Charles University

Faculty of Social Sciences

Institute of Economic Studies

MASTER'S THESIS

Emotional Anchoring in Experimental Asset Markets

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, January 6, 2017

Signature

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ABSTRACT

Human decision making process is influenced by many external as well as internal factors. Our behaviour cannot be deemed as fully rational. This thesis investigates the effect of emotional anchoring on a propensity to enter an asset bubble. This effect was observed in an experiment ran on an online crowdsourcing platform, Amazon Mechanical Turk. The negative anchor proves to have a significant negative effect, i.e. when a subject is under the negative anchor she is more prone to enter the bubble. The positive anchor does not have any significant effect. This thesis contributes to the general knowledge by confirming that trading decisions we make are subjected to the emotions we feel prior to making the decisions.

JEL Classification	C72, C91, D03, D53
Keywords	Bubble game, anchoring, emotions

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ABSTRAKT

Lidské rozhodování je ovlivněno mnoha externími i interními faktory. Naše chování nelze považovat za zcela racionální. Tato práce zkoumá efekt emočního ukotvení na náchylnost ke vstupu do akciové bubliny. Tento efekt byl pozorován v rámci experimentu, který probíhal na online crowdsourcingové platformě Amazon Mechanical Turk. Negativní ukotvení ukázalo signifikantní negativní efekt, tj. subjekt pod negativní kotvou byl náchylnější ke vstupu do bubliny. Pozitivní ukotvení neprokázalo žádný signifikantní efekt. Závěry této práce přispívají potvrzením skutečnosti, že naše rozhodnutí ohledně obchodování jsou ovlivněny emocemi, které cítíme před rozhodnutím.

Klasifikace	C72, C91, D03, D53
Klíčová slova	Bubble game, ukotvení, emoce

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Proposed Topic:

Anchoring in Experimental Assets Markets.

Motivation:

Historical development suggests that financial markets are susceptible to bubbles and follow-up crashes. Recent rise in share price to unprecedented figures may suggest that another crash may occur again in not-so-distant future. Since fundamental value is an unobservable factor, it is impossible to demonstrate whether crashes are caused by mispricing. Experiments come to hand in the case of testing various reasons for bubble origin. The topic I will be interested in is anchoring - specifically, how emotional anchoring influences trading choices and whether emotional anchor encourages or reduces bubbles occurrence.

Anchoring is a phenomenon which has unquestionable effect on our decisions. This fact has been shown in numerous experiments; for example Ariely et al (2003) ran an experiment in which participants were asked whether they would buy chosen items for the price equal to the last two digits of their social security number and consequently what would be the highest price they would be willing to pay for these items. The results showed that subjects with above-median social security number stated numbers from 57% to 107% greater highest price than subjects with below-median numbers. Baghestanian and Walker (2015) have shown that anchoring via visual stimuli (visual anchor at fundamental value) mitigates bubbles in experimental asset markets, if the anchor in this form is provided in the first period. Even though experimental asset markets settings are somewhat different to those of bubble game (which I will employ in my experiment), because bubble game is a simultaneous one-shot game, but since anchoring is a psychological phenomenon, its effect should be present in both experimental designs. I am interested in emotion as stated by Ackert et. al. (2003) and their mention of Damasio (1994), who found that emotions are important part of decision making and that without emotions our ability to make choices is impaired. Damasio also points to emotions and rational decisions being complementary rather than emotional response being irrational. Ackert et al. (2003) further show that positive mood enhances individual performance and allow individuals to better organize and use information. This would be the motivation for my research - to test whether positive anchoring can reduce occurrence of bubbles and whether negative anchor increases it.

Hypotheses:

1. Hypothesis #1: Bubbles arise in experimental market situation
2. Hypothesis #2: Positive emotional anchor reduces possibility and size of a bubble
3. Hypothesis #3: Negative emotional anchor increases possibility and size of a bubble

Methodology:

Since it is impossible to observe particular psychological aspects effecting behaviour and choices in real world, we use experimental settings to control for those effects which do not interest us. I will use settings for bubble game as carried out by Moinas and Pouget (2013), which are as follows: each player in group of three is endowed with one monetary unit and can chose to buy a no-dividend generating asset for one unit. With each purchase the asset price increases ten times. If needed, external "financing" is provided to participants by financial partner who is not part of the game but shares participants' profit. In addition an emotional anchor in the form of either shorts texts or other technically available stimuli (either negative or positive) will be introduced at the beginning of the game to each participant (with the exception of the control group). The experiment will be run on Amazon Mechanical Turk (MTurk) which is a crowdsourcing internet marketplace platform that can be used to post jobs, known as HITs (Human Intelligence Tasks), which employ human participants who are rewarded with small monetary prize. At the moment these participants are limited solely to those who are US-based. Testing will be done using logistic regression.

Expected Contribution:

Much research has been done on bubbles in financial markets and the bubble game has become the popular choice for experimental research. Also behavioural economics is increasingly popular with its challenges and criticism of classical approach. With my research I would like to combine these two and provide some insight on the influence of emotions on our choices, specifically in the bubble game, with respect to bubbles in financial markets. Since stock indices have seen five years of growth to unprecedented heights and with Greek crisis in Europe and ISIS threat in the Middle East, we might be experiencing period of bubble trading, that is repetitively anchored by negative emotions (through media).

Outline:

1. Motivation; bubbles are repeatedly occurring in financial markets
2. Literature review; Research already done on both bubble games and anchoring
3. Experiment design and procedures; I will describe the experiment itself and the data gathered
4. Results; Discussion of tests and comparison of effects of negative and positive anchor
5. Conclusion; Summary of results and their potential implications and possibilities for further research

Core Bibliography:

Ackert, Lucy F. and Charupat, Narat and Deaves, Richard and Kluger, Brian, The Origins of Bubbles in Laboratory Asset Markets (May 2006). FRB of Atlanta Working Paper No. 2006-6. Available at SSRN: http://ssrn.com/abstract=903159

Baghestanian, Sascha and Walker, Todd B., Anchoring in Experimental Asset Markets (February 10, 2014). SAFE Working Paper No. 54. Available at SSRN: http://ssrn.com/abstract=2456941

Damasio, Antonio R. 1994. Descartes' error: Emotion,
reason, and the human brain. New York: Putnam.

Kahneman, Daniel. 2003. "Maps of Bounded Rationality: Psychology for Behavioral Economics." American Economic Review, 93(5): 1449-1475

Moinas, S. and Pouget, S. (2013), The Bubble Game: An Experimental Study of Speculation. Econometrica, 81: 1507–1539. doi: 10.3982/ECTA9433

Smith V., G. Suchanek, and A. Williams, 1988, Bubbles, Crashes, and Endogenous
Expectations in Experimental Spot Asset Markets, Econometrica, 56, 1119-1151.

Author **Supervisor**

1. INTRODUCTION

Our decisions, even though we tend not to think so, are not based only on our personal internal reasons and objectives. They are also influenced by many external factors, maybe even more than we are willing to admit. Bounded rationality, framing effects, anchoring and effect of emotions, among many, are the cases that violate the rationality assumptions of various economic models which the various researches have identified. Our daily life decisions are affected, see for example the research of Ariely, Shampanier and Mazar (2007) and their investigation of the zero price which disproportionately changes the consumers' decisions. Kahneman and Tversky (1981) showed how different framing of a choice option completely changes our point of view or the study of Kahneman (2003) in which he explored the consequences of bounded rationality. He explored the systematic biases in rational-agent models. These biases were the result of separate beliefs that people have about the consequent choices they make. One of the most interesting studies carried out in the last 10 years, from my point of view, is the one by Edmans, García and Norli (2007). It studied how results of sports matches and football matches especially influence stock returns on the day following the match. They found out, that losses of national teams negatively affect the stock returns on the following trading day. Wins however did not have any significant effect. Some of the factors that influence our behaviour and final decision could be quite understandable and presumable, such as good performance of a favoured sports team or the amount of sunshine or the weather in general. Hirt at al. (1992) found out, that college students deem their own performance to be better after watching their college basketball team win and deem it worse after watching the team lose. Some factors on the other might one find surprising. An example of such surprising factor could be the lunar cycles. This phenomenon was investigated by Yuan, Zeng and Zhu (2006). They found out that stock returns are lower on days around the full moon than around the new moon. Another example is the study of Frieder and Subrahmanyam (2004) who found abnormally positive returns around the Jewish festivity of Yom Kippur and negative returns around another Jewish festivity of Hashanah.

The objective of this thesis is to further explore how our decision making process is impaired by external influences. Specifically, how emotions affect the propensity to enter stock market bubbles. If the asset prices are above its the fundamental value for prolonged period of time, we then speak of a bubble. Bubbles are also followed – after some time – by a decrease in prices towards the fundamental value (which is observable only as an aggregate provided by e competitive market, while the individual fundamental values are unobservable), i.e. a crash. Bubbles usually lead to over-investment and misallocation of capital, because the investors are not endowed with the right information about the market. Since the crash of a bubble makes the investments in overpriced assets unprofitable, the consequences are, not in all cases and not for all investors, wealth redistribution and spillover of the crash consequences to different markets or countries. There has been a number of bubbles in the history throughout the time, from the oldest ones like the Dutch Tulip Mania (1634-1637), the South Sea and Mississippi Bubbles (1716-1720) to more recent ones the Stock Market Crash in 1929, Black Monday crash in 1987 to the most recent ones, the Dot-Com Bubble in late 1990's and the US real estate bubble that popped in 2008/09.

I am interested in how positive and negative emotions affect human decision to enter a bubble. In order to explore the effect, I use anchoring. It means, that a subject is inconspicuously influenced and a specific information is put into their subconscious. This information is then recalled when a similar information is encountered or needed. Examples of how anchoring works can be found in Ariely, Loewenstein and Prelec (2006), where they showed how an unrelated information as the last three digits of participants' social security number affects the amount that participants were willing to bid in a wine auction. Baghestanian and Walker (2015) explored how visual anchor affects price patterns in an experimental asset market (EAM). I follow a similar course; I set up a bubble game, a type of centipede game, and anchored the participants by showing them either positive or negative pictures and observed their consequent decision. They were to decide whether or not they buy an asset for the proposed price. The game was set up in a way, that every buy decision meant entering the bubble.

The results showed, that the negatively anchored participants were more prone to enter the bubble. I tested whether the different treatment groups were of the same distribution. The results showed no significant result but pointed to the fact that the emotional anchors might have some effect on the buy decision. The significant effect of negative anchor was confirmed by two logit regressions, first with the treatment variables – anchors – only and the second with all obtained variables – anchors, education, age, sex, trading experience and similar survey experience. The second regression also showed that the people aged 45-54 are less prone to enter the bubble. The positive anchor showed no significant effect, neither did any of the other supplementary variables. The negative effect of negative anchor corresponds to the findings of Arkes, et al., (1988), Geva & Isen, (1987) and Isen & Patrick, (1983) that happy people more often avoid meaningful risks. My findings contribute to the current literature in the way that it further confirms that trading decisions we make are subjected to the emotions we feel prior to making the decisions. It also points to the fact, when it comes to stock trading, that the negative emotions worsen our assessment or overestimate our beliefs in others' consequent behaviour, whereas the positive emotion makes our judgement neither better nor worse. This result is supported by the findings of Isen (2001) and Isen & Carnevale (1986). Future research might aim on the effect of the emotion power or magnitude on our decision, because even the positive anchor showed some although insignificant effect on the subjects' decision in my experiment.

The thesis is structured as follows; the second section provides a literature review. Firstly, the various effects of emotions on decision making are discussed, next various types of experimental game designs are introduced. The third section describes two models – Quantal Response and Analogy-based expectations – that could be used to predict the behaviour in the centipede and the bubble games respectively. Quantal Response model is further divided into three sub-models with different assumptions about the decision making process. A theoretical use for prediction is introduced for both models. The fourth section describes the main experiment, namely the experimental environment, the design of the experiment, how the emotional anchor was set and how were the participants incentivised to take part in the experiment. Fifth section describes the data collected and the results of various tests and the sixth section concludes.

2. Literature Review

The following section reviews previously conducted researches and experiments, that are related or of significance to my experiment, I review papers exploring emotions, basic principles of human decision making and various game designs for exploring and testing human behaviour.

2.1. Emotions

When one takes a look at what effect different emotions may have at our decision process, one may find contradictory results; Isen (2001) arrives to the point, that positive affect improves our skills as long as the situation is either interesting or important. In particular the author concludes that when people are positively affected, this positive affect makes them more creative, cognitively flexible, they are responding more innovatively and are more open to information. Carnevale & Isen (1986) found out that happy people show higher levels of cognitive flexibility and openness to information and they are better at taking other party's perspective in negotiations. This finding is further supported by the fact that positively affected people are better at solcing problems. Among other findings is the fact, that positively affected people more often avoid a real and meaningful risk Arkes, et al., (1988), Geva & Isen, (1987) and Isen & Patrick, (1983), and that these people may have a greater negative utility for a loss, Nygren, et al., (1996). This is extremely important skill in situations when ones benefits depend on the anticipated decisions of others such as stock markets or experimental asset markets. The latter is the most important finding for this paper since I will be employing EAM in my experiment. In conclusion, Isen (2001) arrives to the result that being set in a good mood enhances our abilities and improves our results. But one may also argue that happiness and accompanying excitement distract and therefore impair our performance.

