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Do information cascades arise easier under time pressure? Experimental approach.

Master Thesis

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Abstract

Information cascades as a form of rational herding help to explain real-life phenomena such as fads, fashion, creation of 'bubbles' in financial markets or conformity in general. In this thesis I model both the propensity to herd as well as the propensity to view public information that may lead to herding. I carry out a laboratory experiment where I let subjects perform a simple task under different treatment conditions with the possibility to herd. Researchers normally imposed the uncertainty about the private signal by providing a task probabilistic in its nature such as drawing balls of different color from an urn and the decision-making was sequential. I conduct an experiment where the order of decision-making is endogenous and a task that is not probabilistic, but I impose uncertainty of private signal by increasing time pressure. This is expected to make participants prone to imitate the behavior of others, even though the others will be exposed to the same conditions. The time-pressure is also expected to induce stress reaction, which I measure as a physiological proxy variable – the heart rate frequency. Participants after each task state the subjective level of stress they felt to be in. I compare these two indices of stress if they bring same results. I also account for personality differences by measuring them in the "Big Five" dimensions by a battery of standardized questions. If significant, the personality traits may provide another piece of evidence that the original informational approach to herding is not exclusive and personality is also an important underlying factor. Apart from that I examine the effect of reputation (also called endorsement effect) as an addition to the public pool of information, which is expected to increase the probability to herd.

JEL Classification: C25, C91, D03, D80

Key words: Information cascades, herding, experimental economics, heart rate measurement, personality traits, endorsement effect.

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Abstrakt

Informační kaskády jako forma racionálního stádového chování pomáhají vysvětlit celou řadu ekonomických jevů, kde neoklasická teorie zaostává, jako například módní trendy, tvorba 'bublin' na burze, konformismus nebo obecně následování rozhodnutí ostatních. V této práci se snažím modelovat sklon ke stádovému chování stejně jako sklon k zobrazení informace, která může ke stádovému chování vést, za použití laboratorního experimentu. Účastníci měli za úkol splnit jednoduchou kognitivně nenáročnou úlohu za různých experimentálních podmínek. Zatímco v doposavad provedených laboratorních pokusech na tvorbu informačních kaskád se pro zavedení nejistoty soukromého signálu používala pravděpodobnostní úloha, já provedu pokus s úlohou jistou, nicméně potřebnou nejistotu výsledku vyvolá uvalením účastníků do časové tísně. Účastníci budou také rozhodovat v reálném čase, čímž bude pořadí odpovědí indukované endogenně. Časová tíseň by měla vyvolat kromě nejistoty o vlastním výsledku i stresovou reakci, která sama o sobě ovlivňuje rozhodování jednotlivce, což budeme sledovat měřením objektivní fyziologické veličiny – tepové frekvence. Ta bude poté srovnána se subjektivním pocitem stresu, který účastníci sdělovali po každé úloze. Další z faktorů, které mohou ovlivnit sklon ke stádovému chování, jsou osobnostní charakteristiky, které měřím pomocí baterie standardizovaných otázek „Velká pětka“. Pokud budou významné, bude to další argument proti exkluzivitě informačního přístupu k vysvětlení stádového chování. Kromě efektu časové tísně zkoumám také efekt reputace tím, že k veřejné informaci o odhadu jednotlivce přidám jeho dosavadní výkon. Reputační efekt jedinců s vysokou úspěšností v předchozích kolech by mohl tvorbu kaskád ještě více podpořit.

Klasifikace JEL: C25, C91, D03, D80

Klíčová slova: Informační kaskády, stádové chování, experimentální ekonomie, měření tepové frekvence, osbnostní charakteristiky, efekt reputace

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature. The author grants to the Charles University permission to reproduce and to distribute copies of this thesis document in whole or in part.

Prague, June 30, 2010

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Signature

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MASTER THESIS PROPOSAL

Name: Bc. Lubomír Cingl
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Proposed Thesis: **Do information cascades arise easier under time pressure? Experimental approach**.

Topic characteristics:

Information cascades as a form of rational herding (Bikhchandani, Hirshleifer, and Welch (1992)) are already quite well-documented phenomenon in most of its dimensions in laboratory (Anderson and Holt (1998, 2008)) as well as on the field data in many practical applications as in Bikhchandani, Hirshleifer, and Welch (2008). However, researchers normally imposed the uncertainty about the private signal by providing a task probabilistic in its nature and the decision-making is sequential. We will provide a task that is not probabilistic and the order of decision-making is exogenous in the real time. Furthermore, we impose uncertainty by making the payoff time-dependent and gradually reduce the total time for processing the task, which is expected to make the participants prone to imitate the behavior of others (create the information cascade) even though the others will be exposed to the same conditions. The time-pressure is expected to induce stress reaction, which we control for by objectification of stress by measuring a proxy variable – the heart rate. If the results show that the less time the participants have, the more they rely on actions of others, it may cast light on everyday decision making mechanisms that are made under time pressure as well as help to explain excess volatility during market crises, when under time-pressure, the traders are expected to (rationally) follow the crowd.

Hypothesis and research question:

When under time pressure, do people rationally incline to form their decision more on information relevant for the decision from other sources, such as imitation of behavior of other agents and ignoring their own private signal, which is known as a creation of an informational cascade? Do they perceive the time pressure as a stressor? If so, does it influence their performance?

Methodology:

I conduct a full-computerized laboratory experiment with n-times 18 participants per experiment session where n=3-5 depends on funding and other exogenous circumstances. Prior to the experiment itself we will run a pilot-version of the experiment to verify the structure of the experiment and to calibrate the tasks with approximately 18 participants.

Before the game starts, subjects have to fill in a short questionnaire where we want to find out their age, gender, attitude to risk (paid-for protocol based on Falk et al., 2009) and personality profile based on the personality traits questions.

Subjects are then introduced to the game they are going to play, which is followed by a confirming question to check their understanding of the tasks. They earn tokens which are afterwards converted to cash, which should create explicit motivation on a good outcome of the game. The aim of the game for them is implicitly of course to collect as much tokens as possible.

Task

The participants perform a simple cognitive effort task, which will not be demanding on previously earned skills or innate cognitive abilities with learning effect. This game was introduced by Falk, Huffman and Sutter (2006). Participants are required to count a correct number of zeros from a sheet of 600 symbols (zeros and ones only). The payment should be similar as in Falk et al. (2008) 2€ per sheet if counted exactly, 80% if in the range of +/- 1 or 40% if in range +/- 2.

The participants will go through several stages of the game:

First stage - introduction

The first part will be simply an introduction in that they will have free time to complete 2 tasks for a fixed payoff per task.

Second stage – time-dependent payoff

The second part will put them under time pressure in the sense that the payoff will be a decreasing linear function of time – the participants will thus be motivated to answer as fast as possible and waiting for others to answer is thus costly. The fractions of average time on which the payoff-function would be based on will vary from 1.2, 1, 0.8 over 0.75 to 0.5 to stimulate the time pressure, which should substitute the private-signal imperfection in the information cascade setting. The average time will be based on the performance of the group in the first stage, not individuals. (The participants will know about this setting beforehand, but not that the time-pressure would be based on their performance in the first stage, as it might motivate them to behave strategically.)

Each task will be evaluated after all participants will have finished or the time runs out and all participants see their payoffs real-time. It is a matter of further investigation whether to make the order of levels of time-pressure randomly, or gradually intensify it, because in normal situations the stress before deadlines also intensifies. The exact calibration of the difficulty of the task and the number of tasks is subject to changes after the pilot-test.

Test of self-confidence

After the two stages we need to find out, how self-confident the participants feel about the tasks. We try to infer it from a bet the participants can make on their future outcomes and/or their estimate of relative position to others (e.g. "In what percentile do you think you are – upper 10%, …, lowest 10%)

Third stage – time-dependent payoff with possibility to look at the aggregate choices

This stage proceeds the same way as the second but with a difference in that the participants will have an opportunity to have a look at the aggregated results of others (histogram) in real-time. The participants will have to enter their own estimate of the number of zeros first, then the task-sheet disappears and then they will have the opportunity to look at the decisions of others and change their mind on their final choice. They do not need to use the additional information and make their final choice straight. By first entering their own estimation we spot their private signal and infer its accuracy. (We consider making a bonus for the fist three movers so that they have a greater incentive not to wait for information of others.)

Fourth stage – added reputation effect

This stage will proceed the same as the third stage with the difference that the information about the choice of others will be supplemented by the information about the performance (payoffs) of participants that have already made their final choice (in the histogram of final choices). The logic is that there may emerge few leaders with high accuracy of guesses and their decision may have impact on the decisions of others.

Control for stress

Participants will be during the experiment controlled for physiological stress-responses, particularly the heart-rate, by heart-rate monitors, which will be either bought from the grant or borrowed from a specialized institution (Either the FTVS UK or the Military Hospital in Prague).

After the end of the experiment the subjects will get a questionnaire to state their subjective feeling of being in stress, which will then be compared to the results of measuring of the heart rate.

Other experiment (Social-preference test, loss-aversion, public-good experiment)

After the four stages of the game, the subjects will have already earned significant amounts of money and thus there is an open space to test other features of current research such as social preferences, public-goods game or loss aversion. I will try to find another experimenter that would like to join me; otherwise I end after the fourth stage.

Expected results

The time pressure in the second stage should stimulate eustress reaction and thus enhance the effort of the participants, but decrease the accuracy/quality of their counts as in Kocher and Sutter (2006).We expect the payoff-per-time to be higher in the second stage than in the fist stage.

In the third stage, the subjects are expected to use the information about the decisions of others with increasing time-pressure more often, which can be inferred from comparison of the difference of the private and final estimates. We also expect that the latter the participant answers, the more public information she will use, i.e. the more prone to herding she will become. We expect them to use the public information, even though the information is not fully reliable. This should stimulate the herding and also creation of erroneous cascades. In the fourth stage we expect the people to follow the information of the previously-successful players and not of the unsuccessful; therefore we expect less of erroneous cascades to emerge. The heart rate should increase with higher time pressure and should serve as a proxy of the stress-indicator, so it should be negatively related to the accuracy but positively to the productivity over time.

Outline

1. Attitudes of conflicting views of rationality on social behavior
2. Information cascades and rational herding
3. Limitations to cognitive abilities
4. Experiment
5. Results of the experiment

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1.2 ORGANIZATION OF THE THESIS

In the first chapter I explain my motivation for choosing this theme as well as the method used. The second part summarizes major works in the field of herding and information cascades with an emphasis on the laboratory experiments. In the third section I go in detail through the underlying methodology, specification of the model and the estimation techniques I finally use to evaluate the model. In this section I also state tested hypothesis. The fourth part is the general description of the experiment, reasoning for the design and of the complete organization. After this I start with the analysis of the data. The fifth section contains mostly general findings and behavior of variables, but also treatment comparison and tests of some of the simple hypotheses. The part six is the most technical one, because I analyze here in detail the model by using logit estimator. After it I only summarize the results of the hypotheses and the most remarkable findings of this paper.

To a technically not too skilled readers I recommend to focus on the section one, three (the second half), four and seven. Part five is also not very difficult to read as only basic statistical methods are used. Finally, summaries of the models are written with respect to general public as well as the hypotheses evaluation in the section seven.

1 INTRODUCTION

"It is safe to say the economists' traditional idea - that we're all hyper-rational calculating machines who unfailingly act in our own self-interest - has not been among the more productive ideas of science. One might even say that it stands out as a monument to the incursion of a completely non-scientific way of thinking into human science."

- Buchanan (2007), p. 191.

1.1 CONTRIBUTION OF THIS PROJECT – MOTIVATION

In everyday life, we face lots of situations in which we have to make a decision and we do not always have enough time to process all information which furthermore is not always available or perfect. Generally, in a majority of cases we face decision-making tasks that can be resolved by our own cognitive abilities – we just solve the task and state the action we want to do on the basis of the input information. However, if there is simply not enough time to process all the information (or e.g. acquiring information is costly), then we stand in a position of also not knowing exactly what the result of our decision-making process should be – we face uncertainty about our *private signal* and thus we cannot be sure whether the action we want to take is the proper one or not. In such a case, it is completely rational to look at the behavior of others, how they acted in a similar situation and with what result. If we consider that the public information we observe is worth following and we ignore our own private signal, (i.e. the publicly revealed information has a higher probability of being correct than our own private signal), and behave the same as our predecessors, we become a part of what is called an *information cascade* by Bikhchandani, Hirshleifer, and Welch (1992)[1], who also proved the rationality of such behavior. Additionally, people who face the same task and see us following the action taken by others have an even stronger motivation to believe that the action taken by others is the correct one and thus the incentive to herd is reinforced. Eventually, there is a cascade of people taking the same action. However, the action taken in the cascade does not always lead to a correct outcome, as for example in the case of smoking, where people get uncertain private information about the effects of smoking and some of them decide to follow the crowd. What is more, in the case of financial markets such an incorrect cascade can even lead to huge losses, which is actually what economists are really interested in.[2] To summarize, this experiment examines the evolution of the individual propensity to herd (or of the creation of an information cascade) on the

[1] Further BHW (1992)
[2] This explanation of herding behavior is only one among a few others, which will be discussed further.

basis of the increasing time pressure and leadership effect of successful players. In the experiment I use a simple cognitive task that can be solved easily with enough time. However, with a lack of time, the outcome becomes unsure and simulates the imperfection of private information as in the Information Cascade (IC) experiments. I also track various individual characteristics to try to explain the variability of the propensity to herd, see part 3 Methodology.

1.2 CONTRIBUTION OF EXPERIMENTAL ECONOMICS

World-wide, there has been a vast disappointment with traditional economic theories due to their inability to predict or to cope with the global crisis. Paul Krugman (2009) wrote recently in The New York Times about the disdainfulness of theoretical economics which had built extremely complicated mechanistic concepts of the human economic system, but still stood on the very shaky ground of its own assumptions: *"...the central cause of the profession's failure was the desire for an all-encompassing, intellectually elegant approach that also gave economists a chance to show off their mathematical prowess.*" The basic flaw is to infer that if the people behaved the same in the past, they will behave the same way also in the future, even if the conditions change (ceteris paribus does not hold anymore). And eventually, the core of economics was tragically simplified if not ignored competely – the individual behavior itself.

