56–62.

Powell, O., & Shestakova, N. (2016). Experimental asset markets: A survey of recent developments. *Journal of Behavioral and Experimental Finance, 12*, 14–22. http://www.sciencedirect.com/science/article/pii/S2214635016300399.

Sapienza, P., Zingales, L., & Maestripieri, D. (2009). Gender differences in financial risk aversion and career choices are affected by testosterone. *Proceedings of the National Academy of Sciences, 106*(36), 15268–15273.

Scherbina, A., & Schlusche, B. (2014). Asset price bubbles: A survey. *Quantitative Finance, 14*(4), 589–604.

Smith, V. L., Suchanek, G. L., & Williams, A. W. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica, 56*(5), 1119–1151. http://www.jstor.org/stable/1911361.

Stöckl, T., Huber, J., & Kirchler, M. (2010). Bubble measures in experimental asset markets. *Experimental Economics, 13*(3), 284–298.

Sutter, M., Kocher, M. G., Glätzle-Rützler, D., & Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review, 103*(1), 510–531.

Wang, J., Houser, D., Xu, H., et al. (2017). Do females always generate small bubbles? Experimental evidence from US and China. *Technical Report*.