Bless et al. (1996) studied how moods, happy or sad, influence our choice process. They tested the hypotheses that happy moods induce scripted problem assessment, in other words that happy people rely on rooted and therefore automated problem analysis, and that sad people employ ad hoc analysis and thusly they carry out analysis specific to each problem. These hypotheses are based on previous research, which can be summarized as follows; positive state (calm and peaceful state without a sign of danger) leads the organism to behave based on habits and negative state engages learning (when fear or anxiety is felt the organism needs to cope), Gray (1971). The research of Wegener, Patty and Smith (1995) further argues, that happy individuals do not avoid investing cognitive effort in various tasks as long as these promise to keep them happy or ehance their happiness. This points to the fact that happy states do not signal for any particular action, whereas the negative states on the other hand might signal, that a situation poses a problem and an appropriate action is needed. (*It is crucial to mention that number of these arguments depend on the postulator's point of view*).

In their first experiment Bless et al. (1996) found out, that happy people do rely on scripted behaviour. During the experiment, the authors presented subjects with a „going out for a dinner" story, after which the subjects, in either happy or sad induced mood, should have recognized related or unrelated information to the story. Some information were mentioned in the story and some were not. They also found that happy people make more errors regarding the story related information meaning that happy people wrongly associated more information with a presented story. This could be a crucial finding related to human behaviour on stock markets; if this finding really is true and correct, it could mean that market participants overreact to what they wrongly believe to be relevant and related circumstances. This would not specifically apply for my experimental design, its intepretation would be precarious to say the least, but it certainly may play its role. Participants with induced sad mood made fewer errors on related items recognition as confirmed by the first experiment. Interestingly enough both groups, happy and sad, performed equally well concering items unrelated to the story presented in the experiment. The second hypothesis, more relevant to my research, investigates; since happy people employ general knowledge structures, and thus use less effort, they could use this saved mental capacity on other tasks. This was tested in a similar design as in the first experiment, with the exception that the participants were given a secondary task during a faked technical problems and thus having two tasks assigned at once. As expected, happy participants performed better at the secondary task than participants in neutral or sad mood. The authors concluded, that happy participants' reliance on script-based processing allowed them to use additional mental resources on the additional task. This result was impaired when happy participants were presented with larger amount of atypical[1] related items, since these used up more of their mental resources and they could spare less of it on the secondary task. This equalized the performance of happy and sad participants.

The effect of different emotions to behaviour on stock markets (and EAM) is however very difficult to predict. As stated above, happy mood makes us more flexible, creative, more open minded. In my case, probably the most important enhancement would be improving one's

[1] Atypical item is related to the story but it can't be identified using the scripted analysis therefore happy participants should show poorer results recognizing atypical items.

ability to identify with the perspective of others. The open mindedness, however, could also make us connect unrelated information and therefore produce errors. Being sad on the other hand makes us analyse given problem from a particular not general perspective, which is more mentally demanding, but could be more precise. To make the insight furthermore difficult, let us take a look at the findings of Bless and Fiedler (2012); as they state, the early approaches of psychology proposed that affective state itself – either negative or positive – could reduce one's capability to think rationally and therefore impair one's judgement and decision." They claim that positive mood promotes assimilation – imposing internalized structures onto external world – and negative mood promotes accommodation – modification of internal structures with accordance with external restraints. Bless and Fiedler mention Trope (2001) who suggests that positive affect may act as a back-up for coping with unpleasant tasks, furthermore that individuals in happy state are more likely to expose themselves to potentially negative information when in happy mood rather than in sad mood. For example patients suffering from depression have been shown to be unable to intentionally expose themselves to negative incentive or to accept short-term disadvantage in order to get long-term advantage. Even watching sad films have supported profit maximization, as shown by Hertel and Fiedler (1994). Furthermore, happy mood encourages people to take more risky situations, negative mood induces conservative strategies. This would point to the belief that happy people should be more prone to participate in bubble-crash pattern.

In summary, the effect of emotions can go both ways. I believe that the results vary based upon the underlying experiments. Bless et al. (1996) tested what one could call "soft" skill, solving a problem of communication, whereas Isen (2001) and others mention results of more analytical[2] problems. What could show more of predictive findings, would the one of Hertel and Fiedler (2012), that watching sad film supports profit maximization. Since my experiment poses more of an analytical problem and because the emotional state is induced after the game is explained, I expect the positively affected people to perform better. I believe they could perform better because they should better anticipate other's behaviour, which is the key to success in the bubble game.

2.2. GAME DESIGNS

The following section briefly describes experimental game designs important for my design.

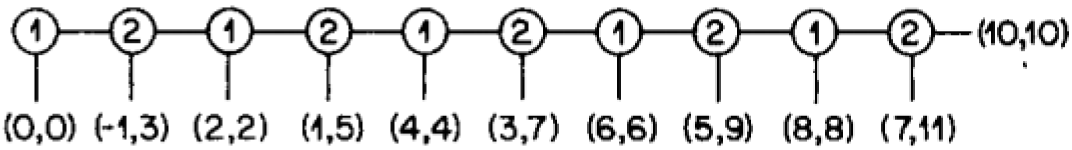
2.2.1. CENTIPEDE GAME

Centipede game was introduced by Robert Rosenthal in 1981. It explores the backward induction in perfect information games and its paradoxical nature. What made it different from

[2] In the mathematical meaning of the word.

other researches was that retreated from the perfect information setup. It questions not only the perfect information but also the assumption that all players ac in their best interest.

The centipede game is a finite n-person game with perfect information and connected nodes which are partitioned into sets (that is various outcomes of the nodes), probability distribution over the immediate followers of that node, terminal node and a vector R^n where the i^{th} component is the i player's utility[3] for the outcome represented by the terminal node. Every game defined like this, that is finite perfect information game, possess at least one Nash equilibrium (called principal equilibrium) and this equilibrium can be constructed by backward induction through the game's course and thus selecting the inductively defined immediate follower at each node. Now what might happen is, that some players might deviate from their principal-equilibrium strategies. It could happen by mistake or for example by the players do not



Example of centipede game, Rosenthal (1981)

Source: Rosenthal (1981)

analyse the game tree completely (because the time and effort required are below the potential gains). An example of such game might look like this:

In the example, two players take turns, provided that the previous player chooses the Right option. All Nash-equilibria in this example involve Player 1 to pick Down on his first move. If both players have identical view of each other's propensities to deviate from principal behaviour, these views are, that the probability assigned to the better of the two choices is $\min(1; 0.5 + 0.4D)$ where D is the utility difference between the two choices. This means, that Player 2 in the last node chooses option Down with the probability of 0.9 and Right with the probability of 0.1. At the previous node, Player 1 would choose Down with probability 0.78 and Right with 0.22 respectively. In a nutshell, the probabilities of the choice Right increase as the induction proceeds backwards through the game tree. This is the same effect as the snowball effect in bubble game of Moinas and Pouget (2013).

2.2.2. *Experimental Asset Markets & Bubble Game*

[3] A von Neumann-Morgenstern utility.

Complex Experimental Asset Market experiment was established in 1988 by Smith, Suchanek and Williams. Before their experiment, a number of double-auction experiments were conducted by Miller, Plott and Smith (1977), Williams (1979) and Williams and Smith (1982). But the settings of the two former ones did not allow for carrying assets units across market cycles; the traders could only buy in one period (the low-priced one) and sell in the second period (the high-priced one.) The traders were also required to close their positions at the end of this two-period cycle. All of these experiments in some way limited the speculative option of the traders and the asset also did not generate any kind of dividend.

Forsythe, Palfrey and Plott (1982); Plott and Sunder (1982) and Friedman, Harrison and Salmon (1984) made the settings different in a way, that the asset was generating dividend at the end of each trading period. The main difficulty with the settings of these experiments was, that the inventories of both assets and money of the traders were reinitialized at the beginning of each trading cycle. In this framework, the asset market experiments were interpreted as yielding prices that overtime tend to converge toward levels that are consistent with the rational expectations hypothesis. This was possible because agents bid for assets in period A based on their private information, but slowly learned, across the replicating cycles, to adjust their contracting so that it accounted for the additional information concerning the period B market value of the asset, as mentioned by Smith, et al., (1988). Hence the results of these experiments were biased.

The authors therefore set their objectives to (i) determine whether the agents would actively trade an asset even when all the investors faced the identical uncertain dividend pay-out schedules (as they did not in previous experiments) and (ii) characterize the observed price adjustments, whether the price converges to the rational expectations equilibrium and how the price expectations of subjects are formed. The setting of this first *bubble game* follows.

Smith et al. (year) made an improved version of a double auction with intertemporal speculators. Traders were free to switch between buying and selling, they could quote their bid or ask price and the highest bids and lowest offers were the first deals made and only then were followed by lower-ranked prices. Trading went over time-limited periods. Traders were endowed with both asset and cash. At the end of the experiment the participants were paid the cash they had accumulated during the experiment. Important feature of the whole experiment setting was that the participants were informed about the "probabilistic nature of the dividend structure" they could encounter, i.e. they knew the possible dividend values and the respective probabilities of each dividend.

Smith et al. (year) ran 27 experiments with either slightly different settings or participants (experienced, inexperienced or a specific mixture of both). Out of these, 22 experiments were conducted without any experimenter intervention and 14 of these experienced a price bubble (as defined by the authors)[4]. All experiments both with experienced and inexperienced traders converged to REM prices[5] and authors therefore concluded that expectations are adaptive.

Their main results were as follows: Expectations and uncertainty about behaviour of other traders appear to determine starting price and development of prices (not significantly affected by introducing price ceiling or a price cap), sensitivity to external sources (of subjective uncertainty), i.e. markets are prone to psychological elements. More general conclusion is that people ordinarily do not solve problems of maximization by ex-ante reasoning and backward induction. These are rational when there is insufficient reason to believe that expectations are common. What follows are the two most important and influential researches for my experiment.

Baghestanian and Walker (2015) ran a series of EAMs in which they tested whether (and how) the bubble-crash pattern will be affected by introducing a visual anchor. Their results, as well as the result of a similar study done by Cason and Samek (2014), in which the participants were provided with a price chart in EAM mitigated bubbles, show, that when a visual incentive with a figure near the asset fundamental value is introduced, the probability of a bubble formation is significantly reduced[6]. Necessary feature of this form of anchor is that it is introduced in the initial period of trading otherwise its bubble-reducing effect is not utilized. Furthermore, if the anchor is set higher than the fundamental value of the asset, the price initiates slightly above the anchor and consequently converges to the fundamental value from above. Interestingly enough, if the anchor is set below the fundamental value the price does not

[4] A price boom followed by a crash.
[5] Rational Expectations in the sense of Muth (1961).
[6] This is an example of how the bounded rationality obstacle can be overcome.

move the other way around; if the anchor is significantly below the fundamental value, the asset price initiates below the FV, then overshoots it and converges to it towards the end of trading.

Baghestanian and Walker (2015) employed the double-auction setting with a dividend-paying asset, a setting similar to the one of Smith et al. (1988). It is different to the one that I employed but still worth mentioning. The asset's dividends were either positive or negative with 50% chance of each, the fundamental value (FV) was kept constant over all trading periods and a terminal buyback value was equal to the FV. Price charts – the anchor – depicting the transaction price history were used within all trading periods and in the first period the prices initiated at the FV. Crucial property was, that after the initial transactions took place and the new offers by subjects were made, the price chart jumped back to the FV and thus pointing the participants towards it. For the consequent trading periods the price chart initiated at previous-period average price. This visual presentation of trading was sufficient to significantly reduce the occurrence of bubbles. If the jump back was left out, the price dynamics changed significantly. Under the jump-back-anchor conditions the price started and moved very closely to the FV, but under the no-jump-back-anchor condition the price began at much higher value than the fundamental one and then gradually decreased towards it over trading periods. It seems that the fact, that subjects saw the price jump back towards the FV artificially in the first period was enough to change the price pattern completely. It could be therefore said, that the jump back ushers the subjects to the FV.

Findings like this can be easily applied – on a theoretical level – to a real stock markets and IPO's; as Baghestanian and Walker (2015) point out, the pre-opening auctions on New York Stock Exchange, which determine stocks opening prices, may have significant effect on intra-day price dynamics (e.g. if the pre-opening auction sets the opening price well below the FV one could expect at least one price rally peaking above the FV etc.) Similar facts apply for IPO's. These findings do not point to the fact that when an opening price is set below or above the FV that the price will grow or decrease. Instead they point to the path pattern that the price will take, as it is induced by the traders, who have been anchored to it.

At this point, I would like to just briefly mention the work of Drehmann, Oechssler and Rioder (2004) on herding and contrarian behaviour in financial markets. Interesting feature or their experiments was one of their tests – whether college students behave differently from businessmen (they conducted a control experiment with McKinsey consultants and their results did not differ from those of students'.[7]) Among their findings we can distinguish couple of

[7] Authors found out one interesting thing that subject with a Ph.D. were more in line with theoretical behaviour, physicist performed most rationally and psychologist least rationally. However they state that rational behaviour can only be profitable when others behave rationally as well, therefore profit results were quite the opposite – physicist made the worst profits and psychologists the best. This points to the fact that it might not be the *financial knowledge* about the market but the *psychological knowledge* and the ability to judge the thoughts and behaviour of others that makes a trader "profitable".

results, that could be related to my research: in only 50-70% of experimental cases subjects followed their private information – let me recall the finding of Bless et al. (1996) that happy people associate more information as related, thus happy participants could have considered more information as related to their own and act on these - (hence they must be looking at other information available or behaviour of other subjects), if prices are flexible, there is no evidence of herding behaviour but the contrarian behaviour exhibits itself. They concluded by employing an error model, which allowed for the subjects to have doubts about the rationality of other participants and consequently mistrust the decisions of the others. The error model showed that, for moderate prices, it was successful to act on one owns signals and for extreme prices to be a contrarian. To sum it up, for average prices the subjects acted as expected and for extreme prices they acted differently to others just in order to set themselves apart from others. It is interesting to think of the fact that when being a contrarian proved to be profitable that not more people had done it and like so make the contrarian choice a common choice.