From my point of view, if we want to study such a complicated thing as an economy, we have to first examine the functioning of the most fundamental parts of it – of the individuals – in every single way to be able to simplify it and build models upon it. We have to understand very well the way people act, react and make decisions under different conditions. We have to improve the assumptions of our old theories thereby creating solid grounds for our new theories and start building new models of economy, not necessarily with the conventional methods we have used. Network analysis, computational economics, agent-based modeling and other new approaches based on more realistic assumptions about individual behavior should be taken very seriously as they can inform us much more than aggregative approach of neoclassical models. I strongly believe that behavioral economics can help to provide these grounds. On the other hand, I also believe that the old models should not be completely abandoned: they mostly still provide valuable insights into economy and in most cases only need to be treated with caution about which situations they can be used in.

1.3 LABORATORY EXPERIMENTS

Every reliable science needs to test its theories in a controlled experiment, even economics. Some prominent economists such as Samuelson himself denied the possibility of conducting controlled experiments, but thereafter changed his opinion. Generally speaking, with the exception of psychology, social sciences have been a little slower in adopting controlled experiments in comparison to the natural sciences. Starting in the 1940s, economic experiments were very rare. Then, in approximately 1975, the average number of published papers per year grew from about 10 to 30 (Falk and Heckman, 2009). The renaissance in this field occurred during the mid-1980s and since then the number of published papers relatively to all published papers grew from around 3% in the 1990s to 4.15% in the years 2000-2008. The first journal specialized in this field was Experimental Economics, founded in 1998.

In economics there are mostly two types of experiments: laboratory and field experiments. Both of these approaches have some advantages and disadvantages when compared to one another. Laboratory experiments provide the opportunity to create an environment specific to testing one certain aspect of interest while controlling for all other sources of possible influence. However, the environment is often very artificial and, when not correctly designed, a laboratory experiment may lose its connection to the real world. Field experiments apply the experimental examination of an intervention into the real world rather then in the laboratory, but it is very difficult to extract the particular effect of interest from other simultaneously functioning effects. (Smith, 2008)

Common objections to the laboratory environment are that the participating sample of population that consists mostly of students is unrepresentative and the samples are too small to be able to generalize the results to the real world: the so called sample selection bias. However, the lab provides a unique environment for tightly controlled variation of the experimental conditions which is very hard or even impossible to create in the field or find in naturally occurring situations. The proponents of field experiments highlight the more realistic conditions, which is however not really an argument – the point is to perfectly isolate the studied effect and moreover to identify the direction of causality if possible. Another objection to laboratory experiments is the problem of the Hawthorne effect (Cameron and Trivedi, 2005), which stems from the fact that human subjects may change or adapt the behavior while participating in the experiment. In this case the variation that is observed under the treatment can not be attributed to treatment only.

1.4 DEFINITIONS FROM LITERATURE

BHW (1992) define information cascade as "*a situation in which every subsequent actor, based on the observations of others, makes the same choice independent of his/her private signal.*" Bikhchandani and Sharma (2001, pp. 286) define for the purpose of searching for them in financial markets "*an invest cascade (reject cascade) iff the number of predecessors who invest is greater (less) than the number of predecessors who do not invest by two or more.*" Smith and Sørensen (2000) and Çelen, and Kariv (2004) emphasized that there is a significant difference between informational cascades and herds. Informational cascades occur when subjects ignore their private signals in making predictions, whereas herds may occur when subjects happen to make identical predictions, not necessarily ignoring their private signals.

For the purpose of my experiment, I define the occurrence of *herding* according to Scharfstein and Stein (1990) when *an individual ignores her own private information after seeing the publicly available information and switches from her result to a result similar to/same as that of the majority*. Further I define the occurrence of *information cascade when the results of subjects in a given period do not differ*. When the number that is followed is different from the true number but not more than 2, I define the cascade to be *weak*. An erroneous cascade emerges when the followed number is incorrect and does not bring any payoff.

Other definitions can be found in the text. Until the definition appears in the text, discussion using a term is meant to be taken in general.

2 LITERATURE REVIEW

2.1 SEMINAL PAPERS ON INFORMATION CASCADES

Even though there had been papers on very similar topics or on examples of them before, information cascades were first comprehensively described and analyzed by Bikhchandani, Hirshleifer, and Welch (1992), (also Bannerjee (1992) and Welch (1992), but I focus on BHW (1992)) when they illustrated in a model that ignoring a private signal after observing public information can actually be rational on the basis of the process of Bayesian updating of personal beliefs. (Of course Bayesian rationality is not the only proposed explanation of herding – it competes with psychological explanations that herding is an innate quality and is motivated by emotional and personality traits; see section 2.1.2) The model consisted of a binary signal, binary action spaces and fixed order of decision-makers with observable signals or actions. A less rigorous explanation is in Bikhchandani, Hirshleifer, and Welch (1998)[3], where they illustrate the idea in the example of a book that has become a bestseller only because the authors were smart and wealthy enough and secretly bought 50,000 copies from monitored stores all over the USA which caused the book to get onto the list of top-sold books. In spite of public reviews rating the book to be an average one and the authors' trick being revealed, it continued to be a bestseller. Why are the top-ten lists published? Probably because when the public sees that so many other people have bought the item from the list, it suggests it must be good despite contrarian signals as for example mediocre ratings and thus the probability of being sold increases.

2.1.1 BHW MODEL DESCRIPTION

In the model in BHW (1998) which is the same as in BHW (1992) they show the difference between a model with observable actions and a model with observable signals. The fundamental difference stems from the different effectiveness resulting from the creation of the information cascade. The observable-action model has the fundamental property that the public information at one point stops accumulating because the private info, which was not already revealed will, in a cascade, be ignored. This happens at a point where the public pool of information becomes only a *little more* informative than the private info of a participant, which means that for each next decision-maker in the decision row, it is profitable to conform and follow the crowd. It is striking

[3] Further BHW (1998)

when they compute[4], that if a probability *p* of a private signal is correct is only slightly above 50%, say that *p*=0.51, then there is a chance for a cascade to appear at the *third* decision-maker (if the two predecessors took the same action) 75% and after eight players moving, the same the probability becomes 99.96%. However, the probability of a cascade being correct in the outcome is only 51.3%. Even when the private signal is more precise, the chance of ending-up in a correct cascade is not much higher than with the private signal alone. Furthermore, BHW (1998) state that the cascade is very fragile, because when in a row of the same actions one new appears, then the process of the creation starts again from the beginning. Also, people do not always see the actions of predecessors systematically in a row but they observe only summary statistics, like how many people chose action A and how many of them chose B, but this should not really change things. If the set of actions gets larger and richer, it results in a later creation of a cascade thus aggregating more information and creating greater incentive to follow the crowd. However if the action space becomes continuous, then every individual will at least partially base her decision on her own private signal. The assumptions have been eased and discussed in many papers since then, with different results, see further on. Generally, BHW (1998) suggest that the IC theory can also explain stock-market crashes.

2.1.2 OTHER EXPLANATIONS OF HERDING THAN INFORMATION CASCADES

BHW (1998) then provide more examples from real life, like people hired to applaud loudly at musical performances, mourn professionally at funerals or those advertisements that often use the fraction of professionals who use the product as an indicator of quality rather than reviews or other "real" quality measures.[5] They call the influence on personal actions stemming from observation of other people's action *observational learning* and they stress that there may also be other factors that cause such convergent behavior, like *payoff externalities* or explicit *sanctions upon deviants*. Bikchandani and Sharma (2000) suggest that among the payoff externalities, the role of *incentive schemes* for managers of mutual funds may play a role. Their salaries are sometimes based on comparison with the average in the industry, thus conformity is even explicitly rewarded in this case. Also reputational concerns may have an impact on the decision making of a fund manager or an analyst – "conformity with other investment professionals preserves the fog" (Bikchandani and Sharma, 2000, pp. 291) and the owners can not be sure about the true abilities of the portfolio manager. Apart from that, individuals may have concrete intrinsic *preferences for conformity* so

[4] See exact computation in BHW (1998), pp. 153- 156

[5] E.g. slogan of a type "78% of doctors prescribe the medicine XY!"

going with the crowd is inherently included in their utility function. Generally, there are two ways of explaining the phenomenon of herding: the informational-rational approach as in BHW (1998) and the other is the behavioral approach. Cao and Hirshleifer (2000) tried to merge these two approaches into one model as did Baddeley et al. (2009) who employed this dual approach in an experimental design and wanted to reconcile the two hypotheses (see further for details). What is interesting, here the authors also discuss the evolutionary background of herding. The occurrence of herding is very common in the animal kingdom, in a variety of species, so evolutionary pressure may have led to the emergence of these social instincts: human instincts are of course very hard-wired, complex processes and it is not easy to identify regularity in them[6]. What we can say with certainty is that these natural instincts have not had enough time to adapt to the modern world, e.g. we cannot have a special instinct or other ability for making financial decisions. What we probably have are the instincts that were originally aimed at a different task and now they help us in tasks that the body identifies as similar to those original ones, but often arise even at times when we do not want them to, such as survival instincts in stressful situations.

2.1.3 Information cascades and herding: reviews

The information cascades and herding behavior that arise due to informational externalities in general have been subject of many papers since then, see Raafat, Chater and Frith (2009) for a cross-discipline review, please see Bikhchandani and Sharma (2000) for a review of literature on herding in financial markets or Hirshleifer and Teoh (2003) for a review about cascading in capital markets. A very good theoretical work about herds is Chamley (2004). Weizsäcker (2008) has made the first meta-analysis by using data from 13 similar experiments where he also discusses the original works and approaches (see Meta-analysis for more).

2.2 Information cascades in the laboratory

2.2.1 Anderson and Holt experimental setting

In examining herding behavior laboratory experiments are particularly useful because private information can be observed and manipulated by the experimenter and the flow of information can be precisely controlled, same as the sequence of decision-making. The seminal experiment on

[6] However, the field of neuroeconomics trying to disentangle the processes that occur in our brain and body and influence individual behavior has been one of the most rapidly emerging parts of economics, see for example Camerer et al. (2005), Camerer (2007) or Camerer et al. (2004) for motivation for this kind of analysis, an introduction to the methods and review of most important experiments.

information cascades was done by Anderson and Holt (1997)[7] who used a binary-signal binary-action framework in which private signals were drawn from an unobserved urn. Here, two states of nature, *A* and *B*, are *ex-ante* equally likely. Each decision-maker received an imperfect private signal, *a* or *b*, each of which had a probability of telling the correct state of the situation of two-thirds, i.e. $Pr(a \mid A) = Pr(b \mid B) = 2/3$, and this private information was revealed only to the subject, not to the public. In this experiment, the states of the situation were urns A and B, from which balls labeled *a* or *b* were pulled. Subjects were then asked to make a publicly observable prediction in a randomly pre-specified sequence and were paid if they correctly guessed which of the two urns was used for the draws. The correct answer was revealed after all subject made their choice. To sum up, results were overall consistent with the behavior predicted by the theory based on BHW (1992).

2.2.2 ALSOP AND HEY EXPERIMENTAL SETTING

Alsop and Hey (2000) conducted an experiment on the basis of the second of the seminal papers, Banerjee (1992), where the subjects have a finite pool of assets, where only one yields a positive payoff. Each participant receives imperfect private information with probability α and this information is correct with probability β. Theory predicts that if two or more people select a different asset than indicated by their private signals, it is optimal for the subject to choose the most commonly chosen asset regardless of the values of α or β, provided the subject makes no mistakes. The results of the experiment show the incidence of cascades, but it is lower than predicted by the model and the individual behavior is highly affected by the parameters, despite the theory's claim of independence from them. Typically, the subjects ignored the public information and relied on their private signal even in situations when this was not optimal.

Hung and Plott (2001) augmented the AH framework in two ways: in the "majority rule institution" the subjects received a premium if the group decision was correct, whereas the "conformity rewarding institution" yielded a premium when one's prediction matched the majority whether it was correct or not. The first modification caused participants to reveal more private information at the beginning of the sequence and the second one increased the tendency to herd as conformity per se was rewarded.

2.2.3 PARIMUTUEL BETTING: ANALOGY TO HORCE RACES

[7] further "AH"

An original simulation of market conditions is in Plott, Witt and Yang (1997) where they present a type of pari-mutuel betting. The game is similar to betting on horses, where the prize is divided by the people who bet on the correct horse in proportion to the amount of their individual bets. Each participant receives imperfect private info about the true state of the world (i.e. the "winning horse") and based on this, she can bet on six different "horses" (states of the world, but for the sake of simplicity it can be called a horse) and see the bets of others in real time. The more the others were betting on a particular horse, the more probable it seemed it was supposed to be the winner and the less profitable it was to bet on it in the terms of return per dollar bet. Information aggregation occurred to a large extent and in most cases the correct horse was bet on, creating a herding of betting on only one horse. However, in some cases there was an incorrect cascade – the most heavily purchased tickets were not bet on the winner. In this experiment, however, the creation of an incorrect cascade may be in a player's strategic interest, because the game has a zero sum. Suppose a player knows which horse is the winner; then the less the others bet on the correct horse and the more the player bets on the correct one, the more the player earns, so it is in his best interest to start betting on a wrong horse thus creating an incorrect herd and then bet the rest on the correct horse. This experiment is hence a little different to AH or others as the incorrect cascade is not a defeat for everybody, but a victory for a few.

2.2.4 Financial experiment incorporating both approaches

Baddeley et al. (2009) test different theories of explanation of herding against each other on the basis of results of a financial experiment: the Bayesian and the behavioral (or socio-psychological as they call them) theories. The experiment was based on a binary-choice task between two assets and the participants were given social information about a group or herd decision when faced the same binary choice. The Bayesian model incorporates the Bayesian reasoning approach in one variable, which is essentially only the decision time for a task. The behavioral model incorporates individual attributes such as conformity, impulsivity or extraversion which are measured by using standardized questionnaires. Authors also estimate both models together to find out that neither Bayesian nor socio-psychological explanation can account alone for the propensity to herd – both have something that the other approach lacks.

2.2.5 Meta-analysis

Weizsäcker (2008) created a meta-data set out of 13 experiments based on Anderson and Holt (1997) and tested general questions such as how much more of the possible payoffs the subjects earn when it is empirically optimal to follow others. The answer is 53%, only a little more than if they had guessed at random and theoretically they could have earned 64% of the high prize. Another question of interest was about what the empirical odds ratio that an average player considers informative enough to contradict her own signal was (the answer is 2:1 rather than 1:1 as predicted by theory). Interestingly, in a situation where it was optimal for them to stay only with their private information, subjects were more successful and earned 73% out of 75% if they behaved optimally. This suggests that people generally tend to stick to their own information and are reluctant to switch.