Moinas and Pouget (2013) and their study of the bubble game and speculation is the main inspiration for my work in the technical sense. Bubble game is a form of a centipede game with a no-dividend asset and only 3 players playing sequentially. The players however do not know their position in the sequence and the last player in the sequence cannot resell the asset. The player can however induce the probability of their sequential position and thus by backward induction deduce not to enter the game at whatever price level. I will use this bubble game settings and expand it – being inspired by the work of Baghestanian and Walker (2015) and their use of anchors – by adding an emotional anchor to the setting and thus induce either positive or negative mood and observe its effect on formation of bubbles. More detailed description of the bubble is provided in the third section, what follows here is a brief summary of their results: bubbles arise independent on whether a price cap on the initial price is introduced or not. When there is no cap (i.e. the cap is infinite), then the bubble can be rational because no trader then could ever be sure to be the last in the market sequence. When the price cap is finite (which is a reasonable assumption since the wealth of the economy is also finite (in a way)), then only irrational bubbles can be formed, because when the last trader receives an offer for the highest possible price, he knows, that he is last in the sequence and would not be able to sell the asset if he bought it. The previous trader, even though he cannot be sure to be the last in the sequence, should refuse to buy, because he anticipates that the next trader will realize, that *he* is the last and will not trade. This induction therefore rules out any possible existence of a bubble. Increasing the price level of the cap also increases the number of steps of reasoning that are needed to rule out the bubble. A snowball effect is also present; authors explain the snowball effect as the propensity for player to enter a bubble. This propensity increases with the "distance" between the offered and maximum price. In other words, the higher the price cap and the number of steps needed to rule out the bubble, the higher the propensity to enter the bubble since it is harder to work out more induction steps.

Apart from the finding that bubbles arise in all experimental settings, there is another interesting result; even the subjects that are sure to be last in the sequence, and thus unable to sell the asset if bought, entered the bubble (3 out of 29). Authors state that no behavioural game theory model can explain this in a different way than simply stating that people make random errors. In my opinion, this could be explained by the finding of Drehmann, Oechssler and Rioder (2004), mentioned above, that some people, especially for extreme prices, act as contrarians. I acknowledge the fact that in this particular EAM setting it is difficult to simply apply the contrarian behaviour argument since the bubble can arise even for small prices.

3. THEORY

In this section I will present two behavioural game theory models, as chosen by Moinas and Pouget (2013), which can be used to predict agents' choices in a setting similar to mine. The first model is the Subjective Quantal Response Equilibrium (SQRE) of Rogers, Palfrey and Camerer (2009) and the second is the Analogy-Based Expectation Equilibrium of Jehiel (2005).

3.1. SUBJECTIVE QUANTAL RESPONSE EQUILIBRIUM

In this section various Quantal Response Equilibrium (QRE) models are introduced. Their introduction is followed by the introduction of Analogy-Based Expectation Equilibrium model.

3.1.1. HETEROGENEOUS QUANTAL RESPONSE EQUILIBRIUM

Models like QRE are one approach how to incorporate rationality limits in game theory. QRE maintains the assumption of equilibrium in the way, that beliefs are statistically accurate, but it relaxes the assumption that players choose the best response. Rogers, Palfrey and Camerer (2009) introduced the Heterogeneous Quantal Response Equilibrium (HQRE) model; it is a model where players' choice follows logit quantal response functions but contains heterogeneity with respect to the responsiveness parameter. The whole definition of HQRE follows:

Let $\Gamma = [N, \{A_i\}_{i=1}^n, \{u_i\}_{i=1}^n]$ be a strategic form of a game, where $N = \{1, \ldots, n\}$ is the set of players, $A_i = \{a_{i1}, \ldots, a_{iJ_i}\}$ is $i's$ action set and $u_i: A \to \Re$ is $i's$ payoff function, where $A = A_1 \times \cdots \times A_n$. Let $\Delta A = \Delta A_1 \times \cdots \times \Delta A_n$ denotes the product set of probability distributions over $A_i, i = 1 \ldots., n$. If $\alpha \in \Delta A$, then player $i's$ *expected* payoff is denoted by

$$U_i(\alpha) = \sum_{\alpha \in A} \left(\prod_{k=1}^{n} \alpha_k(a_k)\right) u_i(a)$$

We denote the player $i's$ *expected* payoff from using action $a_{ij} \in A_i$ by

$$U_{ij}(\alpha) = \sum_{\alpha_{-i} \in A_{-i}} \left(\prod_{k \neq i}^{n} \alpha_k(a_k)\right) u_i(a_{ij}, a_{-i})$$

Each player is by nature independently assigned a response sensitivity λ_i (called $i's$ type) which is drawn from a fixed distribution $F_i(\lambda_i)$ with smooth density function, full support on $[0, \infty)$ and finite moments. Quantal response functions are logit transformations of expected payoffs, so for player i with type λ_i and with actions having expected payoffs $U_i = \left(U_{i1}, \dots, U_{iJ_i}\right)$ the probability of choosing action j is

$$p_{ij}(\lambda_i) = \frac{e^{\lambda_i U_{ij}}}{\sum_{k=1}^{J_i} e^{\lambda_i U_{ik}}} \tag{1}$$

Any measurable functions $p: [0, \infty) \rightarrow \Delta A_i$ is called a strategy for player i.

Assumption of HQRE is that $F_i(\lambda_i)$ is a common knowledge, but player $i's$ type λ_i is a private information known only to player i. If we take some fixed profile of expected payoffs to i, the equation above would imply a choice probability function that depends on λ_i, which is denoted by $p_i(\lambda_i) = \left[p_{i1}(\lambda_i), \dots, p_{iJ_i}(\lambda_i)\right]$. Therefore, given $i's$ profile of choice probability functions, the ex-ante probability that i chooses action j (that is before λ is drawn) is

$$\sigma_{ij}(p) = \int_0^\infty p_{ij}(\lambda) f_i(\lambda) d\lambda \tag{2}$$

The authors then call $\sigma_i = \left(\sigma_{i1}, \dots, \sigma_{iJ_i}\right)$ $i's$ induced mixed strategy. Given σ_{-i}, $i's$ expected payoffs $U_i(\sigma_{-i}) = \left(U_{i1}, \dots, U_{iJ_i}\right)$, the induced mixed strategy profile for all players other than i can be expressed as

$$U_{ij}(\sigma) = \sum_{\alpha_{-i} \in A_{-i}} \left(\prod\nolimits_{k \neq i}^{n} \sigma_k(a_k)\right) u_i\left(a_{ij}, a_{-i}\right) \tag{3}$$

In heterogeneous quantal response equilibrium with logit response functions equations (1), (2) and (3) must all be satisfied simultaneously. The result is that in HQRE the players have rational expectations about the distribution of mixed strategies; these are then self-fulfilling given the commonly known distribution of profiles of quantal response functions. The solution (strategy) to the problem is a fixed point of a mapping from the type to the choice probability.

3.1.2. Subjective HQRE

In order to be able to estimate and model participants' behaviour more accurately, especially as in our case of a one-shot game, a better model – Subjective HQRE – is at hand. It allows for expectations about choice probabilities to be inconsistent with the actual choice frequencies of other players. Rational expectation assumptions are replaced by assumption of subjective expectations; in this model then the equilibrium strategies of all players are common knowledge in the equilibrium, but players have different beliefs about the type distribution. The conditional subjective beliefs of player i about the type of player k are denoted by $F_k^i(\lambda_k|\lambda_i)$. From this it is clear, that player's beliefs depend on his own type. The subjective HQRE is of course the same as HQRE if $F_k^i(\lambda_k|\lambda_i) = F_k(\lambda_k)$ for all $i, k, \lambda_i, \lambda_k$. General notation is similar to the HQRE but with the subjective version the induced mixed strategies are more complicated; their role is to compute U, i.e. induced mixed strategies represent the beliefs players other than i have about $i's$ action choice without knowing $i's$ type. Players do not share common prior about F and therefore do not share identical beliefs about action choices.

Player $i's$ expected payoff, for any subjective belief about action profiles $\hat{\sigma} \in \Delta A$, is given by

$$U_i(\hat{\sigma}) = \sum_{a \in A} \left(\prod\nolimits_{k=1}^{n} \hat{\sigma}_k\,(a_k) \right) u_i(a)$$

The subjective expected payoff to player i from using action $a_{ij} \in A_i$ is

$$U_{ij}(\hat{\sigma}) = \sum_{a_{-i} \in A_{-i}} \left(\prod\nolimits_{k \neq i} \hat{\sigma}_k\,(a_k) \right) u_i\left(a_{ij}, a_{-i}\right)$$

With logit response functions, if player i has type λ_i and the actions by player i have expected payoffs $U_i = \left(U_{i1}, \dots, U_{iJ_i}\right)$, then the probability of player i choosing action j as a function of λ_i is

$$p_{ij}(\lambda_i; U_i) = \frac{e^{\lambda_i U_{ij}}}{\sum_{k=1}^{J_i} e^{\lambda_i U_{ik}}} \tag{4}$$

Again, any measurable function $p_i: [0, \infty) \to \Delta A_i$ is called a strategy for player i. Given some fixed vector of expected payoffs to $i, U_i = \left(U_{i1}, \dots, U_{iJ_i}\right)$, the equation (4) implies induced mixed strategy for i that depends on λ_i: $p_i(\lambda_i) = \left[p_{i1}(\lambda_i), \dots, p_{iJ_i}(\lambda_i)\right]$. Due to different subjective beliefs about the distribution of λ, players k and k' can have different beliefs about the induced mixed strategy of player i. We however assume that any differences in their beliefs are due to the differences in beliefs about the distribution of λ_i; that is the strategy profile p is assumed to be common knowledge. The type λ_k of player k about player $i's$ induced mixed strategy is denoted by $\sigma_i^k(p_i)$. Given $i's$ strategy, the belief of player k that player i will choose action j, before λ_i is drawn, is

$$\sigma_{ij}^k(p_i|\lambda_k) = \int_0^\infty p_{ij}(\lambda_i) f_i^k(\lambda_i|\lambda_k) d\lambda_i \tag{5}$$

Given $\sigma_{-i}^{i}(p_{-i}|\lambda_i)$, the beliefs of type λ_i of player i about the induced mixed strategy profile of all other players other than i, type λ_i of player $i's$ payoffs $U_i^{\lambda_i}(\sigma_{-i}^{i}) = \left(U_{i1}^{\lambda_i}, \dots, U_{iJ_i}^{\lambda_i}\right)$ are

$$U_{ij}^{\lambda_i}(\sigma_{-i}^{i}) = \sum_{a_{-i} \in A_{-i}} \left(\prod\nolimits_{k \neq i}^{n} \sigma_k^i(a_k|\lambda_i)\right) u_i(a_{ij}, a_{-i}) \tag{6}$$

In subjective HQRE with logit response functions, equations (4), (5) and (6) must all be satisfied simultaneously. Players have rational expectations about strategies (i.e. player's behaviour conditional on his type λ), but may have different beliefs about the distribution of mixed strategies, which are induced by different beliefs about the distribution of types λ.

3.1.3. Truncated HQRE

To further bring HQRE to successful application, Camerer, Palfrey and Rogers (2009) introduced truncated expectations; these mean that players act as if they are not aware of the existence of some more rational types than some maximum upper bound, which depends on their own type. There are three good arguments for setting like this; 1) people with low λ, who can at the same time imagine people with higher λ, will generally want to switch to this higher type; 2) people are generally overconfident about their own skill compared to other people; and 3) a computational argument; it can be seen as a reduced form of cost-benefit calculation leading people to ignore information that are too hard to process and not too costly to ignore. In other words, if there are cognitive costs to computing the expected payoffs, these costs will increase with the number of types the players have to consider, i.e. the benefits from imagining what wider range of types will do are likely to fall as λ rises. The introduction of truncated HQRE follows.

The subjective HQRE model needs to have an upper bound on player $i's$ imagined types of $\theta_i(\lambda_i)$, where $\theta_i(\lambda_i)$ is commonly known. The truncation $\theta_i(\lambda_i)$ is assumed to be uniformly continuous in λ_i and for each i there exists $\bar{\theta}_i$ such that $\theta_i(\lambda_i) \leq \bar{\theta}_i(\lambda_i)$ for all λ_i. Truncated rational expectations, which are a modified form of rational expectations, are assumed. Beliefs of type λ_i of player i about λ_{-i} are rooted in the true distribution, but normalized to reflect the missing density; that is, for $\lambda_i > 0$ the subjective beliefs of i about the type of player k is given by $F_k^i(\lambda_k|\lambda_i) = F_k(\lambda_k)/F_k(\theta_i(\lambda_i))$ for $\lambda_k \in [0, \theta_i(\lambda_i))$ and $F_k^i(\lambda_k|\lambda_i) = 1$ for $\lambda_k \geq \theta_i(\lambda_i)$. As $\theta_i \to \infty$ for all i, the truncated HQRE model (TQRE) converges to standard HQRE since the upper bound on λ is lifted.