2.3 INFORMATION CASCADES: CRITIQUE AND MODIFICATIONS

2.3.1 "CONTINUOUS" CRITIQUE

The early seminal models were criticized for having only binary action space and that the model abstracts from prices. Lee (1993) argued that with continuous investment decisions, the herding disappears, the same as when Avery and Zemsky (1998) allowed agents to trade - prices should reveal all information and herds should thus vanish. However, Chari and Kehoe (2002) disprove both critiques by introducing endogenous time into the model, i.e. the traders are not obliged to trade in a pre-specified sequence, which was crucial in the two cases above. Under endogenous timing, there is a trade-off between investing and waiting as it can bring beneficial information but at the same time it is costly because of discounting. Interestingly, if they employ discrete investment and without asset trade, they get results identical to those they would have gotten with exogenous timing. Similar results can be found in Chamley and Gale (1994) who emphasize the same trade-off between the costly waiting and getting more info from observing others' actions.

2.3.2 FRAGILITY OF CASCADES

Above we mentioned that the BHW (1998) model suggested fragility of information cascades. On the contrary, Ziegelmeyer et al. (2010) demonstrate on the basis of two experiments that cascades are not that fragile. Their experimental setting consists of two groups of participants: one low informed and one high informed. In a matched pair design, the high-informed subjects made similar guesses after having observed the guesses of the low-informed participants. In theoretical equilibrium, the low informed subjects always herd, but the high-informed subjects always follow their private information and thus they always break the cascade. The real behavior they observed was, in the case of the low informed participants, in line with their prediction, but the high-informed subjects broke the cascade only in one third of the observed cascades. The tendency to go with the crowd increased with the number of the identical guesses of the predecessors. This result strongly favors the statement that information cascades are generally not fragile.

2.3.3 *Other modifications*

The original models were many times replicated with a minor modification so as to examine another dimension of the task. Corazzini and Greiner (2007) replicated the AH-experiment without private information to find out that, in such a situation, not surprisingly no herding occurs. Gilbert and Kohan (2005) modify the original experiment in that the action space is made continuous –the players state their belief of probability in an interval between 0 and 1, and secondly that in one treatment a player could observe the private information of others, make a guess, then observe her own private signal and decide to change the guess. In such a treatment players made much more accurate guesses, which was mainly caused by the player-type "inaccurate player" who improved significantly whereas the "accurate player" stayed more or less the same. Nöth and Weber (1999) introduced two different types of private signal and found that the cascades did occur, but much less than predicted by Bayesian theory. They explain it with the fact that participants employed heuristic, which put too much weight on their signal. Similar conclusion can be found in other papers such as Oberhammer and Stiehler (2001).

2.4 Practical cases - examples

2.4.1 *Information cascades*

BHW (1998) discuss strategic imitation in different industries and, on the basis of many examples in other papers, they conclude that it can be proved that businesses imitate one another many times even though they do not admit it. Another example was already provided above – the top-list manipulation of the public tastes. Another area they discuss is crime and enforcement. When individuals see others committing crime, they become generally more prone to update their social perception of the crime as well as their perception of the probability of being caught. Visible (or medialized) crimes can thus be in an endogenous relationship with the crime rate. Early publication of poll results (before the elections) can also influence the result and in some EU countries is prohibited.

2.4.2 *Time-pressure*

Kocher and Sutter (2006) show that it is easy to find real life examples for economic decision making under time pressure: just have a look at floors of a stock exchange, where time is literally money. Second, time-contingent incentives are frequently used as a motivational payment scheme in the labor markets. Or just think of tricks on consumers, such as the sales strategies offering special discounts for calling in a very short period after seeing the advertisement.

2.4.3 HERDING IN FINANCIAL MARKETS AND EMPIRICAL EVIDENCE

Financial markets and the empirical evidence of herding are unfortunately not the main topic of this paper even if there is no doubt that financial markets are the centre of attention when there is a concern about herding. Rather than going through the relevant papers, I advise the reader to read a very good review in Bikchandarni and Sharma (2000). An interesting remark was made by Ghashghaie et al. (1996) who claim that the information cascades in the FX markets correspond to the energy cascade in hydrodynamic turbulences. Chari and Kehoe (2004) mention that there has been a widespread belief that herding is a common thing in financial markets.

Many other examples can also be found in Hirshleifer and Teoh (2001).

2.5 STRESS

2.5.1 REVIEWS

On the field of effects of stress on physical and mental state of individuals I recommend the review in McEwen (2007). Definitions and concepts of the time-dimension are used as in Ariely and Zakay (2001). Maule and Edland (2000) provide a very interesting review of the effects of time-pressure on individual decision making, which have been mainly ubiquitous. Kocher and Sutter (2006) defend experimental economics as the most suitable for the investigation of the effects of time pressure. Kowalski-Trakofler, Vaught and Scharf (2000) review literature related to emergency-management decision-making under time pressure. They use the definition of stress as in Salas, Driskel and Hughs (1996) that stress is *"a process by which certain work demands evoke an appraisal process in which perceived demands exceed resources and result in undesirable physiological, emotional, cognitive and social changes."*They also point out that the stressor has to be perceived as such; otherwise even very difficult conditions need not enforce the physiological reaction.

2.5.2 BIOLOGICAL EFFECTS OF STRESS

The first and the most widely known model of a physiological response to stress was introduced by Selye (1936) and called the General Adaptation Syndrome. It consists of a few stages of the response, namely Alarm, Resistance and Exhaustion. The Alarm stage appears after the immediate recognition of the stressor (which can be eventually anything) and the physical response is the famous *fight-or-flight response*, including sweating, higher heart-rate, higher blood pressure, activation of the hypothalamo-pituitary-adrenal (HPA) axis and massive production of cortisol-like hormones,[8] which are released into the bloodstream. This reaction is provided by the autonomic nervous system, engaging the sympathetic and disengaging the parasympathetic system. The hormones then cause the reaction of the whole body and eventually contribute also to the termination of the reaction with inhibitory feedback. If the stressor persists, the Resistance stage begins and the body adapts to the stress. After the depletion of the body's resources, the initial symptoms may reappear and the body enters the Exhaustion stage, which can become dangerous to the body. Selye (1974) then introduced also the terms eustress and distress. Eustress is the case when the stress has positive effects on the body functions, when we can control the amount of stress, the stressor persists only for a limited time and it leaves a sense of accomplishment, such as challenging work, but it can turn to distress when persistent or recurrent and not resolved by adaptation. Distress can lead eventually to anxiety or depression. A highly stressing moment can even cause the posttraumatic stress disorder, but that is not within our scope here.

2.5.3 Limits of the human body - brain

Pretcher (2001) examines unconscious herding behavior. He claims that human herding behavior stems from impulsive mental activity that originates in the basal ganglia and is reinforced by emotions stemming from the limbic system whereas the neocortex where "rationality" is said to be reside stays behind. From an evolutionary perspective, the neocortex is the youngest part of the brain and controls a person's activity with idea and reason. The other "primitive" parts of the brain are responsible for impulsive and reflexive reactions, which are evolutionarily older and responsible for lifesaving actions. As proved by anatomically related studies, the impulsive emotional reactions of limbic system appear faster than the rational reaction from neocortex. Specifically, basal ganglia should control the herding behavior thus making it a matter of unconscious reflexes rather than rational calculations. The motivator for the herding reaction should be the emotional stress originating from the risk of ending alone in a position which, as a situation, resembles social exclusion which in the past used to have fatal consequence for an individual. Herding and mimicking in general are survival instincts, however uniformed they are. On the other hand, in the modern age of financial speculation on the financial markets, such herding behavior can be counterproductive and people, when speculating, often lose due to their herding behavior. Pretcher

[8] Particularly andrenocorticotropic hormones (ACTH) such as cortisol and other glucocorticoids from the adrenal cortex. corticotropin-releasing hormone (CRH) and locus ceruleus–norepinephrine (LC/NE)-autonomic systems and their peripheral effectors, the pituitary–adrenal axis, and the limbs of the autonomic system.

then concludes that due to the primitive origin of herding behavior, it can not be called “rational”, but due to its very effective purpose neither can it be termed “irrational” and that the herding behavior in financial markets must stem from signals from the social environment.

3 METHODOLOGY: THEORETICAL UNDERPINNINGS

3.1.1 INTRODUCTION

In a laboratory experiment I introduce a simple cognitive task that is performed under different levels of time pressure. My main goal is to discover the effect of time pressure on the propensity to herd, if there is any, and the form of this effect in relationship to various levels of time pressure. As will be discussed below, there have been two main approaches to the theoretical explanation of herding: the informational (or Bayesian) approach that is supported by theories that explain herding on the basis of information externalities such as BHW (1992). This explanation favors the (bounded) rationality of individual decision makers and does not leave much space for alternative explanations. The alternative approaches are either situational, such as the pay-off externalities, or behavioral or socio-psychological that are based on inherent personal and emotional attributes. A theoretical synthesis of these two approaches has already been made (see Cao and Hirshleifer, 2000) and this is not the first experiment that tries to resolve the duality between them (see Baddeley et al., 2009). I assume that both explanations have some merits and some flaws and I test whether both are relevant in my experimental setting. What is innovative in my setting is that I examine the effects of time pressure on both of the underlying theories.

In this experiment I would like to test whether, under time pressure, there is a tendency of one explanation to prevail or disappear or remain constant. First of all I would like to test again whether both theories are relevant, because in Baddeley et al. (2009) the authors used only one and quite a weak variable on the side of the Bayesian approach – the decision time, which should be longer for deliberate decisions and shorter for emotional responses. I argue that this reasoning is not that clear, and provide more variables substituting the role of information in the decision making process. For support of the behavioral explanation I use relevant personal-specific variables such as self-confidence or personality traits measured with the "Big Five" dimensions. One dimension which should be very important in the creation of cascades and which has been so far mostly omitted from the analyses of herding and information cascades is the leadership/reputation/endorsement effect of the decision makers. If the latter subjects see that a highly successful individual has decided substantially differently than their private information suggests doing, the probability of herding should increase. Apart from that I would also like to focus on the stress-side of time pressure: I test if the perceived stress is a relevant variable that influences the probability of herding and if the subjectively stated levels of stress correspond to the objectively measured physiological responses.

In this section I would like to go through the various parts of the underlying theory and state the tested hypotheses. Implications for the experiment are in *cursive* to distinguish the summarized literature to my corollaries. I beg the reader to go back to a particular subsection of this part to see the relevant references as, further on in the analysis of results, I will mostly omit the underlying literature and context. A summary of the tested hypotheses is provided at the end of the chapter.

3.2 Effect of Time pressure on decision making

Generally speaking, if we assume that individual decision-making is based on individual rationality, then we should expect a negative monotonic relationship between the level of time pressure and performance in the task; and a positive monotonic relationship between level of payment and performance. The reasoning is quite straightforward: the less time the subject has for completing the task (which corresponds with a higher level of time pressure) the less precise her private information gets and the more relevant to see and use the public information.

Hypothesis 1: Herding and occurrence of information cascades is more frequent under higher time pressure. Time pressure is a relevant variable in the explanation of the probability of herding.

The central issue of this paper, the effect of time pressure on the propensity to herd has, as far as I know, not been experimentally examined so far, so I can not build on previous the results of other researchers and I have to hypothesize the potential relationship based on insight from research in similar areas.

3.2.1 Reaching agreements

Sutter et al. (2003) study the effects of time pressure on the outcomes of a standard ultimatum game. They set up two treatments (slow and fast) and then compared the behavior of subjects. They concluded that time pressure has high efficiency costs as it lead to significantly higher rejection rates, which can be interpreted as a failure to reach an agreement under a very weak time constraint. However, after repeating the game for 9 rounds, already in the second round the difference disappears. The experimenters did not let subjects think enough before start of the experiment so only the learning effect and not the effect of time pressure may have been significant.

Also, most of the subjects indicated that the feeling of being under pressure vanished after the first two or three rounds.

Therefore I have chosen a task (See the part Task for more details) where the learning effect is very weak and as soon as the subjects practice for one round, there should be no effect of improving performance only due to the number of repetitions. I also test the order effect on the level of performance in the periods.

3.2.2 STRATEGY SELECTION

The closest paper to the relationship of time-pressure and propensity to herd is Rieskamp and Hoffrage (2007) where the authors study how the magnitude of time pressure affects the way people select strategies of a task solution. They conducted three experiments where the participants searched for information on a computerized information board. The time pressure was induced either by imposing opportunity costs of being slow or by imposing a deadline for each choice. The observed effect of time pressure was that people under high pressure generally acquired faster a greater amount of information in a given time, focused on more important information and used more selective information search.

This suggests that the effect of time pressure on herding will be ambiguous – it will depend on the relevance of the public information for the subjects. If the subjects consider the public pool of information more valuable than their private information, they will tend to herd more, but on the other hand, if people feel confident about their information, they will just stick to it and ignore the decisions of others.

3.2.3 TIME PRESSURE OR DEADLINE

Kocher and Sutter (2006) discuss the influence of severe time-pressure on the quality of decision-making in an experimental beauty-contest game. They criticize the psychological literature on their topic as focusing too much on individual tasks and ignoring the interactive or strategic environment that is central to economics. They distinguish time-pressure induced from deadlines and from time-dependent payoff saying that the effect of deadlines does not involve time pressure in the sense of limiting decision-making time to a short period but rather fix a certain point in time by which the decision has to be made. This leads to different effects than those seen with time-contingent payoff. They also review psychological literature and existing theories explaining the accuracy/speed tradeoff such as closing of the mind, lexicographic orderings, heuristics or simply rules of thumb.

I introduced a combined pressure of both time-contingent payoff and a strict deadline. In reality, though, probably only the time-contingent payoff was effective as the time was not really binding for the vast majority of subjects. I will refer to this combined pressure as the "time pressure" further on.

3.2.4 Pay for Performance

Pink (2009) points out that time-dependent incentive schemes do not work and illustrates it with the famous candle-problem experiment, which was introduced by Duncker (1945) and in the incentive setting conducted by Glucksberg (1966). The candle problem is an example of a creative problem that can not be solved by any heuristics, but rather by unconventional thinking. Participants receive a candle, a box of nails and matches and their task is to attach the candle to the wall such that it would not drip onto the table below. The only solution is that the nail-box is pinned to the wall as a candle holder. (See Figure 1 and Figure 2) Striking is, that Glucksberg already in 1966 demonstrated that if the participants were paid time-dependently, they performed significantly worse, also when they were only told they have a time limit. This indicates that the relationship between the increasing level of payment and the resulting performance is not linear.