The truncation can be described as player $i's$ imagination. TQRE is a model of bounded rationality, since $\theta_i(\lambda_i)$ is finite, because for any type λ_i of player i, all λ_{-i} types beyond certain level, that is $\theta_i(\lambda_i)$, are unimaginable (player i assigns 0 probability to all those higher types.)

3.2. ANALOGY-BASED EXPECTATIONS EQUILIBRIUM

A different explanation for the emergence of a bubble can be found in the Analogy-Based Expectation Equilibrium (ABEE) of Philippe Jehiel. The difference between QRE and ABEE is that the agents (i.e. players) have inaccurate expectations regarding the behaviour of other players. Detailed analysis of ABEE follows.

Jehiel approached the matter of players‘ expectations formation in a different way; he investigated the „situations in which players form their expectations about others‘ behaviour by analogy between several contingencies as opposed to for every single contingency in which each of these other players must move.“[8] In other words, each player i bundles nodes at which other players can and must move during the course of the game. This bundle is called an analogy class. The player i then forms only the expectations about the average behavior in each analogy class (that he considers). This approach is most useful in games similar to the game of chess; there are many options for every board position and it is impossible to consider all the possible moves the opponent may make, therefore an average of behaviour in each bundle of game nodes is considered. If two nodes belong to a same class (bundle), the expectation formed by the player is the same for both these nodes. Therefore, the word “analogy” is used. The nodes which are “visited” more often will have larger impact on the expectation. Also the behaviour of other players in these nodes will taint the expectation for all other nodes in the same analogy class. Jehiel believes that this extrapolation[9] is the key feature of this analogy idea.

3.2.1. GENERAL FRAMEWORK

In this section the general framework and various concepts are introduced.

The general framework for ABEE considers multi-stage games with (almost) perfect information and recall. This means, that in each stage every player knows all the actions taken at

[8] P. 2

[9] Extrapolation of expectation from the more visited to less visited possibilities.

any of the previous stages. This class of games is referred to as Γ. It includes the set of players $i = 1, \dots, n$ denoted by N, the game tree Υ (this specifies who moves when and over which space and includes exogenous events chosen by Nature) and the preferences $\%_i$ of every player i over the outcomes of the game. A node in the game is denoted h and it contains all the information about all actions taken at any stage prior to the node h. The set of nodes is denoted by H and the set of nodes at which the player i must move is denoted by H_i. For every node $h \in H_i, A_i(h)$ denotes player $i's$ action.

Each player i forms his exepcations about the behavior of other players j $(j \neq i)$. Player i however does not form expectations about *every* player $j's$ behaviour in every contingency $h \in H_j$ in which player j must move. Player i therefore pools together several of the contingencies in which other players must move and consequently forms an expectation of the *average* behavior in these pooled contingencies. This pool is referred to as a *class of analogy.* Each player i partitions (or separates) the set $\{(j,h) \in N \times H_j, j \neq i\}$ into subsets α_i, referred to as analogy classes. Player $i's$ collection of analogy classes (referred to as analogy partition) is denoted by An_i. In two contingencies, (j,h) and (j',h') from the same analogy class, that player i treats by analogy, the action space of the involved players should be the same. The common action space in analogy class α_i is denoted by $A(\alpha_i)$ and the profile of analogy partitions $(An_i)_{i \in N}$ denoted by An. An_i than refers to partitioning of nodes where players other than player i must move. The way how various players then partition the set of nodes (at which the other players must move) into analogy classes is specified in *strategic environment*. It also specifies the set of players N, the game tree Υ and players' preferences $\%_i$.

The concepts of analogy based expectations, strategy and sequential rationality are presented in the following section.

Analogy based *expectation* of player i is denoted by β_i. It specifies a probability measure over the action space $A(\alpha_i)$, for every player $i's$ analogy class α_i. This probability, denoted by $\beta_i(\alpha_i)$, is to be interpreted as player $i's$ expectation about the average behavior in analogy class α_i. This probability measure is an expectation or a belief about the average behavior of players other than i, it is not a belief for example about the likelihood of the various elements (j,h) pooled in α_i analogy class.

A behaviour strategy (for player i) is a mapping that assigns to each node $h \in H_i$, at which player must move, a distribution over player's action space at that node. It is formally denoted by σ_i and it specifies a distribution according to which player i selects actions in $A_i(h)$ when at the node h and as such is denoted by $\sigma_i(h) \in \Delta A_i(h)$. Strategy profile of players other than i is denoted by σ_{-i} and σ denotes strategy profile of all players.

Next, the criterion that players use to choose their strategies, given their analogy based expectations, is as follows; player i, given his analogy based expectation β_i, constructs a strategy profile, for players other than him, that assigns player j to play accordingly to $\beta_i(\alpha_i)$ at node h whenever $(j,h) \in \alpha_i$. The criterion, considered by player i, is the best response against this induced strategy profile after every node where player i must move. That is, for every β_i and $j \neq i$ the β_i-perceived strategy of player j $\sigma_i^{\beta_i}$ is defined as

$$\sigma_i^{\beta_i}(h) = \beta_i(\alpha_i) \text{ whenever } (j,h) \in \alpha_i.$$

We let $\sigma_i|_h$ denote the continuation strategy of player i, induced by σ_i from node h onwards. Correspondingly, $\sigma_{-i}|_h$ and $\sigma|_h$ denote the strategy profiles induced by σ_i and σ from node h onwards. We let $u_i^h(\sigma_i|_h, \sigma_{-i}|_h)$ denote the expected payoff gained by player i. This payoff is obtained when the play has reached the node h and all players behave in accordance with the strategy profile σ. Player $i's$ strategy σ_i is the sequential best response to the analogy based expectation β_i *if and only if* for all strategies σ_i' and nodes $h \in H$ the following condition is met

$$u_i^h\left(\sigma_i|_h, \sigma_{-i}^{\beta_i}|_h\right) \geq u_i^h\left(\sigma_i'|_h, \sigma_{-i}^{\beta_i}|_h\right).$$

In the equilibrium the analogy based expectations of players are expected to be consistent. This means, it has to correspond with the *real* average behaviour. Jehiel describes this consistency as a result from a learning process. In this process the player eventually have correct analogy based expectations.

3.3. MODEL APPLICATION IN BUBBLE GAME

Let's now see how both models can be applied on the bubble game design and choice prediction.

3.3.1. QRE IN BUBBLE GAME

In the application of QRE to the bubble game I will, for brevity, focus only on the case with a finite price cap K, which corresponds to the experimental design I have used. The application can also be shown for the case when $K = +\infty$, but I deem it unnecessary to do so here. It can be found in the Supplementary Appendices of Moinas and Pouget.

The trader, after being proposed a price $P = 100K$, correctly infers, that he is the last in the market sequence and buys with probability $\boldsymbol{P}(B|P = 100K) = \frac{1}{1+e^{\Lambda}}$ [10]. Other trader, after

[10] Λ says how an agent acts to his beliefs, that is, if $\Lambda = +\infty$ then the agent best-responds to his beliefs.

observing a price $P = 10K$, infers that he has a probability not to be last, denoted by $q(K, P = 10K)$. He then correctly anticipates the probability to buy of the last trader is not equal to zero. His expected payoff from buying is then $u(B|P = 10K) = q(K, P = 10K) \times \frac{1}{1+e^{\Lambda}} \times 10$. Therefore his probability to buy is then

$$\boldsymbol{P}(B|P = 10K) = \frac{1}{1 + e^{\Lambda \times \left(1 - \frac{10q(K,P=10K)}{1+e^{\Lambda}}\right)}}.$$

If we apply this logic backwards, we find the predicted probability that a trader buys for all potential prices.

3.3.2. *ABEE IN BUBBLE GAME*

When it comes to ABEE, it is necessary to mention that two types of analogy classes can arise naturally in the bubble game; the traders might use only one analogy class assuming that other traders' behaviour is the same across all the potential prices. On the other hand, the traders might assume two-class analogy, where Class I includes all the prices at which traders are *not* sure to be last in the market sequence and Class II, which includes the remaining prices (i.e. at which the trades might think or know to be the last in the market sequence).

Let's now apply ABEE to the bubble game and for brevity we focus only on the case with price cap $K = 1$. Again, the other cases are mentioned in the Supplementary Appendices of Moinas and Pouget. The actual probabilities, that a trader buys for a proposed price of 1, 10 and 100, are p_1, p_2 and p_3 respectively and let $\boldsymbol{P}(B|P = 1), \boldsymbol{P}(B|P = 10)$ and $\boldsymbol{P}(B|P = 100)$ be the corresponding probabilities as perceived (or misperceived) by traders when using the analogy classes.

In the case of only one analogy class, the trader knows he is the last, after being proposed the price $P = 100$ and consequently his probability to buy is $p_3 = \frac{1}{1+e^{\Lambda}}$. The other trader, after observing $P = 10$ price has the expected payoff $u(B|P = 10) = 10 \times \boldsymbol{P}(B|P = 100)$. Since this is the one-class case (i.e. all other traders' behaviour is the same for all potential prices), we have $\boldsymbol{P}(B|P = 100) = \frac{p_1+p_2+p_3}{3}$ (this is because the probability of $\frac{1}{3}$ corresponds to the ex-ante probability of observing prices 1, 10 and 100. This is in line with ABEE logic, since in this experimental design, the players need to choose their action irrespective of the action of the player, who is in the sequence before them. The probability in the extensive case of the game, would be $P(B|P=100)=\frac{p_1+p_1p_2+p_1p_2p_3}{1+p_1+p_1p_2}$). The probability to buy for $P=10$ therefore is

$$p_2=\frac{1}{1+e^{\Lambda\left(1-\frac{10}{3}(p_1+p_2+p_3)\right)}}.$$

The last player – that is the first player in the sequence – has the expected payoff of $u(B|P=1)=10\times P(B|P=10)=10\frac{p_1+p_2+p_3}{3}$ and his probability to buy is therefore $p_1=p_2$.

Let us now take a look at the two-class case. For the trader, who is proposed to buy for the price $P=100$, the probability to pay is the same, $p_3=\frac{1}{1+e^{\Lambda}}$. Other trader, after observing the price $P=10$, has the expected payoff from buying of $u(B|P=10)=10\times \boldsymbol{P}(B|P=100)$. Now Class II (i.e. the class where the player thinks or knows that he is the last) is a singleton, the $\boldsymbol{P}(B|P=100)=p_3$. Thusly we have $p_2=\frac{1}{1+e^{\Lambda(1-10p_3)}}$. The final trader, after observing the price $P=1$ uses Class I to form his expectations and his expected payoff is then $u(B|P=1)=10\times \boldsymbol{P}(B|P=10)=10\frac{p_1+p_2}{2}$. His probability to buy is then $p_1=\frac{1}{1+e^{\Lambda(1-5(p_1+p_2))}}$. The intuition from ABEE is, that trader expect that the probability to buy is *constant* across different prices and this leads them to overestimate the likelihood that other traders will buy towards the end of the game.

If we take a look at a case with a price $K=1$ and apply the above information for speculative bubbles, the following implications arise: the QRE, after observing the price $P=10$, predicts the probability to buy to be $\boldsymbol{P}(B|P=10)=\left[1+e^{\Lambda\left(1-\frac{10}{1+e^{\Lambda}}\right)}\right]^{-1}$ and the probability, after observing the price $P=100$, to buy to be $P(B|P=100)=\left[1+e^{\Lambda}\right]^{-1}$. The propensity to buy can be considered pretty low, since the trader will only lose by doing so and it is higher for $P=10$[11], because there is some chance that the next player will buy the asset. The higher chance of reselling induces a higher propensity to speculate (i.e. the snowball effect). For one-class ABEE the model predicts the probability to buy for $P=10$ to be $p_2=\left[1+e^{\Lambda\left(1-\frac{10}{3}\left[\left(1+e^{\Lambda}\right)^{-1}+2p_2\right]\right)}\right]^{-1}$ and $p_3=\left[1+e^{\Lambda}\right]^{-1}$ after observing the price $P=100$. In the case when $\Lambda=1$, and because of the analogy-based expectations, the second trader in the sequence (that the one who is proposed to buy for $P=10$) believes, that the probability to buy of the next

[11] Recall the centipede game of Rosenthal and the increasing probability of choosing going on with the game when going backwards in the game tree.

trader in the sequence is $\frac{p_1+p_2+p_3}{3}$ instead of p_3. Such beliefs then leads him to overestimate the probability that the next trader will buy and this increases his propensity to speculate. This results is remarkably similar to the one of Bless et al. (1996) mentioned earlier in this paper; that the market participants overreact to what they wrongly believe is relevant and a related circumstance. It is important to note that this is only for the one-class analogy case. In the two-class case it may the other way around, under specific conditions.

4. EXPERIMENT

The next section describes the environment in which I ran the experiment, the experimental design itself and how I managed to overcome various technical difficulties.

4.1. ENVIRONMENT

First of all, I had to tackle the difference between the lab conditions that Moinas and Pouget (2013)[12] could have exploited in their version of the experiment and the web environment of Amazon Mechanical Turk where I decided to run my version of the experiment. Even though in both of these environments the subjects are participating voluntarily, the circumstances differ; in the lab conditions the experimenter has time to explain the settings in detail to the participants, they themselves can also ask additional questions. In this way, both sides can be fairly sure, that the participants understand all the aspects and consequences of the bubble game. The experimenter also has control during the course of the experiment. When experimenter uses an online labour market as a task force, he does not have the benefits, such as were described above, as he has in the lab conditions. The experiment has to be set perfectly ex-ante, since it is impossible to make any changes once it is launched. The experimenter also has to anticipate the structure and background of the participants and tailor the experiment accordingly. I will summarize the upsides and downsides of running a survey online in the next part.

4.2. AMAZON MECHANICAL TURK

The reason, why I have chosen to run the experiment on Amazon Mechanical Turk (Mturk) platform, which is an online labour market, instead of university lab conditions, was that Mturk is a rapidly growing platform used by many researchers. It is possible to conduct experiments cheaply and quickly and get more representative samples Paolacci and Chandler (2014), Chandler, Mueller and Paolacci (2013). Running an experiment in an environment where you do not have any physical contact with the participants and where there is thus very little room for any interaction between both sides has, both perks and merits. These were thoroughly explored

[12] Their participants were junior and senior undergraduate students in Business Administration at the University of Toulouse.

(and supplemented by research results of other authors) by aforementioned Paolacci and Chandler (2014) and Chandler, Mueller and Paolacci (2013) and both these downsides and upsides are summarized in the next paragraphs.

Mturk provides large and diverse pool of workers. It is however important to keep in mind, that his pool is not representative of general population[13] - among others the pool tends to be younger, overeducated and underemployed however more representative than students. How the workers chose which tasks they perform, poses another problem for researchers: inadvertently using samples not representative of the population. This could be caused either by the experimenters (e.g. when the experimenter, in order to eliminate those, who are new to the website, makes the task available only for workers with large number of accomplished tasks, who, naturally, could already have experience with experimenter's type of research) or by the workers themselves (e.g. when worker selectively performs similar kinds of tasks). Both these factors influence randomness of the sample. Regarding the data quality itself, Mturk workers exhibit the same cognitive biases (e.g. framing effects), logical fallacies (e.g. conjunction fallacy) as traditional participants do (e.g. Amir, Rand and Gal (2012); Goodman et al. (2013); Horton, Rand and Zeckhauser (2011); Klein et al. (2014); Paolacci et al. (2010)).[14] What is probably the most important for my experiment are the findings, that Mturk workers are generally truthful when providing information about themselves, they are consistent when providing these information and they are not more likely cheat than college students. Mturk workers may remain in a participant pool far longer than university students or traditional participant pools members. Unlike university students the workers are not restricted to a specific type of studies. These two features increase the likelihood that the workers might work on conceptually related surveys. This is a partly solvable problem since Mturk provides a function which makes a task available to a worker only once. Using multiple accounts per worker can be spotted when looking at IP addresses.[15] Chandler, Mueller and Paolacci (2013) argue, that having multiple accounts is uncommon and that Amazon is continuously on the lookout for duplicate accounts and deletes them. It seems, that having few workers providing multiple responses is not a problem, it is however important to bear in mind when designing an experiment.

What might pose a more serious problem, are workers' forums through which workers share information either about interestingness or lucrativeness of various tasks (or HITs16). What workers also share with each other are the features of particular surveys. Edlund et al.

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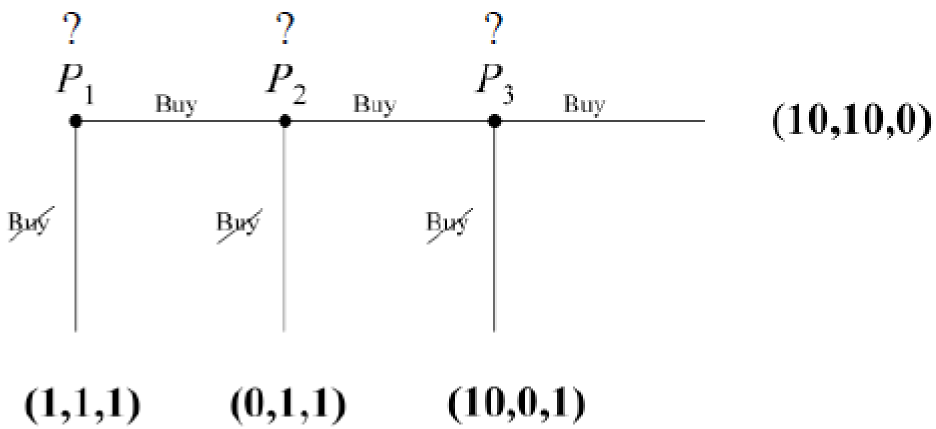
[13] Author of this paper however thinks that this statement will need to be revised in few years due to the expansion of internet availability and usage.
[14] P. 186
[15] Identical IP address may be a result of multiple accounts in the same household. Internet service providers usually assign one public IP address to a connection point (e.g. a router) and this connection point then distributes private IP address among devices in the household. These private addresses are not reachable from the internet.
[16] *Human Intelligence Task*

(2009) have shown, that college undergraduate students share information when some incentive is offered for a correct response. Buchanan (2000) has shown similar behaviour in online forums. Therefore there could be no doubt, that also Mturk workers reveal important information regarding HITs to each other. This effect might be amplified by the fact, that workers follow their favourite requesters. I tried to mitigate this by adding 5 control questions for each participant, that participants had to answer correctly in order to continue with the survey. If more than 1 control question was answered incorrectly, the participant was asked 3 additional control questions. Since these merits and faults are common to all similar online crowdsourcing platforms, I decided to use Amazon's Mechanical Turk as it probably is the most well-known one. It provides a large pool of about 500 000 workers as well as a comprehensive reward payment system through which it is easy and convenient to manage and approve payments. This could also be done on individual worker level, which means that faulty or mocking answers could be discarded and not awarded with a payment. What needs to be acknowledged is that the vast majority of Mturk workers at the moment come from USA and India. This seeming disadvantage could be turned to a benefit; the financial markets in the United States differ to those in Europe. By this I allude to the fact, that a number of companies in the US obtain financing via stock markets and hence the US citizens might be more familiar with stocks and their trading. This means, that the limits of the online environment, particularly the fact that the settings must be as brief and short as possible, could be somewhat offset by the participants' general knowledge.

4.3. Experimental Design

In my experimental design I will use the bubble game scheme as used by Minas and Pouget (2013); it features assets with fundamental value of 0, which might be traded. The trading proceeds sequentially, but there is only one trading period in which there are only three traders. The position of each trader, i.e. the first, second or the last, is randomly chosen with the same probability of 1/3 and the traders do not know their position in the market, but they can infer some information from the price of the asset they are being offered. The prices are given exogenously and are of power of 10. The first trader is offered the asset for the price of $P_1 = 10^n$ where the n follows geometric dist. of parameter ½, i.e. P (n = j) = $\frac{1}{2}^{j+1}$, $j \in \{0,1,2, \ldots\}$. Setting the price distribution like this is handy, because it is simple to explain – for example the conditional probability of being last in the market is equal to 0 if the price offered to the traders is 1 or 10, and, vice versa, the probability of being first is equal to 1 if the offered price is 1 etc. All participants are offered to buy for the given price at once. This is possible because if a trader decides for purchasing the asset for the price P_t, the assets is then offered to the next trader for $P_{t+1} = 10P_t$, so once the starting price is determined, all the other prices can be easily computed.

All traders will get all the information – like the probabilities of each of first prices and probabilities of each positions they could be in - prior to the start of trading but only after one of affective states will have been induced (a version of the experiment can be found in the



Distribution of payoffs for traders, Moinas and Pouget (2013)

Appendix 1). Each trader is endowed with 1 unit of capital. This of course would be sufficient only for one trader in the case the initial price is equal to 1, therefore the possibility of obtaining additional capital (provided by the experimenter) is introduced. Payoffs are divided between the trader and the financier; the trader receives $\frac{1}{P_t}$, as this was his proportion of invested capital and the financiers share is $\frac{P_t-1}{P_t}$. If trader is unable to resell the asset, he ends up with 0 as well as the financier. If the trader is able to resell the asset which he bought for P_t, he then receives $\frac{1}{P_t}$ percent of $10P_t$ i.e. he ends up with 10 and the financier ends up with $10P_t - 10$. This separation of payoffs allows for limited liability for both traders and the experimenter; the maximum potential loss of the trader is 1, the maximum total payment per game round for the experimenter – since he plays both roles of the issuer (receives the initial amount i.e. the first price P_1) and the external financier (provides subject with additional capital and shares profit with successful traders and provides three subjects with initial 1 unit of caiptal for each one of them) - is 20 and that is only in the case when all subjects decide to enter the bubble.

The design described above served as basis for my version of the experiment – expanded by setting up an emotional anchor prior to the subject decision. Creating the whole experiment on Amazon's platform would however require an extensive knowledge of HTML, Java or other programming language. Fortunately, Mturk offers on option for requesters unfamiliar with advanced programming methods – a survey link. Workers would be then – after accepting to participate in the survey – redirected to whatever website the experimenter has set the research. I have chosen Qualtrics. It is a website that enables its user to collect data online. These services are mainly provided to companies which use them to do market researches, monitor customer satisfaction or product testing. These possibilities are used by researches as well. After accepting the task and being redirected, the participants had 10 minutes to complete the survey. After the participants' responses were recorded, they received a unique code, which they in turn entered on Mturk. After comparing the code entered on Mturk and response set with the same code on Qualtrics, a reward was approved to the worker.

Because of no interaction with participants simplification was necessary (needless to say, that the simplifications should not affect the participants). In the original experiment, there was a probability distribution of the initial price; 50% chance for the initial price to be 1, 25% chance for the price to be 10, 12.5% chance for 100 and 6.25% chance to be 1 000 or 10 000. Since the second and third price was immediately calculated and simultaneously offered to the second and the third participant, the participants could therefore induce their probabilities of being first, second or last. This was presented to the participants in the experimental setting both in the original and mine versions. The difference was in determining the prices to be offered; since the Qualtrics software does not provide any simple way how to programme the calculation of all quoted prices (not to mention the problem of sorting the participants into groups of three), I used the distribution of the initial and consequent prices from the original experiment. This was unknown and undiscoverable for the participants in the web experiment as they were asked to indicate their buy or pass decision in the same way (the price and question whether they buy the asset or not) as their lab experiment forerunners. The settings, which were presented to the web participants, contained the same information as it did in the original, but substantially and subtly shortened. This was crucial as Mturk workers do not accept tasks with long and complicated texts.[17] All the essential information, like being divided in a group of three, being endowed with 1 unit of capital, the possibility of buying even if the price exceeds 1, illustrative example of all possible payoffs in the case the initial price was 10 and the probabilities of being first, second or last for each possible price, were presented to each participant. What followed, was inducing an emotional state and was not included in the original experimental design.

4.4. SETTING UP EMOTIONAL ANCHOR

[17] In my case, of course, the participants could not have known the length of the experiment settings prior to accepting it. They could however, drop out of the experiment when they felt the setting being too long to read (or to put no effort to the consequent filling of the survey).

Emotional states can be induced by various ways, for example by showing the participants specifically aimed pictures, playing music, telling them a story or asking the participants to write a report on their happy or sad life story like Bless et al. (1996) did in their research. In the laboratory conditions virtually any method can be used. On the Mturk the options, how to induce particular emotional state, are either technically limited or unfit with respect to the nature of online workers; asking workers to write a vivid report on their own happy or sad life experience would be more effective than for example playing them a story that is perceived either as happy or sad, but it at the same time would be too demanding. Letting the participants to choose their own anchor on an individual level is more effective than anchoring them across the board based on states that are deemed happy or sad only on a general level. This approach is extremely useful in lab environment and with voluntary research participants who might expect extensive forms of requirements and complex tasks. Mturk workers also complete the tasks voluntarily but they themselves pick which ones they will accept *and* finish, therefore a dropout rate is to be expected. It is necessary to mention here, that even though some dropout rate is to be expected, I did not encounter any, as a matter of fact, there was only one case when the participants did not finish the task. Hence, the selection between the treatments cannot be a reason for any observed effects. I therefore chose to anchor the subjects by visual stimuli, i.e. by showing them pictures that are perceived by the society as either happy or sad. Each set included 4 different pictures and the participants were asked to assign a number to each picture. They were supposed to sort the pictures from the most positive (or negative) to the least positive (or negative) from their point of view (the pictures can be found in the Appendix 2). This anchor was presented to subjects after they correctly answered 5 control questions about the EAM bubble game design and the subjects were told they will be divided into the group of three based on their ranking of the pictures. A control group, which was not presented with any picture-evaluation question, was included besides the two test groups. The set of positive pictures consisted of a picture happy smileys, baby rabbit, smiling baby and sunny beach. The set of negative pictures consisted of chopped-down and dead forest, seabird covered in crude oil, painted picture of a hammer breaking a heart and a face of man in pain with either a headache or anxiety. Introducing the anchor after presenting the settings was done in order to see how the subjects make their choices in different emotional states rather than to see how they use cognitive effort for understanding an assignment. After indicating their choice regarding the pictures the participants were presented with the bubble game question whether they buy the asset or not. This question was followed by a short questionnaire in which the participants were asked to indicate their sex, age, prior experience with stock trading and prior experience with a similar survey.

4.5. PRICING

In order to get an idea on how much I should pay the workers for complete my HIT, I went through number of other available HITs on Mturk. I was interested in how much other requesters pay their workers for similarly demanding tasks. Since I had based the distribution of the quoted price for the bubble game on the original experiment, I also wanted to gather similar sample. This meant to aim for around 66 participants per group. Amazon charges 20% fee on the reward and an additional 20% on reward on HITs with more than 10 responses. To set the reward in a way that it would be appropriate with respect to similar tasks and be lucrative enough to attract workers was the main price setting challenge. By setting the reward high enough I wanted to gather the responses quickly enough in order to avoid my HIT to be anyhow discussed on any Mturk forum. However, setting the price below certain level might discourage potential participants as shown by Horton and Chilton (2010).