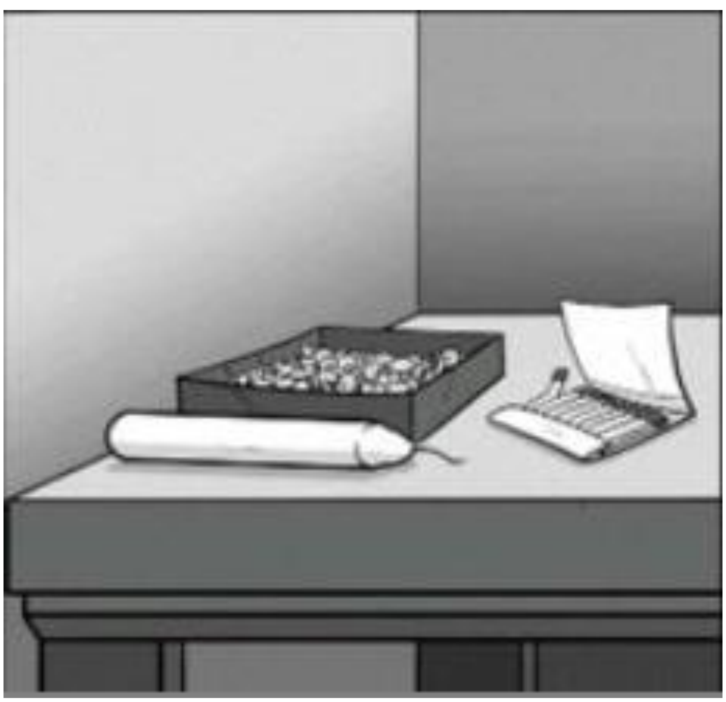

FIGURE 1: THE CANDLE PROBLEM, SETTING

FIGURE 2: THE CANDLE PROBLEM, SOLUTION

3.2.5 *LARGE STAKES, BIG MISTAKES*[9]

The non-monotonous relationship between payment and resulting performance was confirmed by Ariely et al. (2005) when they conducted a series of experiments to test whether very high monetary rewards can decrease performance through supra-optimally increased motivation and effort. Higher effort does not always mean higher performance. They conducted three experiments with different tasks and three levels of payment in three culturally different environments – at MIT in the USA; in Chicago and in rural India. The first treatment was aimed at concentration and motor skills, the second treatment was aimed at cognitive effort and the third was designed to reveal the difference between financial and social incentives. With the exception of a very mechanical work performed in the first treatment, with higher payoff the performance worsened. The authors do not suggest any explanation for this phenomenon, but from the discussion above we can think of an uncontrolled body reaction of the type "fight-or-flight" and feeling under pressure that goes against the traditional suggestion of microeconomics of a monotonous relationship.

This suggests that if people are paid significantly more for a task, they should generally perform worse, if it is not a very simple mechanical task. The decrease in performance should be

[9] This is actually the name of the paper Ariely et al. (2005)

reinforced by the pressure so we should expect a monotonous decrease in performance from the low to high level of time pressure.

Hypothesis 2: Performance decreases with increasing time pressure as the time pressure consists of both strict deadline and a time-contingent payoff that is higher with a higher level of time pressure.

3.2.6 ENDOGENOUS TIMING

Chari and Kehoe (2002) introduce endogenous time into the BHW model of information cascades, which means the agents do not act in a pre-specified order, but rather when they want. Under endogenous timing there is a trade-off between investing and waiting as it can bring beneficial information but at the same time it is costly because of discounting. Park and Sgroi (2009), in comparing other studies, find that in such a case the herding and contrarianism in experiments simulating financial markets is even more pronounced and they also identify significant clustering of decision-making in time.

I also implement endogenous timing because it resembles reality much more than pre-specified order. Herding and information cascades are primarily a phenomenon of the real world and not of the laboratory.

3.2.7 SHOWING THE INFORMATION

We should expect that the possibility to learn from seeing the results of other players improves their immediate results. Gilbert and Kogan (2005) add that learning from others may have implications also in other dimensions, namely the subjects can improve their own decision making processes, not only results. On the basis of their experiment, they argue that in the bounded rationality setting there emerge different types of players differing in the way they use the information and update their ideas – accurate and inaccurate players. The effect of improving decisions by observing actions made by other players is then almost solely driven by the inaccurate players.

In my experiment, the information about the correct outcome (the number of zeros) is designed to be imperfect and asymmetrically distributed across agents according to their skills and seeing the information is a little costly. Therefore any subject can then benefit from observation of others' actions, in our case their estimates. As in the bounded rationality setting above or in Ziegelmeyer et al. (2008) I expect that there will be some subjects performing well and giving *accurate estimates, who will generally not be interested in the results of others because it would be unnecessarily costly for them, but also some players that will welcome and use the available public information. However, if the subjects have the same cognitive power in dealing with the task and no time limits affect their performance, they should ignore the public information because it is designed to be a little costly for them (the time is running out and so also the payoff).*

Hypothesis 3: Some players will use the public information and improve their results with it whereas other players will rationally not use it because it would not have any added value for them.

Alternative 3: Because the information is costly and uncertain, the subjects will rationally ignore it.

Cao and Hirschleifer (2000) connect theoretical informational-herding models with word-of-mouth learning models[10]. The models of information cascades as described earlier focused on settings where rational individuals spontaneously receive private imperfect information about a value of an alternative action and the subjects can see the actions of predecessors. The word-of-mouth learning models assumed that the subjects observed the payoffs of the predecessors; agents were imperfectly rational and could observe only the past payoffs of the other players. The authors find that in their model, information cascades still occur, and, with a positive probability, can even last forever. They also provide the example that the ability to communicate past payoffs can reduce the average welfare and the accuracy of action choices.

Hirshleifer and Teoh (2003) show that the arrival of a signal public disclosure may make things even worse and the followers can make even noisier decisions than they would without this information, because new information can encourage individuals to fall into a cascade sooner and the total outcome may not be improved – a little knowledge may even be a dangerous thing.

I also expect that some players will decide not to compete in the task and just guess the solution. If there happens to be a similar estimate by some players in the first positions that answered and these just guessed so there is no real information in their answers (the mean value of 200 is intuitively appealing, see the part Task *for details.), it may start a reverse cascade.*

3.2.8 Rationality

[10] Baddeley et al. (2009) did the same but more on an empirical level.

If we compare the theoretically predicted numbers with the actual behavior of the experimental subjects, we can infer the percentage of individuals who behaved rationally. For example, Anderson and Holt (1997) find 70% rationality in their setting, Cipriani and Guarino (2005) find 73% rationality, Park and Sgroi (2009) found again 70%. However, we can not predict the correct behavior as we don't know the value function of how the individuals perceive the trade-off between the benefit from acquiring additional information which is relevant to their task, but which is also costly and uncertain as the other people may perform worse. A theoretically relevant consideration is that from viewing the public information the subjects could not lose anything, because if there was no relevant information for them, they could quickly proceed and lose say maximally 10ECU from the time-dependent bonus, whereas when they did find the relevant information, they could benefit in the sense that they received the payoff from the task, which they would not receive otherwise, or they would receive considerably less.

3.3 Personality traits

Intuitively, some personality types may be more prone to herding behavior than others, as for example in every team there have to be leader(s) and followers, which then predetermines their behavior. Borghans et al. (2008) provides a very useful overview of the relationship between economics and psychology in the matter of measuring personality traits. The most dangerous thing that may arise is the misinterpretation of psychological methods by economists. Personality traits are defined as "patterns of thoughts, feelings and behavior."[11] They suggest that new studies in microeconomics should include validated personality, IQ and preference measures. We use the "Big Five" factors that are Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism. Each factor represents a summary of a large number of specific personality characteristics and most commonly they are measured with NEO Personality Inventory[12] by Costa and McCrae (1992). We use an inventory of questions very similar to it, however available for free. The battery of questions used in the experiment is from IPIP[13] project which is a collaboratory for the development of advanced measures of personality and other individual differences.

[11] Borghans et al. (2008), pp. 3

[12] Neuroticism, Extroversion, Openness to experience—Personality Inventory—Revised.

[13] International Personality Item Pool: A Scientific Collaboratory for the Development of Advanced Measures of Personality Traits and Other Individual Differences (http://ipip.ori.org/). Internet Web Site.

Formy-Duval (1993, pp. 5–61)14 has provided the following descriptions of the five factors:

3.3.1 EXTRAVERSION

The core characteristic of Extraversion seems to be sociability. Individuals high in Extraversion prefer stimulating environments to relaxed ones, filled with social interaction. This dimension is characterized by an active, outgoing, assertive style. Traits which typically appear on the Extraversion dimension include talkative, frank, adventurous, energetic, and enthusiastic.

3.3.2 AGREEABLENESS

The Agreeableness dimension may best be characterized by the traits kind and loving. Agreeable persons are nice to be around because of their trusting nature, and their ability to believe the best of others. Traits which usually appear highly on this dimension are affectionate, cooperative, sensitive, good-natured, gentle, and warm.

3.3.3 CONSCIENTIOUSNESS

The conscientiousness dimension is characterized by achievement motivation and organization. The conscientious individual is self-disciplined and competent, and is therefore likely to accomplish desired goals. This dimension is characterized by the following traits: deliberate, dependable, responsible, thorough, efficient, persevering, scrupulous, and reliable.

3.3.4 NEUROTICISM - EMOTIONAL STABILITY

It is easiest to describe this dimension in terms of its negative pole, Neuroticism. The characteristics of Neuroticism are anxiety, hostility, and impulsiveness. Whereas emotionally stable individuals tend to be "calm, cool, and collected," individuals high in Neuroticism are more likely to display their emotions frequently. Traits describing the stable individual are likely to be calm, contented, and stable. However, the neurotic individual is more likely to be described as nervous, tense, high-strung, moody, temperamental, touchy, and emotional.

3.3.5 OPENNESS TO EXPERIENCE

This dimension is characterized by curiosity, or a desire to explore the world, trying new things as opposed to the commonplace. Individuals high in Openness are likely to be characterized by the traits artistic, imaginative, insightful, intelligent, original, clever, polished, inventive, sophisticated, and foresighted.

[14] Formy-Duval, D. L..”Scaling the Adjective Check List for the Five-Factor Model of Personality.” Unpublished master’s thesis, Wake Forest University (1993). As cited in: Williams, J. E., Satterwhite, R. C. and Saiz, J. L.: „The Importance of Psychological Traits.“Kluwer Academic Publisher, London: 2002 ISBN: 0-306-47152-3, pp. 33-34.

You can see the overview of the facets with their respective characteristic qualities in the Table 1 (Hogan and Hogan, 2007)

Factor	Facets	Definition of a factor
I. Openness to Experience	Fantasy, Aesthetics, Feelings, Actions, Ideas, Values	The degree to which a person needs intellectual stimulation, change, and variety.
II. Conscientiousness	Order, Dutifulness, Achievement striving, Competence, Self-discipline, Deliberation	The degree to which a person is willing to comply with conventional rules, norms, and standards.
III. Extraversion	Warmth, Gregariousness, Assertiveness, Activity, Excitement seeking, Positive emotions	The degree to which a person needs attention and social interaction.
IV. Agreeableness	Trust, Straightforwardness, Altruism, Compliance, Modesty, Tender-mindedness	The degree to which a person needs pleasant and harmonious relations with others.
V. Neuroticism (Emotional Stability)	Anxiety, Angry hostility, Depression, Self-consciousness, Impulsiveness, Vulnerability	The degree to which a person experiences the world as threatening and beyond his/her control.

TABLE 1: THE BIG FIVE DOMAINS AND THEIR FACETS. SOURCE: HOGAN AND HOGAN (2007)

Baddeley et al. (2009) also use in their specification measures of dimensions of an anti-social/dissocial personality together with non-conformity, recklessness, disregard for others and risk-seeking. They assume that sociable individuals should be more responsive to social influence and that social pressure will have a greater impact on conformist, empathic and extraverted individuals. They also add age and gender as conformity is supposed to be an inverse function of age and should be more prevalent in women.

In light of these facts, I expect that individuals with higher scores in the extraversion and agreeableness will tend to follow the crowd with a higher probability than the rest. Openness to experience may be significant for the people who want to see the public information. On the other hand, conscientiousness should be strong for the people with strong individual behavior and thus this dimension should be negatively associated with herding. Neuroticism may be important due to the idea that people high in Neuroticism are nervous and to feel more confident, they may be willing *to see and use public information. I include these ideas in the model specification. However, the simple fact that only one of them significantly explaining the probability of herding proves the importance of the behavior-based explanation suggests the following hypothesis:*

Hypothesis 4: Personality traits as part of the behavior-based approach toward herding significantly influence the probability of herding.

Alternative 4: The propensity to herd is purely information-based and does not depend on an individual personality type.

3.4 RISK ATTITUDES

3.4.1 RISK ATTITUDE AND THEE EFFECT OF THE PAY-FOR-PERFORMANCE SCENARIO

Attitude to risk is also an important variable that should not be omitted when we are considering which individual attributes may explain the probability of herding. The relationship of the attitude to risk and incentive effect of performance pay was investigated by Cadsby et al. (2009) who found that there is a significant inverse relationship between productivity improvement and risk-aversion under increasing stress levels. They also show that the more a person is risk-averse, the higher the probability that pay-for-performance decreases the actual performance is: by 25% of the participants, the performance deteriorated under performance-based pay. Risk-averse people also exhibit a greater increase in perceived stress when being paid for performance than by fixed-payment. The task given to the participants was an anagram word-creation game, which may be considered to be a creative-demanding so according to Ariely et al. (2005) the effect of performance-based reward may be different to the effect that arises by the task set in the experiment in this paper.

3.4.2 OBSERVING OTHERS AND RISK-TAKING

Yechiam et al. (2008) examine the influence of observing actions of others on individual risk-taking. They use experience-based decision tasks which were performed either alone or in pairs, with the two members being presented the public information about others' choices and outcomes. Their results show that for both risk-types, the social exposure increased the proportion of risky decisions. This effect was stronger when the subjects could observe others but not when they were observed. Authors conclude that it is important to distinguish different types of risky situations to be able to explain contradictory findings in the relevant literature, because their findings suggest that situations where risky behavior results in common favorable outcomes, social information becomes an important factor promoting risk-taking.