Rewards for other HITs varied from extremely low prices, like \$0.01, to substantial rewards like \$10 for survey answering. If I was to gather 200 responses (66 per each group) and being limited by a budget of \$100 and Amazon fees, the reward for answering my survey could be no more than \$0.36.[18] As this was not different from survey of similar length, I used this reward. By this I also wanted to avoid the possibility of "being discussed" on any forum in the case of my survey being on for too long. I gathered the data within a day, therefore the pricing should not be a problem.

[18] That is the amount the worker gets, I would pay \$0.5. The difference is comprised of the Amazon fees.

5. DATA AND RESULTS

The next section describes the composition of respondents and tests the applicability (whether the distribution of samples is the same, the randomization of the proposed prices) of the data for further testing. The main tests and findings of this paper, done through logit regressions, follow. A brief comparison of QRE and ABEE models and their ability to predict the results follows. A significant effect of the negative anchor was found.

5.1. DATA

Total of 201 Mturk workers participated in my survey. This figure was primarily limited by the budget of $100 USD. I originally collected 204 responses, but discarded 3 as inadequate. I regarded these as inadequate because the elapsed time for answering the survey was way too short for the participant to even read through the settings and questions. I was unable to match 3 responses from Qualtrics with Mturk completed HITs, but I kept these responses as they were complete. The workers, unfortunately, were not paid for their work in these cases.

The IP address localization showed, that 151 respondents were from the USA, 41 were from southern India and the remaining either from France, Canada, Costa Rica, UK, Venezuela, Singapore or Japan. 119 respondents were of the age of 25-34, 32 respondents were 35-44, 23 were 18-24, 20 were 45-54 and 7 respondents indicated they were 55 or older. Regarding the education of the respondents, half of them, 100, claimed to have a Bachelor Degree, 41 claimed to have a Graduate Degree, 13 Associates Degree, 29 claimed to have spent some time in college but achieved no degree and 18 respondents have finished High School "only". When it comes to stock trading experience, 147 respondents answered to have a little or none experience, 35 had moderate experience and 19 had a lot or a great deal of experience with stock trading. Only 9 respondents claimed to had had a similar survey experience. Interestingly enough, only 2 respondents refused to buy the asset. 67 respondents were female and 134 were male. In order to investigate how these observables differ among anchor groups, I ran a series of Wilcoxon rank-sum tests. Its hypothesis is that two independent samples are from populations with the same distribution. This allows for a "randomization check", which is to check whether the participants, based on their background, are randomly distributed. The *Sex* variable differs when compared between Control and Positive and Positive and Negative groups; there were 43 males in the control group and 52 males in the Positive and 39 in the Negative group. The *Trading Experience* also significantly differs between Control and Negative groups. Therefore, to show the robustness of my results, I control for these variables in the logit regression. Interestingly, both *Sex* and *Trading Experience* variables part however show as strongly insignificant presented in the following section. The detailed results of the rank-sum tests can be found in the Appendix 3.

As mentioned earlier, due to technical limitations, I followed the price distribution of Moinas and Pouget (2013). I was, however, unable to programme the Qualtrics survey accordingly as it only enables to randomize the questions with equal probabilities.[19] I therefore prepared 66 game questions "Your proposed price is…" with the price distribution (both initial and consequent reoffered) as if distributed by probabilities and Qualtrics had to randomize the questions with the prices equally and correctly. This was a major technical difference between mine and the original version. The original actually worked with the response further and the participants were paid higher sums if they successfully sold the asset, whereas I was only interested in the answer itself. Constructing the survey in the same way as the original was beyond the technical and financial options. Nevertheless, due to the backwards induction of steps in the bubble game, the only information that is of interest in the end, is whether the subject enters the bubble or nor for whatever proposed price.

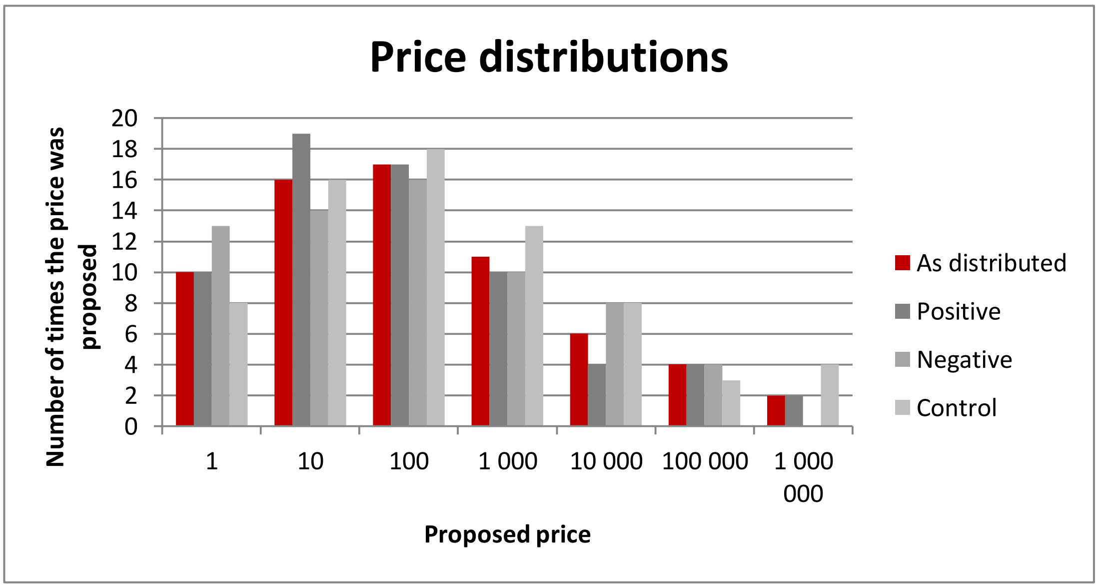


Figure 1: Price distributions

[19] At least with the free account.

The prices distribution is shown in Figure 1. The control group consisted of 70 responses in total, compared to 66 in positive and 65 in negative group. The increase for prices 10 and 100, compared to the frequency of price of 1, is due to the simulated *buy* decision of players that are first in the sequence (those who have been offered to buy for 1, 10 or 100) and their consequent offering for ten-times their buying price (i.e. 10, 100 or 1 000) to the next player. In order to check the distributions of the randomized proposed prices, I used the Kolmogorov-Smirnov test, which null hypothesis is that the two samples it tests are drawn from the same distribution. The results are as follows:

Group	D	p-value	Group	D	p-value	Group	D	p-value
Control	0,0000	1,000	Positive	0,0455	0,873	Negative	0,0485	0,857
Distribution	-0,0515	0,835	Distribution	0,0000	1,000	Distribution	-0,0028	0,999
Combined K-S	0,0515	1,000	Combined K-S	0,0455	1,000	Combined K-S	0,0485	1,000
Observations		136	Observations		132	Observations		131

Table 1: Kolmogorov-Smirnov test for different distributions – proposed prices

Each test compares the distribution of possible prices with the actual distribution of control, positive and negative groups. Since the p-values are close to one, I cannot reject the hypothesis that the groups are from the same distributions.

The constitution of the results, that is three main test groups, positive, negative and control, accompanied by four supplementary categories, *education*, *age*, *sex* and *trading experience*, provide many alternatives for comparison. Some of these combinations are suggestive, such as comparing responses from Indian and American workers, but difficult to compare, since none of the Indian workers was offered to buy for price higher than 10 000. Also these comparison give only a little evidence of any effect as it is done on a sample that is not representative. I will therefore restrict my analyses only to the general level.

5.2. RESULTS

The distribution of accepted offers is shown in Figure 2. Overall, 125 participants entered the bubble. As in the original version, there are two participants who accepted the offer even though they were the last in the sequence and had no one to sell the asset to. The presence of the snowball effect for all test groups is clearly visible. What is interesting, is the negative group, which show little variation for proposed prices of 1, 10, 100 and 1 000 especially, where the acceptance exceeds both positive and control groups.

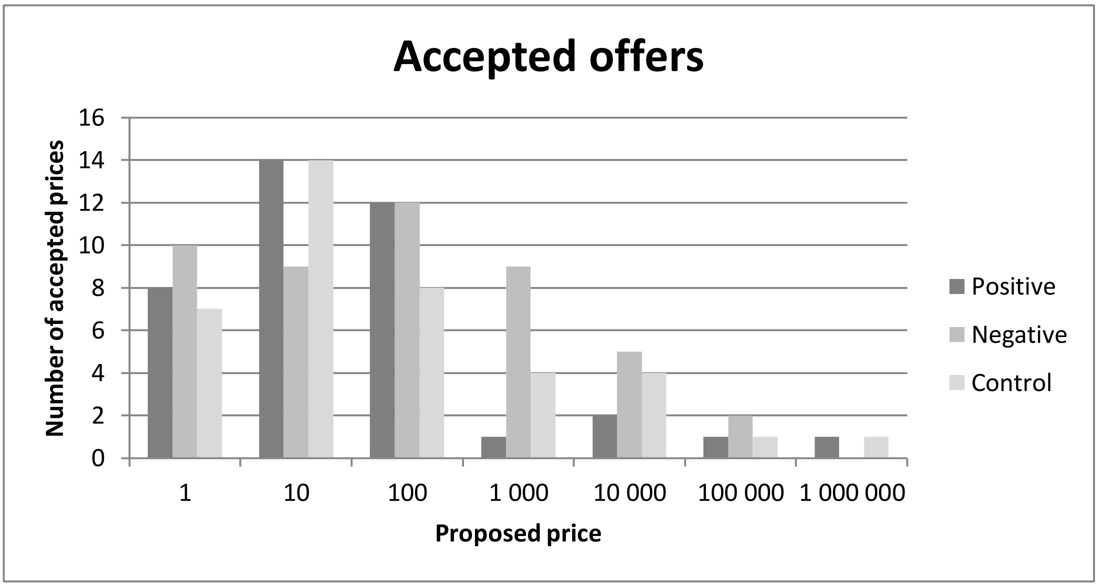


Figure 2: Accepted offers

In order to compare the accepted prices, I again used the test of equality of distributions (Kolmogorov-Smirnov test). Proposed prices (i.e. 1, 10,…) were compared within the given treatment groups. The results are presented in Table 2:

Variable	D	p-value	Variable	D	p-value	Variable	D	p-value
Control	0,0000	1,000	Control	0,1342	0,464	Negative	0,0256	0,972
Positive	-0,1282	0,527	Negative	-0,0333	0,954	Positive	-0,2122	0,147
Combined K-S	0,1282	0,906	Combined K-S	0,1342	0,837	Combined K-S	0,2122	0,292
Observations		78	Observations		86	Observations		86

Table 2: Kolmogorov-Smirnov test for different distributions

Even though I cannot reject the null hypothesis (i.e. that the groups come from the same distribution), it is important to note the difference of negative and positive groups and the low p-values of the positive and the Combined K-S variables. This indicates, that there actually might be some difference. Therefore further tests are required in order for me to investigate the effects of the anchor.

First of all, I ran the Wilcoxon rank-sum test to compare the mean decisions of the buy decision for different treatments, i.e. Control, Positive and Negative. The dependent is the binary variable whether the subject accepts the offer, the grouping variable is a binary variable which indicates whether the subject was in the Control, Positive or Negative group. The results of the rank-sum tests are presented in Table 3:

Compared Groups	p-value
Control / Positive	0,6918
Control / Negative	0,0459
Positive / Negative	0,1126

Table 3: Wilcoxon rank-sum tests

The p-values for comparisons of Control and Positive and Positive and Negative mean that I cannot reject the hypothesis that the groups are of the same distributions. However, the p-value for comparison of Control and Negative groups means that the null hypothesis can be rejected. This points to the fact that the negative anchor actually has some effect on the propensity to enter the bubble.

Secondly, I ran a logit regression of all the anchor and control treatment variables on the decision whether the participants enter the bubble. The results of this regression are presented in Table 3:

VARIABLES	(1) Logit
Positive	0.138
	(0.347)
Negative	0.730**
	(0.367)
Constant	0.230
	(0.241)
Observations	201

Table 4: Logit regression: Entering bubble - Anchors

From the results it can be seen, that the negative anchor has significantly (at the 95% level) positive effect on the log odds of entering the bubble. In other words, being negatively affected increases the propensity to enter the bubble. The positive anchor has also positive but insignificant effect on log odds of entering the bubble. The control group, to which no pictures were shown, has lower log odds of entering the bubble (the case were variables positive and negative are of the value of 0). Next, I ran a second logit regression now with all the variables. Variables *Education*, *Age* and *Trading Experience* were treated as categorical variables. Only 194 from 201 observations were used. This is because all the participants in the age group of 55 years or more decided to enter the bubble. The category *6* of *Age* variable has therefore been dropped from the regression as it predicted the bubble entry perfectly. The only significant variables are *Age* category *5* (45-54 year olds) and the negative anchor. It can be therefore said, that being negatively anchored to increases the log odds of entering the bubble by 0,83 and being older than 45 and younger than 54 on the other hand decreases the log odds of entering the bubble. All other variables are insignificant to entering the bubble. Compared with the results of the first logit regression, the effect of negative anchor on log odds of entering the bubble is even larger. In the second regression the negative anchor is also slightly more significant (the p-value in the first regression is equal to 0,047 and to 0,043 in the second regression).