3.4.3 Stress and risk-taking in financial decision making

Porcelli and Delgado (2009) let subjects participate in a financial experiment that consisted of a recognition-memory task and a financial decision making task. In one treatment they induced stress by immersing subject's dominant hand into cold water. Stress was measured by the skin-conductance level (SCL) over the whole experiment and it was significantly higher in the stress-blocks. Subjects performed in the recognition-memory task significantly worse under stress than under no stress. In the financial-task the subjects exhibited notably fewer risky decisions when under stress than in no-stress condition. In the stress-phase the authors also observed an increase in the reflection effect (people make risky decisions in loss domain but in the gain-domain they behave conservatively).

I expect that risk-averse subjects (in our case those with a lower certainty equivalent) will suffer from a deterioration of performance under time pressure and therefore will have an incentive to look at the results of others, possibly using the information. Their subjectively felt stress levels should also be higher than of the risk-neutral or risk-seeking subjects. The fact that they will be presented the public information may lead to more risky decisions, which in the context of the experiment, may lead to a higher frequency of switching from original values to a value conforming to the observed information.

Hypothesis 5: Risk-averse subjects have a higher propensity to look at the public information and their perceived level of stress will be higher than the level of stress perceived by the other subjects.

3.4.4 Variables significant for risk-taking

Dohmen et al. (2009) studied risk attitudes in a large representative survey and a complementary experiment conducted in selected subjects' homes. They identify gender, age, height and parental background to be economically significant variables that influence attitude to risk. Interestingly, they found that the direct question of the willingness to take risks that is used in the questionnaire in the large survey[15] serves well as a predictor of the actual elicited risk-taking

[15] German Socio-Economic Panel which measured, among other attributes, also the risk on 22,000 individuals who comprised a representative sample of the German population. The question was simply "On a scale of 0 to 10, please rate how much you are willing to take risks in general."

behavior that arose from a lottery experiment, which suggests that the data on risk-behavior may be collected in normal surveys that are relatively easy and cheap to conduct even though the survey questions are not incentive compatible. They use the same protocol as Dohmen et al. (2009), which is in a similar[16] setting to that which is used in the experiment in this paper (see "Test of self-confidence and the lottery card"). Authors find that about 78% of population are strictly risk averse; 9% are strictly risk seeking; females are less willing to take risks in general; with increasing age, the willingness to take risks decreases; if the participant's parents have completed high-school there was a positive effect and finally height also had a positive effect on the willingness to take risks. Dohmen et al. (2009) also find that lower cognitive abilities measured by standard IQ tests are associated with a lower willingness to take risks in general and more pronounced impatience.

Intuitively, the overall effect of risk-attitude on the propensity to herd is not that clear due to a trade-off between the uncertainty about the subject's own signal imperfection and the reliability of the public information. On the one hand, the risk-averse subjects with imperfect information should minimize the risk of having a wrong signal by using the publicly available information, but on the other hand there is also a risk that the other participants have created a reverse cascade. It is a question which effect will finally prevail.

Hypothesis 6: Risk-preferences significantly influence the propensity to herd.

Alternative to hypothesis 5 and 6: According to the information-based approach, risk-preferences do not have any influence on the propensity to herd.

3.4.5 *ENDORSEMENT EFFECT*

In the context of herding literature, reputation effect is mostly considered to cause herding in the sense that investment managers under certain circumstances mimic the decisions of other managers thus behaving rationally from their perspective in the labor market as in Scharfstein and Stein (1990) or Bikchandani and Sharma (2000). So reputation is considered in the sense that the subject making the decision wants to keep her own reputation and that is why she decides to conform to the majority. The effect when the reputation of an important player in the market can make other participants follow her investment decisions is called by Hirshleifer and Teoh (2003) the *endorsement* effect.

[16] The original setting is that the subject chooses between lottery where she can win 300€ with a 50% chance and a certain amount of cash. In my experiment however I could not afford that so I used only 600ECUs.

I implement the endorsement effect in the sense that the estimate of a participant shown on the screen with public information is supported by her previous results – her total payoff. The reason for this I take from BHW (1992) when the authors suggest that a leading authority in a certain field may have an advantage in starting / breaking a cascade. Also, the information revealed by a subject with a good reputation should have higher value in the eyes of the followers. If combined with a higher probability of being correct, the endorsement effect (or as I call it further, the reputation effect) should also cause the inaccurate subjects to improve their performance more than in the condition without information about reputation and overall the group-performance should be higher. However, in the task it may not prove significant when the subjects perceive the most important part of the information to be in the present guesses and not in the reputation.

Hypothesis 7: The reputation effect enhances the probability of herd formation.

Hypothesis 8: In the treatment with the reputation effect the overall group performance is better than in treatment without it.

3.4.6 Social Preferences and herding

According to the standard theory, individual utility function does not include the utility of other subjects – homo economicus is solely individualistic and has no other-regarding preferences whatsoever. Corazzini and Greiner (2006) examine the role of social preferences and psychological artifacts on the emergence of herd behavior. For some players, their relative position may be a relevant variable for making a decision as their subjective utility may be higher when they conform and follow the crowd. Of course, the opposite situation should hold true when people try to be unique may also play a role. They show that inequality aversion predicts herding quite well in their anonymous as well as in non-anonymous settings. They also find no correlation between social preferences that subjects elicited in a simple dictator game and the herding behavior, but this may be due to their specific setting with no private information.

During the experiment, subjects were asked to state how much kind they perceive a hypothetical split of 1,000CZK between themselves and an anonymous partner. After this, they were asked about how much they would expect to have received had this event actually happened. From this input, I computed an artificial variable *ExpectedKindness* as a simple implication of the subject's stated perceived kindness over the expected received share on the 1,000CZK[17].

3.5 MEASURING PHYSIOLOGICAL RESPONSES

Lo and Repin (2002) experimentally explore how emotions influence the rationality of decision making. They measure real-time psycho-physiological characteristics such as skin conductance, blood volume pulse, heart rate, electromyographical signals, respiration and body temperature in professional traders during live trading sessions thus showing the feasibility of such measurement. They use portable bio-feedback equipment and measure the physical responses to certain events that happen on the market, such as periods of heightened volatility. Among other measures, they measure the averages of heart rate (HR) over periods of interest and they regress it together with other proxies on the vector of market events. The authors conclude that emotions are a significant factor in the studied task which is the real time financial decision making under risk. This is in stark contrast to the traditional view of rationality in the financial markets. However, they had only 10 pilot subjects, which means they could not draw very conclusive statements upon their findings.

I use a similar approach because HR is optimal in the sense that it is relatively easy data to obtain and it should give rough but relevant results. Moreover I will compare the physiological responses to the stated feelings of being under pressure.

Hypothesis 9: Stress induced by the time pressure causes the individual's heart rate to be different from the base level during the performance and is positively correlated with the subjectively stated level of stress. With higher time pressure, objective stress (measured by the heart-rate frequency) increases.

[17] If, for example, a subject expected to get 500CZK share and she previously reported perceived kindness over share 500CZK "10", then her *ExpectedKindness* is 10.

3.6 SUMMARY OF THE TESTED HYPOTHESES:

Hypothesis 1: Herding and occurrence of information cascades is more frequent under higher time pressure. Time pressure is a relevant variable in the explanation of the probability of herding.

Hypothesis 2: Performance decreases with increasing time pressure as the time pressure consists of both strict deadline and a time-contingent payoff that is higher with a higher level of time pressure.

Hypothesis 3: Some players will use the public information and improve their results with it whereas other players will rationally not use it because it would not have any added value for them.

Hypothesis 4: Personality traits as part of the behavior-based approach toward herding significantly influence the probability of herding.

Alternative 4: The propensity to herd is purely information-based and does not depend on an individual personality type.

Hypothesis 5: Risk-averse subjects have higher propensity to look at the public information and their perceived level of stress will be higher than the level of stress perceive by the other subjects.

Hypothesis 6: Risk-preferences significantly influence the propensity to herd.

Hypothesis 7: The reputation effect enhances the probability of herd formation.

Hypothesis 8: In the treatment with the reputation effect the overall group performance is better than in treatment without it.

Hypothesis 8: In the treatment with the reputation effect, the overall group performance is better than in the treatment without it.

Hypothesis 9: Stress induced by the time pressure causes the individual's heart rate to be different from the base level during the performance and is positively correlated with the subjectively stated level of stress. With higher time pressure, objective stress (measured by the heart-rate frequency) increases.

3.7 MODEL SPECIFICATION

By using the specific task of counting zeros from a sheet of 400 symbols (for more details see the part Task in section General Description) I model the probability of herding, which arises in the situation when the subjects used the information from seeing the estimates of the other participants and changed (switched from) their own estimate. The subjects could choose whether to see the public information so, apart from the probability of herding, I also model the probability that subjects even wanted to see the public information, which is an important part of the overall analysis of herding. I use three general groups of variables: the first group represents the information that was on the screen with the public information, the second group represents the individual personality type and the third group contains other task characteristics that may be important for making the decision. Some variables were added more in an exploratory manner and the sign of their coefficients is not easy to expect.

3.7.1 VARIABLES DESCRIPTION

3.7.1.1 Explained variables: *InfoShown* and *InfoUsed*

This variable "*InfoShown*" indicates whether the subject decided to see the public information or not. It was introduced in treatments 3 and 4 and it can take only values 0 or 1.

If the subject decided to see the public information, then she had the opportunity to change her estimate according to the new information. There emerges the second explained variable "*InfoUsed*", which takes 1 if the estimate was changed or 0 if it remained unchanged. We treat it as result of underlying unobservable probability of herding.

3.7.1.2 Time variables: *TimeLeft, TimeDeciding*

The subjects may have had the temptation to look at the public information, but if they were too early, they knew the revealed information would not be informative enough to lose time and money with it. On the other hand, if they were too slow, the time they spent on the screen with the public information could have cost them the whole payoff when the time ran out. So, the optimal time for them to see the public information was somewhere between when the time left for the task was not high, but still not too small. I construct a variable *TimeLeft* that is the time they had on the screen when they entered their original estimate and I expect it to positively influence the probability of viewing the public information *InfoShown*, because generally the subjects would look there *only* if they had some time remaining to do so. A majority of subjects did not have much time to waste so if they had it, they would probably invest it wisely. On the other hand, if already looking at the results of others, the total time they had left might already be irrelevant because either there was useful info or less useful info, but the time to switch the estimate or to go further was not dependent on the total time the subjects had.

Another explanatory dimension of time can be hidden in the time which subjects spent on the screen with the public information. Intuitively, because they were under time pressure, they must have decided fast whether to use the info and change the value or go further, as described above. Had they decided to change their estimate, they had to think of the new value, which is already a deliberative process and needs more time, so the variable *TimeDeciding*, which indicates the time the subjects spent on the screen with the public info, is expected to be positively associated with the *InfoUsed*. Baddeley et al. (2009) would interpret it as a sign of Bayesian updating and if significant, this variable would, according to them, confirm the rational approach to herding. However, I think that if it were really so and the subjects updated, the time spent on deciding would be the *same for both* the result of switching and not switching, because if a subject updates, then she takes the same amount of time to do so regardless of the positive or negative nature of the input.

3.7.1.3 Time Pressure: *TP_High*

The categorical variable *TimePressure* indicates the level of time pressure that the subjects were in. It enters the regression as a set of dummies *TP_Medium* and *TP_High* (due to perfect collinearity *TP_Low* must be omitted). To prove Hypothesis 1, this variable should be significant in the explanation of probability of herding, especially when indicating the "high" level of time pressure: the variable *TP_High*. The expected sign should be positive as discussed in the section 3.2.1 and stated in the Hypothesis 1. It may prove to be significant also in determining the viewing of the information, also with a positive sign. I expect *TimePressure* to be negatively correlated with *TimeLeft* and *TimeDeciding* as under higher time-pressure there should generally be less time left for thinking.

3.7.1.4 Personality traits: *O C E A N*

At the end of the experiment the subjects filled in a questionnaire where they answered 50 standardized questions similar to NEO-IP. Each question was to be answered on a scale 1 to 5 and for each trait there were 10 questions, 5 of them set in a positive manner and 5 of them negative. The final scores were computed by simply adding up the values of questions belonging to a particular trait when the "negatively" formulated questions had a reverse scale. The variables in the model are named with the first letter of their name - *O* for Openness to Experience, *C* for

Conscientiousness, *E* for Extraversion, *A* for Agreeableness and *N* for Neuroticism. Even though it took some time to fill in, 50 questions are just enough to provide accurate estimates of the personality traits (Hogan and Hogan, 2007).

If they jointly happen to be significant, it will prove the Hypothesis 4 that the individual personality profile is important for explanation of the probability of herding.

Moreover, similarly to the discussion earlier in the text I expect that the variables behave in these ways:

- **Openness to experience** to positively influence the *InfoShown* as this trait is characterized by the desire to explore and keep getting new information, trying things as opposed to conforming. However, his trait says nothing about following the decisions of others, so I do not expect it to influence *InfoUsed*.
- **Conscientiousness** to negatively influence the *InfoShown*, because subjects who score well in this dimension should be deliberate and achievement-striving, so I expect that they will go straight for the result. Furthermore, they may rather be followed than to follow so I do not expect it to play a role when explaining the *InfoUsed*.
- **Extraversion** to positively influence both *InfoShown* and *InfoUsed*; because the very essence of this trait is sociability which means being curious about the behavior of other subjects (*InfoShown*) and also being adventurous thus not being afraid of trying new approaches, such as getting public information (*InfoUsed*).
- **Neuroticism** to positively influence both *InfoShown* and *InfoUsed*, because the positive values of this trait are associated with an emotionally unstable personality that is uncertain about her own outcome, she may want to see additional information about others, and if she sees it, such a person may believe more the judgment of others than her own.
- Because the most important characteristics of **Agreeableness** are kind and loving, cooperative, being of trusting nature and able to find the best on others. A person who scored high in this dimension would probably go with the crowd and even in the case of a failure she would find the better side of it: I expect it to positively influence both.

3.7.1.5 Measure of public information: *score* and *score2*

When explaining the variation of the *InfoUsed* – of the probability of herding – we have to include the public information that the subjects received to follow the informational approach as discussed in the introduction to this section. To interpret the value of the information that subject saw on the screen, I compute two indices: the index *score* is a measure of the similarity of all the results that the subject saw on the screen: it was computed with a simple approach that, with the exception of zero, when two values did not differ by more than 1, the index got one point and the summation over all points creates the index. The idea is that the more information on the screen, the higher probability for the subject to switch from her original estimate.

Score2 is the measure of the similarity of the subject's original estimate to the observed values: if the subject's estimate was not further than 1 from a value of an estimate on the screen, score2 got one point. Again, summation over all observed values yields the final value of *score2*.

I expect that the more similar results were on the screen, the more it was tempting to switch to a new value that accorded with the majority more than the original one, so the coefficient of *score* should be positive. On the other hand, if the subject had a very similar estimate to the observed values, there was no reason to change it. Therefore I expect the effect of *score2* on *InfoUsed* to be negative.

Apart from these two indices I could also use other measures such as simply the order of seeing the information or coefficient of variation of the others' estimates, but these would carry the same information as the indices above. Of course, I expect a high degree of correlation between *score* and *score2* due to the fact that the more information they saw the more information appeared on both indices.

3.7.1.6 Attitude to risk: *CE, RiskAverse*

From the theoretical discussion above as summarized in Hypothesis 6, we can expect that the attitude to risk expressed as a Certainty Equivalent *CE* which I measure from the switching point in the "lottery task[18]," is important when determining the *InfoShown* and also *InfoUsed* but the effect is uncertain. However, only the significance of this variable is enough to help to break the exclusivity of the information-based approach. Apart from only the variable CE I also introduce a simple dummy *RiskAverse*, which is 1 if the subject is weakly risk averse: that is simply if she is not risk-

[18] See Figure 12: Lottery task in the Appendix.

seeking which I can interpret in the terms of *CE* – if *CE* is smaller or equal to 16 which means the certainty equivalent was smaller or equal to the expect payoff from the lottery task.

If the nature of revealing the public information is perceived as a risk, the expected sign should be negative. If one takes into consideration that looking at the public information was costly and there was no certain outcome from this kind of investment, similarly to the switching to another value according to the prevalent type of estimates seen by others, it may be perceived to be a version of lottery and the expected sign in the model of explanation of *InfoShown* as well as of *InfoUsed* will be negative.

3.7.1.7 Other personal characteristics: *Female*, *SubjectiveStress*, *SelfConfidence*, *TotalProfit*, *ExpectedKindness*, *Reputation*

I do not expect *Gender* to be significant in any of the regressions, but it would be interesting to find out that for example women are, due to their greater general sociability, more prone to follow the crowd.

The stress induced by the time pressure should also be an important variable and as part of Hypothesis 1 it should positively influence the probability of herding - *InfoUsed*. We have two measures of it: the subjectively stated level of stress *SubjectiveStress* and the difference of the average level of heart-frequency during the task to the quiescent heart rate *HR_DIF*.

Generally speaking, we can also expect that the subjects with a higher task-specific self-confidence will have lower incentives to look at the public information and if they do, they will be reluctant to conform to the majority. In this case the scale is reversed (1=Top 20% to 5=Lowest 20%) so the effect of *SelfConfidence* is expected to be positive on both explained variables. The total profit (variable *TotalProfit*) that the subject had already earned may have increased her confidence and she may have had greater incentives to risk and try to switch from her value because this, according to the loss-aversion principle, may lead to greater losses as well as greater gains, which normal risk-averse subjects are willing to risk when they already earned something. Because I expect it to behave similarly to the general behavior of wage-related variables; i.e. that it is likely to be log-normal, I transform it by using a natural logarithm so the new variable *lnTotProf* is normally distributed.

VARIABLES	LABELS	***InfoShown*** Significant?	Expected sign	***InfoUsed*** Significant?	Expected sign
score	Score of similarity of others' values among themselves			yes	+
score2	Score of similarity of estimate to the others' values			yes	-
Reputation	1 if reputation shown	yes	+	yes	+
TimeDeciding	Time spent on screen with public information			yes	+
TimeLeft	Time left when original estimate set	yes	+	no	
TP_High	1 if High Time Pressure	yes	+	yes	+
O	Openness to Experience	yes	+	no	
C	Conscientiousness	yes	-	no	
E	Extraversion	yes	+	yes	+
A	Agreeableness	yes	+	no	
N	Neuroticism	yes	+	yes	+
SubjectiveStress	Stress (Subjective)	yes	+	yes	+
Female	1 for female	no		no	
CE	Certainty equivalent	yes	-	yes	-
RiskAverse	1 if Weakly Risk Averse	Yes	-	Yes	-
SelfConfidence	Self Confidence	yes	+	yes	+
lnTotProf	Ln (Total Profit)	no		yes	+
ExpectedKindness	Average perceived kindness	Yes	+	no	
HR_DIF	Difference of quiescent to actual HR	Yes	+	Yes	+

TABLE 2: SUMMARY OF EXPECTED EFFECTS. *NOTE:* SELFCONFIDENCE *HAS A REVERSED SCALE (1=THE BEST, 5=THE WORST)*

ExpectedKindness is higher if people expect others to be kind in the way they personally perceive it and so it may play a role when they would expect others to kindly offer their estimates. Hence, it may be significant when explaining the variation of *InfoShown*.

Finally, the *Reputation* dummy should be significant to prove the existence of the reputation effect as stated in the Hypothesis 7. Summary of the expected effect is in the Table 2.

3.7.2 MODEL: PROBABILITY TO VIEW THE PUBLIC INFORMATION

The overall model for explaining the probability of looking at the public information, or in other words the binary variable *InfoShown*:

$$\log\left(\frac{\Pr[View]}{1-\Pr[View]}\right) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{16} ExpectedKindness + \beta_{17} HR_{DIF} + \epsilon \quad (3.7.2.1)$$

3.7.3 MODEL: PROBABILITY OF HERDING

The overall model for explaining the probability of herding, or in other words the binary variable *InfoUsed*:

$$\log\left(\frac{\Pr[Switch]}{1-\Pr[Switch]}\right) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{16} ExpectedKindness + \beta_{17} HR_{DIF} + \beta_{18} score + \beta_{19} score2 + \beta_{20} TimeDeciding + \epsilon$$

3.8 ANALYSIS: GENERAL DESCRIPTION

We assume that the probability of herding or the probability of looking at the public information is a binary random variable so the outcome y can only take two values:

$$p_i = Pr\left(y_i = 1 \mid \mathbf{x}\right) = F\left(\mathbf{x}_i'\beta\right),$$

where $F(.)$ is a specified parametric function of $\mathbf{x}'\beta$ (a choice function), $\mathbf{x}$ is a $K \times 1$ vector of regressors and β is a vector of unknown parameters. If we perceive the explained binary variable to be a latent index variable of a propensity of the event to occur, we can define the index function model as following: we would like to explain the underlying unobservable variable y^* by using the observed binary variable *y* which attains value of 1 if a certain threshold (or a cut-off value, let's call it *c*) is crossed. The index function model is

$$y^* = \mathbf{x}'\beta + u$$

This form requires homoskedastic errors. However, we observe

$$y = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases}$$

where the threshold of zero is explained in the following:

$$Pr\left[y = 1 \mid \mathbf{x}\right] = Pr\left[y^* > 0\right] = Pr\left[\mathbf{x}'\beta + u > 0\right] = Pr\left[-u = \mathbf{x}'\beta\right] = F\left(\mathbf{x}'\beta\right)$$

where *F* is the *cdf* of *–u*, which equals the cdf of *u* if the density is symmetric around 0. If the error term is thus standard normal distributed, the probit model should be used. Then the $Pr\left[-u = \mathbf{x}'\beta\right] = \Phi\left(\mathbf{x}'\beta\right)$ where $\Phi\left(.\right)$ is the standard normal cdf. However, if $Pr\left[-u = \mathbf{x}'\beta\right] = \Lambda\left(\mathbf{x}'\beta\right)$, where $\Lambda\left(.\right)$ indicates the logistic distribution, then the logit should be used. So, we can make distinction between the two models on the basis of the distribution of the error term *u*. For the identification purposes of the uniqueness of β, the error variance is set to 1 in case of probit and $\pi^2/3$in case of logit. The estimation is then carried out in a MLE fashion; see e.g. Cameron and Trivedi (2010) for details. There you can also find out that if data are independent over i and $F(\mathbf{x}'\beta)$ is correctly specified, using MLE estimation has an advantage that it has a robust estimate of the VCE due to the fact that the ML SEs are obtained by imposing the restriction $Var(y \mid \mathbf{x}) = F(\mathbf{x}'\beta)\left\{1 - F(\mathbf{x}'\beta)\right\}$ which must hold because variance of a binary-outcome variable is $p(1-p)$. However, the dependence between other observations in a cluster is not solved and the assumption of homoskedasticity of u has to be tested.

Greene (2002) also points out that the ordinary probit MLE is often labeled quasi-MLE in the light of possibility that it can be easily mis-specified: the Q-MLE is not consistent in any form of heteroskedasticity, omitted variables, nonlinearity of the functional form of the index, or an error in the distributional assumption. Hence, when we use White's sandwich estimator, we generally remove the inconsistency, only if the Q-MLE converges to a probability limit (which is not guaranteed). In our case, the sample size is large[19] enough to satisfy the asymptotic normality by the law of large numbers.

I also considered the usage of nested multinomial logit because in the data there is practically a nested structure: first the subject decides whether to look at the public information or not, and if so, she can decide to use the information and change her estimate or not. However, the tree structure

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is incomplete and therefore the nested logit can not be used as it needs all nodes at the same level to have some branches.

3.8.1 CHOOSING THE RIGHT MODEL

According to Cameron and Trivedi (2005) we should specify the model according to the underlying dgp[20], which is unknown. On the other hand, the distribution is (unlike other applications of ML estimator) the distribution for a (0, 1) variable is the Bernoulli distribution. So, either the dgp has $p = \Lambda(\mathbf{x}'\beta)$ so the logit model should be used or if dgp has $p = \Phi(\mathbf{x}'\beta)$ and the model should be the probit model. If the estimator is used according to other model than the proper one, the estimator is potentially inconsistent. However, in case of probit and logit, the problem is not that serious because if the regressors are distributed such that the mean of each of them, conditional on the linear combination $(\mathbf{x}'\beta)$ is linear in $(\mathbf{x}'\beta)$, then choice of the wrong function F can only affect the all slope parameters equally so the ratio of the slope parameters is constant across models. The power of the model can be also judged by the log likelihood: we should choose the model with a higher log-likelihood, but in case of logit and probit, the difference is often not significant (Cameron and Trivedi, 2010).

3.8.2 ROC CURVE

A possible distinction can be made on the basis of ROC (receiver operating characteristics) curve which plots the fraction of $y = 1$ values correctly classified against the fraction of $y = 0$ incorrectly specified as the cut-off value c varies. There are two main reference points: for $c = 1$, all predicted values will be 1 and for $c = 0$, all predicted values will on the contrary be 0. Thus, for $c = 1$, all $y = 1$ but no $y = 0$ values will be specified correctly, so the ROC has value (0, 0). Similarly, for $c = 0$, the ROC takes value of (1, 1) and the diagonal line between these two points is the reference line for judging the model relevance. When the model has no predictive power, the ROC is identical with this reference line, and the further the ROC gets and the more area underneath of it, the better predictive power of the model.

3.8.3 ATTRIBUTES

Logit model has favorable attributes that it has a relatively simple form of the first-order conditions and asymptotic distribution, and also the interpretation of the coefficients in terms of the log-odds ratio. On the other hand, probit has the attraction of being motivated by a latent normal random variable and extends naturally to the Tobit models. Empirically, there is not much difference

[20] Data generating process

in using either probit or logit, because the biggest difference is only in tails where the probabilities are close to zero or one, so when we are interested in marginal effects, the difference is negligible and it is a matter of custom which of the two techniques should we use.

3.8.4 Goodness-of-fit tests

3.8.4.1 Pseudo-R-squared

In binary-outcome models, there exists a generalization of the R^2 called pseudo-R^2, usually attributed to McFadden (1974), have similar interpretation as the traditional R^2 – the explained part of the variance of the model. As in my statistical package offers McFadden's R^2 as a default, I will omit the "McFadden's" when I will talk about a pseudo R^2 during the analysis. Generally, the pseudo-R^2 is a comparison of the log-likelihood function of the fitted model L_{fit} with the intercept-only model L_0 that estimates the probability of each alternative to be the sample average:

$$R^2 = 1 - \frac{\log L_{fit}}{\log L_0}$$

In case when there are a greater number of predictors, it is convenient to use the adjusted form of this measure: the number of predictors is subtracted from the log-likelihood of the fitted model. If the predictors happen to be effective, the penalization will be rather small. Unlike the unadjusted version, the adjusted R^2 can decrease with addition of an irrelevant variable and can be even negative.[21]

3.8.4.2 Comparison of predicted probabilities with sample frequencies

I use the Hosmer-Lemeshow (Hosmer and Lemeshow, 2000) goodness-of-fit specification test. It is based on grouping cases into deciles and comparing the observed probability with the expected probability within each decile. The test consists of comparison of the sample average predicted probabilities $\bar{\hat{p}}_g$ to the sample frequency $\bar{\hat{y}}_g$ in a group g by the test statistic

$$\sum_{g=1}^{G} (\bar{\hat{p}}_g - \bar{y}_g)^2 / \bar{y}_g(1 - \bar{y}_g) \sim \chi^2_{(G-2)}$$

and testing that the differences between the probabilities are simultaneously zero. Thus, high p-values indicate that we reject the null and the model has a good fit.

3.8.4.3 Comparison of predicted outcomes with actual outcomes

[21] "FAQ: What are pseudo R-squareds?" UCLA: Academic Technology Services, Statistical Consulting Group. From http://www.ats.ucla.edu/stat/mult_pkg/faq/general/Psuedo_RSquareds.htm (accessed June 26, 2010).

An intuitive way of comparing different models is to compare the actual outcomes with the predicted by the model, not probabilities, in simple percentages of correctly classified outcomes. Common way is to present the so called classification table which has four cells: the columns indicate whether the prediction of the model was zero or one and the rows whether the real outcome was zero or one: then one diagonal includes correct predictions (1|1) or (0|0) and the other diagonal the wrongly classified cases (see e.g. Table 27). The overall classification of correctly predicted cases is sometimes called the "count R^2".