VARIABLES	Logit
Positive	0.103
	(0.380)
Negative	0.826**
	(0.408)
Education	
Some college, no degree	-0.379
	(0.659)
Associates Degree	1.439
	(0.878)
Bachelors Degree	0.552
	(0.578)
Graduate Degree	0.808
	(0.667)
Age	
25-34	-0.728
	(0.543)
35-44	-0.613
	(0.641)
45-54	-1.548**
	(0.708)
55 or older	-
Male	0.473
	(0.363)
Trading Experience	
A little	0.141
	(0.399)
A moderate amount	-0.130
	(0.489)
A lot	1.310
	(0.867)
A great deal	-0.858
	(1.150)
SurveyExperience	1.194
	(0.872)
Constant	-0.0442
	(0.772)
Observations	194

Table 5: Logit regression: Enterin bubble - all variables

5.2.1. GOODNESS OF FIT OF QRE AND ABEE MODELS

In order to test the goodness of fit of QRE and ABEE models, unfortunately, a more extensive survey form would be required. Moinas and Pouget (2013) included a questionnaire with 14 decision questions in their bubble game survey, through which they measured participants' risk aversion, using a procedure inspired by Holt and Laury (2002). They also obtained the estimate of participants' willingness to accept bets at stake. A similar questionnaire was beyond the scope of my survey on Mturk. I however decided to take QRE and ABEE predictions from Moinas and Pouget's (2013) paper and compare them with the results of my survey. Each of the three figures shows the probability of buy decision for the proposed price, i.e. the ratio of buy decision and the corresponding proposed price, and the predicted probability by both models. The models' predictions are, obviously, the same for all three groups. The comparison is presented below.

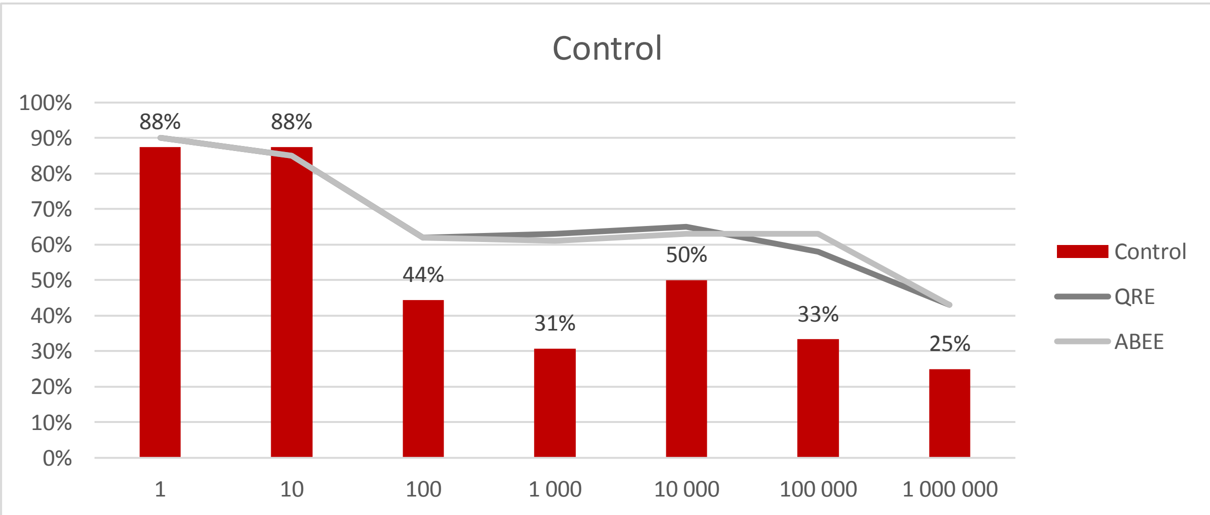


Figure 4: Control group

For the control group, the trend corresponds with the actual choice distribution; the drop between prices 10 and 100, the further decrease towards 1 000, the sudden increase for price 10 000 and then the final decrease towards the maximum price. Neither of the anchored groups are captured by neither QRE nor ABEE. The proposed price of 1 000 stands out in. The two anchor treatments yielded similar results; both overestimate the probability of bubble entrance. The graphs are only presented in the Appendix 3, as the anchor treatments might not only shift the whole distribution but also interact with individual proposed prices. Although the comparison of the actual probability and the one predicted by the models cannot be taken as rigorous, it presents a potential scope for further research.

6. CONCLUSION

The focus of this work was to explore how emotions affect our choices regarding trading with no dividend yielding asset. I ran a modified replication of a bubble game experiment as designed by Moinas and Pouget (2013), which is a version of a centipede game created by Rosenthal (1981). In this game the subjects play sequentially and do not know their position in the sequence. They can only decide whether or not they buy the asset, they cannot influence their successful re-sale of the asset in any way. Participant's success, i.e. making a profit by selling the asset, depends solely on the decision of the participant who is next in the sequence – if there is any. When the potential price of the assets is finite, the backward induction of steps needed to reach the equilibrium rules out any bubble. Therefore, every choice for whatever proposed price and sequence position counts as entering the bubble.

After the game settings were introduced to the participants, they were shown either positive or negative pictures. This was done with the aim to induce either positive or negative affective state and thus anchor them to the respective emotion. It was done in this succession in order to influence their decision only by the anchor and not influence their cognitive abilities required for understanding the task. Consequently, supplementary information about participants' background, such as education, age, sex, trading experience and experience with similar kind of survey, were collected. Randomization test of these variables showed, that the sex of participants is distributed differently between Control and Positive and Positive and Negative treatments. The same holds for Trading Experience between Control and Negative treatments. However, neither of these variables turned as significant in the consequent logit regressions. I ran two logit regressions, first only the anchor treatments on the participants' decision to buy the asset (i.e. to enter the bubble) and all observed variables on the buy decision in the second. Both regressions showed that only the negative anchor has a significant effect on the propensity to enter the bubble. This result supports the findings of Isen (2001), that people are better at solving problems. Even more importantly it corresponds with the finding of Carnevale and Isen (1986), that people are better at taking other party's perspective in negotiations when in happy mood. The finding of Carnevale and Isen (1986) is particularly suitable, since the successful assessment of the behaviour of others is paramount to one's own success in the centipede type of game. The main finding of this paper therefore is, that being in a negative affective state *negatively* affects our decision making process making us more prone to enter a market bubble in an experimental market environment. The data collected unfortunately do not provide me with a possibility to run a goodness of fit test of neither the Quantal Response Equilibrium nor the Analogy-Based Expectations Equilibrium models. These models were proposed as the best potential candidates for predicting the results of the original experiment.

The experimental environment of Amazon Mechanical Turk was unsuitable for collecting the data needed for estimating the parameters essential to estimating the models themselves. However using the models' predictions that Moinas and Pouget (2013) obtained in their research, showed that the models predict the trend of the propensity to enter the bubble in cases when no emotional anchor is set, regardless of systematically overestimating the actual probability. The models need to be revised in order for them to predict the propensity, in cases when either positive or negative emotional state is induced in subjects, correctly. This however requires a research done in laboratory conditions, as gathering the data needed for model estimation would need a closer control over the participants and the course of the experiment. I consider it a possible topic for further research.

When this finding is applied to the real stock markets, a number of implications arise; negative experience might make the stock market participants wrongly assess the behaviour of other traders. The result of this may be, that these participants may enter a stock bubble, if there is any. On the other hand, this bubble may arise simply from the fact that the individual market traders incorrectly anticipate that the other traders will re-buy the asset and thusly create the bubble. What actually poses a problem, is that the time needed for the bubble to burst varies. This variety and the time distance between entering the bubble and its burst would make it difficult to test for the effect of negative emotions on the bubble entrance on the real market data. It would however be a logical next step in studying the effect of emotions.

Regarding the future research, an extended form of this experiment would be desirable. I would find interesting to carry out the experiment in lab conditions, which would enable better control over the emotional anchoring and also it would provide more certainty whether the participants understood the settings. It is important to recall the fact, that unlike Moinas and Pouget (2013), I did not incentivise the participants with money for successful sale of the asset. I believe, that this would change the results, at least in the way that more subjects would enter the bubble. The affective state could be moreover induced through more than one channel, not only through simple pictures, but also through sharing of negative experience. The environment could be accordingly adjusted as well. The latter might bring interesting results – for example whether and how feeling comfortable impairs one's decision. Participants with different background, specifically participants with verifiable stock trading experience, would be a good sample. This kind of data would bring the findings closer to the real world. To test the robustness of negative effect of negative emotions, I would confront the negative anchor with the anchor that Baghestanian and Walker (2015) used. They provided the participants in the experimental asset market with a simple graph, which depicted the fundamental value of the traded asset. This plain figure succeeded in reducing the occurrence of bubbles. Introducing an antagonistic negative anchor would enable one to test which of them has a stronger effect. Result like could be then applied to the real stock markets; for example the pre-opening auctions at the New York Stock Exchange could be accompanied with some positive factor. This would not make the traders performance better, but it would not make it worse, as this is the way towards which the finding of this paper points.

BIBLIOGRAPHY

Amir, O., Rand, D. G. & Gal, Y. K., 2012. Economic games on the Internet: The effect of $1 stakes. *PLoS ONE,* 7(2).

Ariely, D., Loewenstein, G. & Prelec, D., 2006. Tom Sawyer and the construction of value. *Journal of Economic Behavior & Organization,* Issue 60, pp. 1-10.

Ariely, D., Shampanier, K. & Mazar, N., 2007. Zero as a Special Price: The True Value of Free Products. *Marketing Science,* Issue 26(6), pp. 742-757.

Arkes, H. R., Herren, L. T. & Isen, A. M., 1988. Role of possible loss in the influence of possitive affect on risk preference. *Organizational Behaviour and Human Decision Processes,* Issue 42, pp. 181-193.

Baghestanian, S. & Walker, T. B., 2015. Anchoring in Experimental Asset Markets. *Journal of Economic Behavior & Organization,* Issue 116, pp. 15-25.

Bless, H. et al., 1996. Mood and the Use of Scripts: Does a Happy Mood Really Lead to Mindlessness?. *Journal of Personality and Social Psychology,* Vol. 71(No. 4), pp. 665-679.

Bless, H. & Fiedler, K., 2012. Mood and the regulation of information processing and behavior. In: *Affect in Social Thinking and Behaviour.* s.l.:Psychology Press, pp. 65-81.

Buchanan, T., 2000. Potential of the Internet for personality research. *Psychological experiments on the Internet,* pp. 121-140.

Carnevale, P. J. D. & Isen, A. M., 1986. The influence of possitive affect and visual access on the discovery of integrative solutions in bilateral negotiation. *Organizational Behaviour and Human Decision Processes,* Issue 37, pp. 1-13.

Cason, T. N. & Samek, A. S., 2014. *Visual Representation and Observational Learning.* [Online] Available at: www.krannert.purdue.edu/faculty/cason/papers/AssetBubbles_Vis.pdf [Accessed December 2015].

Drehmann, M., Oechssler, J. & Roider, A., 2005. Hedring and Contrarian Behavior in Financial Markets - An Internet Experiment. *The American Economic Review,* Vol. 95(No. 5), pp. 1403-1426.

Edlund, J. E. et al., 2009. Whatever happens in the laboratory stays in the laboratory: The prevalence and prevention of participant crosstalk. *Personality and Social Psychology BUlletin,* Issue 35, pp. 635-642.

Edmans, A., García, D. & Norli, Ø., 2007. Sports Sentiment and Stock Returns. *The Journal of Finance,* LXII(4), pp. 1967-1998.

Frieder, L. & Subrahmanyam, A., 2004. Nonsecular regularities in returns and volume. *Financial Analyst Journal,* Issue 19, pp. 29-34.

Geva, N. & Isen, A. M., 1987. The influence of positive affect on acceptable level of risk: The person with a large canoe has a large worry. *Organizational Behaviour and Human Decision Processes,* Issue 39, pp. 145-154.

Goodman, J. K., Cryder, C. E. & Cheema, A., 2013. Data collection in a flat world: The strenghts and weaknesses of Mechanical Turk samples. *Journal of Behavioral Decision Making,* Issue 26, pp. 213-224.

Gray, J. A., 1971. *The psychology of fear and stress.* Cambridge: Cambridge University Press.

Hertel, G. & Fiedler, K., 1994. Affective and cognitive influences in a social dilemma game. *Journal of Social Psychology,* Volume 24, pp. 131-145.

Hirt, E. R., Grant, E. A., Kennedy, C. & Zillmann, D., 1992. Costs and benefits of allegiance: Changes in fans' self-ascribe competencies after team victory versus defeat. *Journal of Personality and Social Psychology,* Issue 63, pp. 724-738.

Holt, C. A. & Laury, S. K., 2002. Risk Aversion and Incentive Effects. *American Economic Review,* Issue 92, pp. 1644-1655.

Horton, J. J. & Chilton, L. B., 2010, June. The labor economics of paid crowdsourcing. *Paper presented at the 11th Association for Computing Machinery Conference on Electronic Commerce, Cambridge, MA.*

Horton, J. J. & Chilton, L. B., 2010. The labor economics of paid crowdsourcing. In: *EC '10 Proceedings of the 11th ACM conference on Electronic commerce.* Cambridge(Massachusetts): Association for Computing Machinery New York, NY, USA, pp. 209-218.

Chandler, J., Mueller, P. & Paolacci, G., 2014. Nonnaivete among Amazon Mechanical Turk workers: COnsequences and solutions for behavioral researchers. *Behav Res,* Volume 46, pp. 112-130.