3.8.5 TREATMENT EVALUATION

If we define a discrete treatment variable $D = 1$ if treatment is applied and $D = 0$ else, we can try to assess the relevance of imposition of the different conditions in the two distinct cases. Then the triple $(y_{1,i}, y_{0,i}, D_i)$, $i = 1...N$ forms a basis of the treatment evaluation as the $y_{1,i}$ measures the impact on individual *i* of the applied treatment and $y_{0,i}$ measures the response when the treatment is not applied. The effect of the cause D on outcome of individual i can be then measured by $(y_{1,i} - y_{0,i})$ and the average causal effect of D_i =1 relative to D_i = 0 can be measured as the so called average treatment effect (ATE):

$$ATE = \mathbb{E}[y \mid D = 1] - \mathbb{E}[y \mid D = 0]$$

The estimation of ATE-parameters requires random assignment of the treatment followed by a comparison with a set of non-treated cases that serve as controls. The random assignment means that it does not depend on the outcome and is uncorrelated with the attributes of treated subjects.[22]

If we are interested in the effectiveness of a treatment in the sense what happens if we apply the treatment conditions on a person that had not received the treatment so far – the magnitude of $\Delta y / \Delta D$. Because it is impossible to observe an individual simultaneously in two states, the situation is similar to case with missing data. The data have to satisfy a set of assumptions as in Cameron and Trivedi (2005): the conditional independence assumptions $y_1, y_0 \perp D$ states that the participation in the program should be independent on the outcome, after controlling for the variation in outcomes induced by changes in **x**. This implies that the participation in the group does not affect the distribution of potential outcomes. The second assumption – the matching assumptions – states that $0 < Pr[D = 1 \mid \mathbf{x}] < 1$ which ensures that for each value of x, there are both treated and non-treated cases. However, this assumption is not required when we want to identify the

[22] In the experiment, Pearson correlation between the Treatment variable and the outcome variable Diff was -0.12 and insignificant with p-value = 0.721.

treatment effect for a group. The third assumption is the conditional mean independence assumption which implies that the outcome for the non-treated group also does not determine participation: $\mathbf{E}[y_0 \mid D=1,x] = \mathbf{E}[y_0 \mid D=0,x] = \mathbf{E}[y_0 \mid x]$.

3.8.6 Heckman two stage estimator

3.8.6.1 Motivation – history of the two-stage estimator

In 1979 James Heckman published a very influential paper on dealing with the sample selection bias he personally encountered when trying to correct for this in estimation of a wage equation for employed women in a labor market. Later he won the Nobel Prize for this. Basically, what he was trying to do, was to correct for the fact that he had data on wages women, but only for the employed ones and not for those who, as commonly described by economic theory, had their reservation wage higher than the minimum wage offered by the labor market in that time. Therefore, he intuitively expected that the wage equation evaluated only for the employed women would be inconsistent and proposed the below described solution. See Figure 3 for a schematic view of the problem.

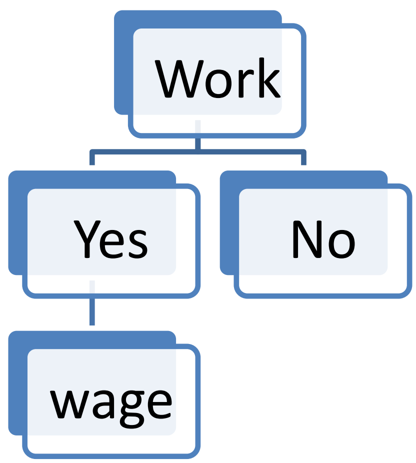


FIGURE 3: DECISION TREE OF HECKMAN'S SETTING

In the Figure 7 you can see the obvious similarity to the decision tree of this experiment. Therefore I decided also to employ the Heckman's approach, namely in the probit modification.

3.8.6.2 Underlying theory

I will concisely introduce the problem of Heckman (1976) and what it implies for my estimation. Heckman wanted to get consistent estimators of wage equation as in (1), but the information on wages was obtained only for the employed women, which is in (2):

$$W_i = \boldsymbol{\beta X_i} + \epsilon_i \qquad (1)$$

$$E_i^* = \boldsymbol{Z}_i\gamma + u_i \quad (2)$$

$E_i^* = W_i - E_i'$ is the crucial difference between reservation wage E_i' and the real wage W_i'. As noted earlier, the reservation wage is the minimal wage at which a woman would work. Therefore, if the offered wage is lower than that, the individual decides not to work: for $E_i^* > 0$ the $E_i = 1$ and $E_i = 0$ otherwise. Further in text I will refer to (2), due to its specific 0/1 selection role, as to *selection equation.*

The assumptions taken are that both error terms $(\epsilon, u)$are normally distributed with the mean 0 and variances are correlated where $\rho_{\epsilon u}$ is the correlation coefficient. Apart from that, the error terms should be independent of both explanatory variables $\boldsymbol{X}$ and $\boldsymbol{Z}$ and the variance of u is for convenience set to 1: $Var(u) = \sigma_u^2 = 1$. The problem arises when we compute the consistency of the estimate that would be obtained only by (1) and not accounting for the selection bias. We start by taking expected values of W_i given $\boldsymbol{X_i}$ if we know that a subject decided to work: $E(W_i|E_i = 1, \boldsymbol{X}_i) = E(W_i| \boldsymbol{X}_i\boldsymbol{Z}_i u_i) = \boldsymbol{\beta X_i} + E(\epsilon_i|\boldsymbol{X}_i\boldsymbol{Z}_i u_i)$, which comes from the (2) and from recognizing that taking expected value from X given X is simply X. We can further simplify the term by noting that it depends only on $\boldsymbol{Z}$ and u and not $\boldsymbol{X}$. Together with a modified (2) we get a form of

$$E(W_i|E_i = 1, \boldsymbol{X}_i) = \boldsymbol{\beta X_i} + E(\epsilon_i|u_i > -\boldsymbol{Z}_i\gamma_i) \quad (3)$$

The key problem is that $(u_i > -\boldsymbol{Z}_i\gamma_i)$, that means the error term u is restricted to be above a certain threshold and those, who do not satisfy it, are excluded. This becomes to cause troubles because we assumed to have correlated error terms by $\rho_{\epsilon u}$, so if u is restricted, so is the correlation coefficient. Heckman treated this problem as a special case of omitted variable bias and he tried to find the $(\epsilon_i|u_i > -\boldsymbol{Z}_i\gamma_i)$. He models it as $E(\epsilon_i|u_i > -\boldsymbol{Z}_i\gamma_i) = \rho_{\epsilon u}\sigma_\epsilon\lambda_i(-\boldsymbol{Z}_i\gamma) = \beta_\lambda\lambda_i(-\boldsymbol{Z_i}\gamma)$,where $\lambda_i(-\boldsymbol{Z_i}\gamma)$ is the inverse Mill's ratio evaluated at the indicated value and $\beta_\lambda$is and unknown parameter. By applying the fact, what the Mill's ratio means, we get to a form of

$$\mathrm{E}(u_i|u_i > -\mathbf{Z_i}\,\boldsymbol{\gamma}) = \frac{\phi(-\,\mathbf{Z_i}\,\boldsymbol{\gamma})}{1 - \Phi(-\,\mathbf{Z_i}\,\boldsymbol{\gamma}\,)}$$

After some derivations we get the central result of what the inverse Mill's ratio in our case is:

$$\lambda_{\mathrm{i}}(-\mathbf{Z_i}\,\boldsymbol{\gamma}) = \frac{\phi(-\,\mathbf{Z_i}\,\boldsymbol{\gamma})}{1 - \Phi(-\,\mathbf{Z_i}\,\boldsymbol{\gamma}\,)}$$

and this term is then used as a supplementary in the conditional regression function.

3.8.6.3 Heck(prob)it: Probit model with selection

However, this procedure is suitable for models, where there is the binary selection equation and in the second stage we want to estimate a continuous dependent variable. In case of the experiment of this paper, we have two binary variables and therefore it is more appropriate to use special modification of this procedure aimed at probit at the second stage as introduced by Van de Ven and Van Pragg (1981). This procedure is sometimes called Heckprobit or Heckit and is provided by most of the statistical packages.[23] To make it clear, this procedure assumes that there is a *latent equation*

$$y_j^* = X_j\beta + u_{1j}$$

and we observe only the binary outcome of the *probit equation*

$$y_j^{probit} = (y_j^* > 0)$$

if the dependent variable was observed, i.e. it was selected by the *selection equation*

$$y_j^{select} = (z_j\gamma + u_{2j} > 0)$$

with the underlying assumptions that the $u_1, u_2$are correlated by ρ and both are standard normally distributed. When the parameter ρ is not zero, estimating the probit equation alone would lead to biased results.

Moreover, for the model to be well-identified, the selection equation should have at least one variable that is not in the probit equation. Otherwise the model would be identified only by its functional form and the coefficients would have no structural interpretation.[24]

3.8.6.4 The implication for estimation of propensity to herd

In case of the experiment in this thesis, the *selection equation* is specified similarly as the equation where the dependent variable is *InfoShown* (3.7.2.1) and the estimated *probit equation* is similar to the equation for *InfoUsed* (3.7.2.2). However, such specification would contain the problem of having the same variables from the selection equation in the probit equation, thus giving no structural interpretation. For the purpose of this method of estimation, I have to re-specify the

[23] Specifically, I use Stata 9, but the choice of a package should not affect any of the computations.

[24] "Stata Reference Manual", Vol. 1, A-J, Release 9, Stata Press Publication, Statacorp LP, College station, Texas, USA: 2005

model and exclude at least one of the dependent variables from the right-hand-side of the equation (3.7.2.2). Without loss of generality and assuming no influence on other variables, I will exclude the variable *ExpectedKindness* to have the possibility of getting reasonable results by this technique. The resulting equations are (3.8.6.4.1) as the *selection equation* and (3.8.6.4.2) as the *probit equation*.

$$\Phi^{-1}\ (\Pr[View]) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{17} HR_{DIF} + \epsilon$$

$$\Phi^{-1}\ (\Pr[Switch]) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{16} ExpectedKindness + \beta_{17} HR_{DIF} + \beta_{18} score + \beta_{19} score2 + \beta_{20} TimeDeciding + \epsilon$$

The package I use, when using the MLE estimation, does not estimate directly the correlation ρ between error terms, but rather "*atanh* ρ" , which is then included in the table with results:

$$atanh\, \rho = \frac{1}{2} \ln\left(\frac{1+\rho}{1-\rho}\right).$$

It is clear that the test for its significance will be equivalent to the test of ρ because *atanh* $\rho\ (0) = 0$. Also, if $\rho = 0$, the log-likelihood function of the two stage model should equal to the sum of both stages when evaluated alone, which let us perform direct LR test for better model. If ρ attains boundary values or the model does not converge at all, it is a sign that the probit model with selection is not the best way to go.

3.8.6.5 Critique

Even this approach has to bear its portion of critique. This two-stage estimator is a limited information maximum likelihood estimator (LIML), which, as shown by asymptotic theory and Monte-Carlo experiments, can be, especially when multicollinearity is present, dominated by full information likelihood estimator (FIML), which is however sometimes difficult to compute (Puhani, 2000). Moreover, if the errors are not jointly normal, the estimator is inconsistent and can bring misleading evidence in small samples.

4 GENERAL PROCEDURE OF THE EXPERIMENT

4.1 INTRODUCTION

I conducted a computerized laboratory experiment with fifteen participants per experimental session while having six sessions in total. I used the mobile laboratory of CERGE-EI, which at the time of the experiment had only fifteen functioning computers, otherwise I would have invited more subjects per session. The experiment was mostly computerized by using Z-tree (Fischbacher, 1999) except for the task where they had to elicit their risk-preferences so that their eyes would have a rest for a while (the so-called lottery card, see Figure 12 in the Appendix).

4.2 PILOT VERSION OF THE EXPERIMENT

Prior to the experiment itself I had run a pilot-version to verify the structure of the experiment, functioning of the programs and to calibrate the payoff of the tasks with another fifteen participants. The pilot-session was monetarily rewarded and very useful as I realized I had overestimated the performance of the computers. The z-tree program was too demanding for the simultaneous synchronization of all computers with the server which resulted in long delays while uploading the screens and eventually even system crashes. This finding made me completely re-program all of the computerized tasks so that the demand on synchronized computations would be minimal. Following feedback from the participants, I also adapted the payoff-function so that it would be more stress-inducing – I set more importance on the bonus than on the accuracy and I doubled the amounts used in the "lottery card".

4.3 TASK: COUNTING ZEROS

4.3.1 DESCRIPTION OF THE TASK

The participants performed a simple cognitive effort task, which was not supposed to be require previously earned skills or any innate cognitive abilities with learning effect. However, subjects with dysfunctions like dyslexia or dyscalculia may have found the task harder than the others as I found out from some written feedback. This task was also designed not to involve any emotions and only positive payoffs were possible to eliminate loss-aversion. In the laboratory setting of experiments on information cascades, the tasks introduced were generally only probabilistic in their nature, but as far as I know, no one ever had tried to induce the signal imperfection by utilizing the subjects' inability to cope with the situation, such as being under time-pressure.

This task was introduced by Falk et al. (2006) for the purpose of examining preferences over workfare as real jobs are associated with disutility of foregone leisure, but it is also suitable here as most of the participants would have to exhibit real effort. Participants were required to count a correct number of zeros from a table of 400 symbols (zeros and ones only) that appeared on the screen. The numbers were randomly generated from a uniform distribution with variability large enough that accurate guessing was improbable.[25] The task is quite tiring and not very interesting, as Falk et al. (2008) point out, so I could not use a lot of repetition and therefore decided on two tasks per participant the first treatment, three in the second treatment (one for each level of time pressure) and six tasks in the third and fourth treatments (two observations per level of time pressure per participant). Each participant was then supposed to solve eleven tasks in total.