Isen, A. M., 2001. An Influence of Positive Affect on Decision Making in Complex Situations: Theoretical Issues With Practical Implications. *JOURNAL OF CONSUMER PSYCHOLOGY*, 11 (2), pp. 75-85.

Isen, A. M. & Patrick, R., 1983. The effect of positive feelings on risk-taking: When the chips are down. *Organizational Behaviour and Human Performance,* Issue 31, pp. 194-202.

Jehiel, P., 2005. Analogy-based expectation equilibrium. *Journal of Economic Theory,* Issue 123, pp. 81-104.

Kahneman, D., 2003. Maps of Bounded Rationality: Psychology for Behavioral Economics. *The American Economic Review,* Issue 93(5), pp. 1449-1475.

Kahneman, D. & Tversky, A., 1981. The Framing of Decisions and the Psychology of Choice. *Science, New Series,* Issue 211(4481), pp. 453-458.

Klein, R. A. et al., 2014. (in press), Investigating variation in replicability: A "many labs" replication project. *Social Psychology.*

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

Muth, J. F., 1961. Rational Expectations and the Theory of Price Movements. *Econometrica,* Issue 29, pp. 315-355.

Nygren, T. E., Isen, A. M., Taylor, P. J. & Dulin, J., 1996. The influence of positive affect on the decision rule in risk situations: Focus on outcome (and especially avoidance of loss) rather than probability. *Organizational Behaviour and Human Decision Processes,* Issue 66, pp. 59-72.

Paolacci, G. & Chandler, J., 2014. Inside the Turk: Understanding Mechanical Turk as a Participant Pool. *Current Directions in Psychological Science,* Vol. 23(3), pp. 184-188.

Paolacci, G., Chandler, J. & Ipeirotis, P. G., 2010. Running experiments on Amazon Mechanical Turk. *Judgement and Decision Making,* Issue 5, pp. 411,419.

Rogers, B., Palfrey, T. & Camerer, C., 2009. Heterogenous Quantal Response Equilibrium and Cognitive Hierarchies. *Journal of Economic Theory,* Issue 144, pp. 1440-1467.

Rosenthal, R. W., 1981. Games of Perfect Information, Predatory Pricing and the Chain-Store Paradox. *Journal of Economic Theory,* Issue 25, pp. 92-100.

Smith, V. L., Suchanek, L. G. & Williams, A. W., 1988. Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Asset Markets. *Econometrica,* Septmeber, 56(5), pp. 1119-1151.

Trope, Y., Ferguson, M. & Raghunathan, R., 2001. Mood as a resource in processing self-relevant information. In: *Handbook of affect and social cognition.* Manwah(NJ): Lawrence Erlbaum Associates, Publishers, pp. 256-274.

Wegener, D. T., Petty, R. E. & Smith, S. M., 1987. Positive mood can increase of decrease message scrunity: The hedonic contingency view of mood and message processing. *Journal of Personality and Social Psychology,* Issue 69, pp. 5-15.

Yuan, K., Zheng, L. & Zhu, Q., 2006. Are investors moonstruck? Lunar phases and stock returns. *Journal of Empirical Finance,* Issue 13(1), pp. 1-23.

APPENDIX 1

This appendix shows the course of the experiment, as it was presented on Qualtrics.

Hi!

Thank you for participating in this survey.

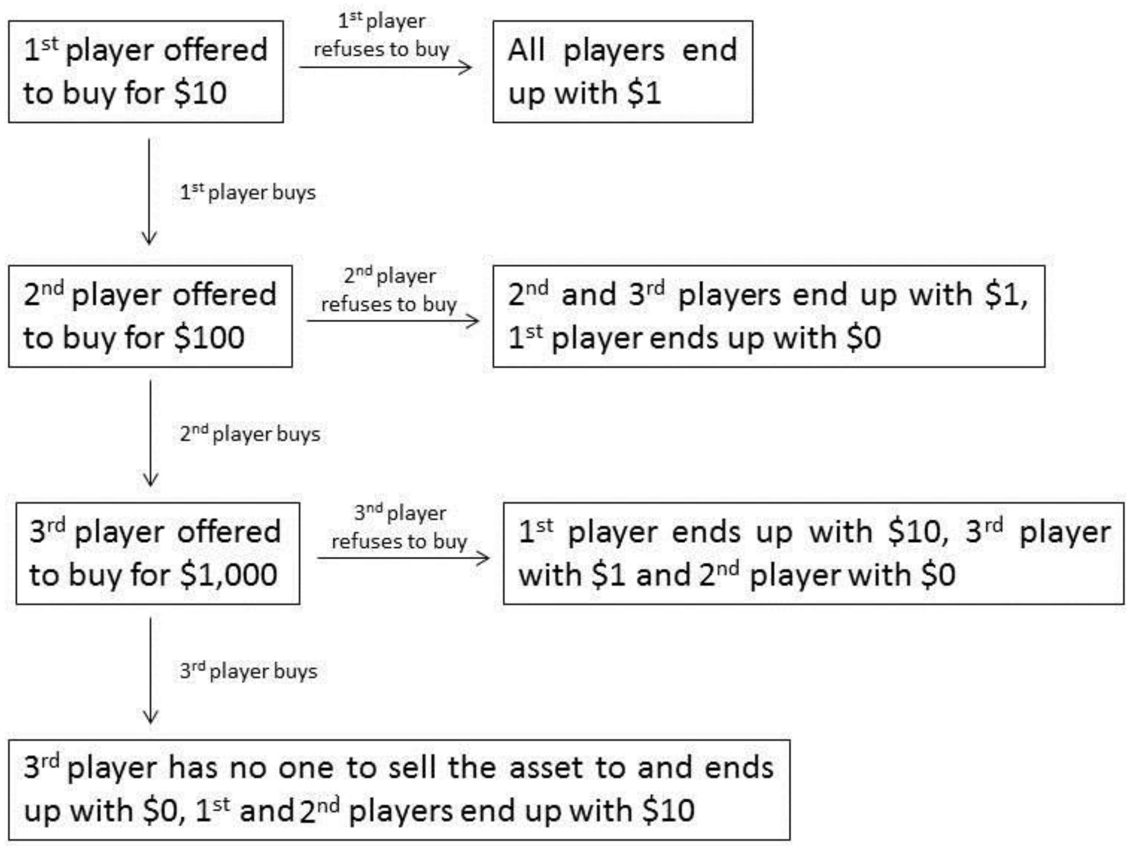
In the following game you will be divided into groups of three. At the end you will fill in a basic questionnaire. It will take you 5-10 minutes for which you will receive $ 0.36

From the following pictures pick 3 which you find the most positive (from the most). Based on your answer you will be assigned to a specific group.

Game instructions follow. Please read them carefully, the game consist of only one question.

In the group you have $1 each for which you can buy a no-dividend bearing asset. Your task is to choose whether or not you want to buy the asset. If the asset price exceeds $1, you can still buy the asset, the funds will be given to you automatically from external financial partner with whom you will share any profit.

Here is an example of how the game works when the initial price (which differs among groups) is $10:



At the beginning of the game, you each have 33% chance to be first, second or third.

Price	Probability that this price is proposed to first player
1	50%
10	25%
100	12.5%
1,000	6.25%
10,000	6.25%

You can deduce the following from the price you have been offered:

For $1 you are sure to be first in the sequence

For $10 you have 33% chance to be first and 66% chance to be second

For $100 or $1,000 you have 14% chance to be first, 29% chance to be second and 57% chance to be last

For $10,000 you have 25% chance to be first, 25% chance to be second and 50% to be last

For $100,000 you have 50% chance to be second and 33% chance to be third

For $1,000,000 you are sure to be last.

Control questions:

If you are offered to buy for $100 can you be the first in the sequence?

If you buy the asset do you automatically have the certainty you will resell it?
If you refuse to buy the asset, you end up with $1.

If you are offered to buy for $100,000 are you sure to be last in the sequence?

If you have bought the asset and you don't resell it, you are left with $0 because the asset does not yield anything.

If you are offered to buy for $100, can you be the last in the sequence?

Can you be certain to make profit if you are offered to buy for $1?

Is there a price for which, if you are offered to buy the asset, you can be sure you won't resell it?

You are offered to buy for $1,000. Can you be last in the sequence and therefore not have anybody to sell the asset to?

Is being the last in the sequence and not reselling the exact same situation?

Now based on your following choice you will be assigned to a group:

Based on your opinion rank the following pictures from the most positive to least positive (1 for the most positive to 4 for the least positive).

The pictures used to anchor the subjects can be found in the Appendix 2.

And now here is the game question:

Your proposed price is 1/10/100/1 000/10 000/100 000/1000 000. Do you buy the asset?

Thank you for your answer.

Now please answer few questions about yourself:

Your gender/age/highest achieved education/experience with stock trading/participation in similar survey.

APPENDIX 2

This appendix present the pictures used a the emotional anchor;

Pictures labelled as *positive*:

Pictures labelled as *negative*:

APPENDIX 3

Control / Positive		Control / Negative		Positive / Negative	
Variable	p-value	Variable	p-value	Variable	p-value
Education	0,7260	Education	0,7524	Education	0,9881
Age	0,6486	Age	0,1904	Age	0,4033
Sex	0,0280	Sex	0,8656	Sex	0,0200
Trading Experience	0,8139	Trading Experience	0,0288	Trading Experience	0,0613
Survey Experience	0,1951	Survey Experience	0,9143	Survey Experience	0,1675

Table 6: Wilcoxon rank sum tests on distributions

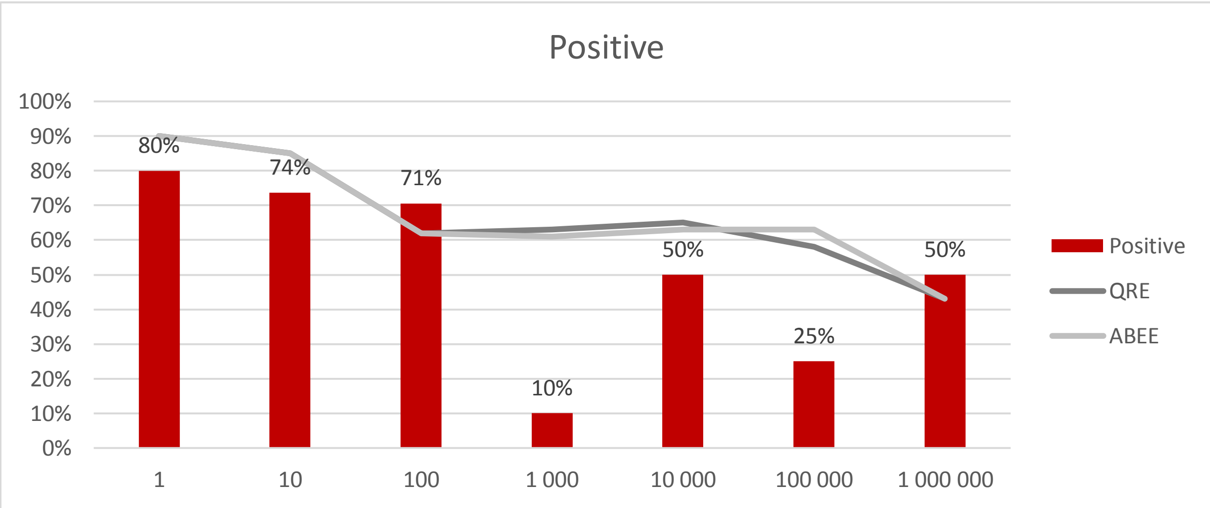


Figure 5: Positive group

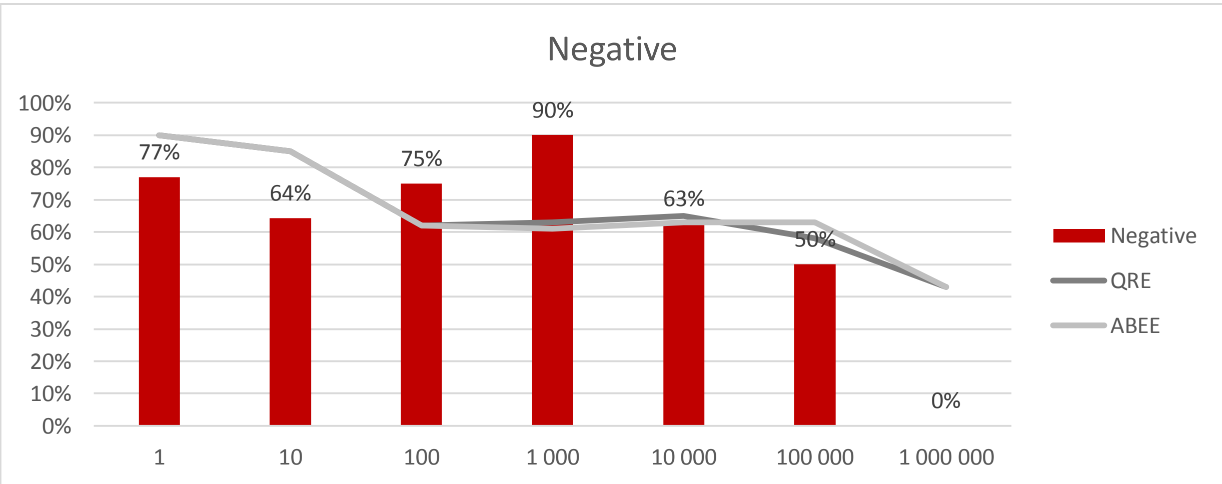


Figure 6: Negative group