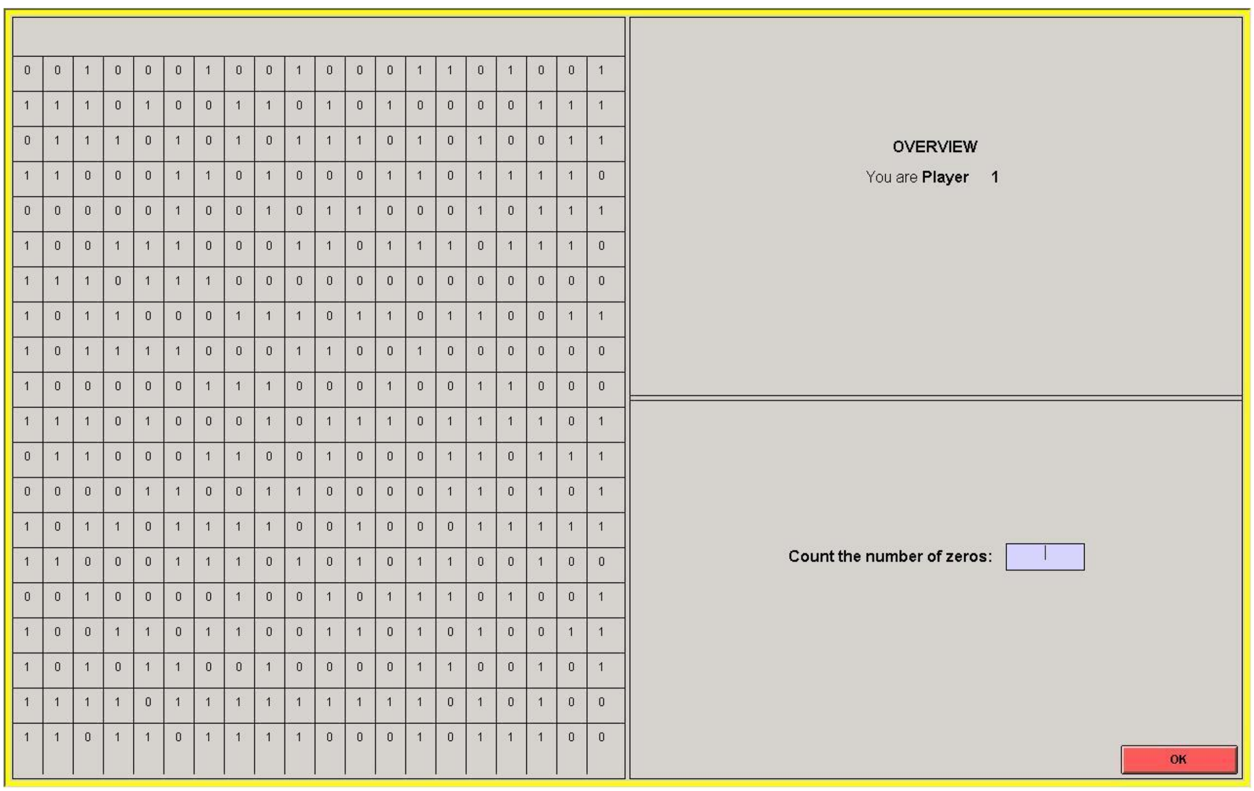


FIGURE 4: TASK SCREEN OF THE TREATMENT 1

4.3.2 PAY-OFF FUNCTION

[25] However, at every session there was at least one subject who tried it more than once.

The pay-off function was supposed to be similar as in Falk et al. (2006) where they paid 2€ per sheet if counted exactly, 80% if in the range of +/- 1 or 40% if in range +/- 2. I paid 100ECU for an exact count, 80 for a difference of 1 and 50 for difference of 2, but the main opportunity to make money was the time-dependent bonus so that the people would be more under pressure. The size of the bonus was different with each level of stress (see Table 3) but generally I aimed at 100ECU after 100 seconds, which was the average time needed as I found during the pilot experiment. Unfortunately, the client computers started to count down the time only some five to ten seconds after the screen with the task appeared, so the time they really had was slightly longer[26].

Level of time pressure	Time limit	Bonus (start value)	Factor of bonus decreasing (per second)
Low	150s	400 ECU	-3 ECU
Medium	130s	500 ECU	-4 ECU
High	100s	600 ECU	-5 ECU

TABLE 3: SUMMARY OF PARAMETERS OF PAYOFF FUNCTION

4.4 ORGANIZATION OF THE EXPERIMENT

Before the game started, subjects were advised about the rules of the experiment, had a chance to go to the toilet and the heart-rate monitors were attached, which prolonged the experiment by some 15 minutes. Ladies had a special changing room. Each participant had the instructions printed out and the most important parts were shown on the screen before each treatment. After reading the instructions[27] aloud and explaining them in detail, I asked the subjects a few questions to check their understanding of the rules. The participants went through three parts of the experiment that were based on the task described above: the first part included the first treatment and participants had to complete two tasks, the second part included the second treatment and the participants had to complete two tasks and finally the third part included the third or the fourth treatment, depending on the group (three groups had the third treatment and the other three had the fourth treatment). Before the end of the experiment, the participants had to fill out a questionnaire and at the end they were asked to stay a few minutes at rest with their eyes closed which was necessary to establish a reference level for the heart rate. In total, the experiment lasted a little less than 2 hours, mostly due to the technical complications with the heart-rate monitors. There were also moments of synchronization of the heart-rate monitors after each part of the experiment when the participants were asked to press the red button on their wrist monitors.

[26] For the analysis I fortunately have the exact lengths of the participants' performances.

[27] See the instructions in the Appendix - 8.1. and 8.2.

4.4.1 THE FIRST TREATMENT: TWO FREE TRIALS

The first part was simply an introduction in that they had free time to complete two tasks for a fixed payoff per task. There was no time-dependent bonus in this part.

4.4.2 THE SECOND TREATMENT: INTRODUCTION OF TIME PRESSURE

The second part had three parts where I put the participants under pressure in the sense that the payoff was a decreasing linear function of time and there was a strict time limit, both dependent on the level of time pressure (see Table 3). The participants were supposed to be motivated to answer as fast as possible; waiting for others to answer was thus costly so the trade-off between acting quickly and using the public information after some time was established. Originally, I wanted to set the time-limits individually as the fractions of average time from the first treatment (factors of 1, 0.8 and 0.5) to evoke the time pressure on an individual level, but due to the computational capacities of the computers in the lab, I preferred to set fixed limits for all participants. Participants were informed about the level of time pressure, the time limit for the task and the bonus they could get on a welcome screen (see Figure 5) I did not need to distinguish between the effect of a deadline that was induced by the time limit and the effect of motivation induced by the bonus because the pressure was the same across the time-dependent tasks.

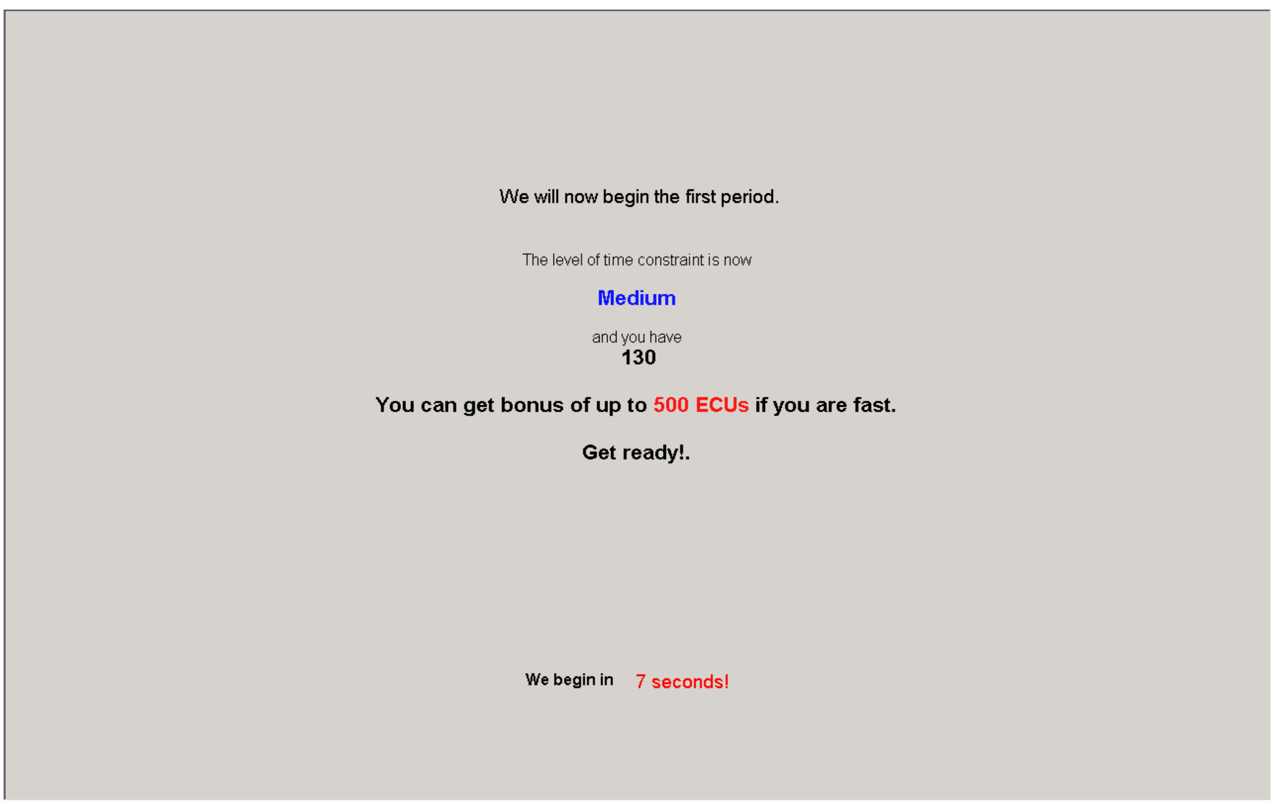


FIGURE 5: INTRODUCTION SCREEN

Each task was evaluated after the participant had set the final estimate or the time had run out. The participants had to wait until everybody had finished the task to go to the next period. Participants saw their payoffs from the task always on the summary screen (see Figure 6), and this screen also included the cumulative payoff from the treatment. There were also breaks of 30 to 60 seconds between the periods with time pressure for both having a rest and calming down the heart rate so that the measurements in the periods would not affect each other.

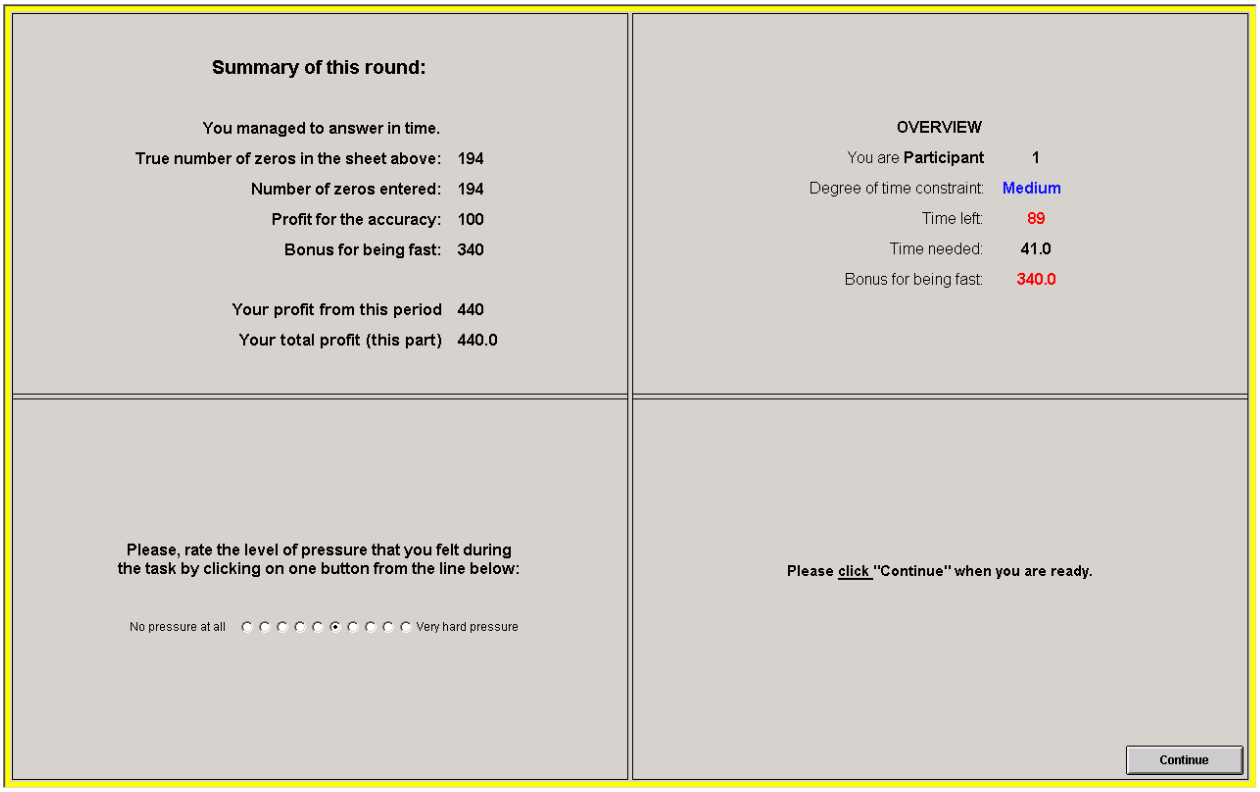


FIGURE 6: SUMMARY SCREEN

The order of the levels of time pressure was meant to be random, but due to the low number of observations I had at my disposal, I had to fix the order, however I tried to make it look random in each period to mitigate the order effect. At the end of each period, the participants had to answer a question on their subjective perception of pressure they were under. This result would be compared to the data from the heart-rate monitors.

4.4.3 TEST OF SELF-CONFIDENCE AND THE LOTTERY CARD

After the first two parts I tried to find out how confident the participants felt about their own performance during the tasks. I gave them a direct question on their respective performances – in which quartile of the distribution of the overall results they thought they were (e.g. top 20% …

bottom 20%). After they were finished with this, the participants were asked to fill out a separate sheet of paper with an extra task based on Dohmen et al. (2009) to find out their attitude to risk. You can see the real look of this task in the Figure 12 in the Appendix. It was set on a paper and not on the screen so that their eyes would get some rest. In this task participants were asked to elicit their preferences in 20 binary choices between a risky lottery and a guaranteed amount of cash (ECU). There were 20 questions where the setting of the lottery always stayed the same (50% of getting 600ECU and 50% of getting nothing) but the option of getting the amount of cash gradually increased from 0 up until 380ECU. This allows us to reveal the certainty equivalent and the general attitude to risk of an individual.

4.4.4 THE THIRD TREATMENT: INTRODUCING THE SCREEN WITH PUBLIC INFORMATION

This treatment proceeded the same way as the second treatment (i.e. the time-pressure was introduced exactly in the same way as described earlier) but with a difference in that the participants had an opportunity to have a look at the individual results of the other participants in the form of a table with a fixed order of participants. The numbers included there were the *original* estimates of the participants, i.e. before they changed their mind (if they did change their mind). The participants had to enter their own estimate of the number of zeros in the sheet first, and then they could choose whether they wanted to see the results of others (Figure 8). If they pressed "NO", the experiment proceeded as before. If they pressed "YES", then they had an opportunity to look at the table with the decisions of others[28] (see Figure 9 for the appearance of the decision screen, but without the past performance; and Figure 7 for a scheme of the decision making tree after setting the info) and change their mind on their final choice – enter a new estimate. If they entered a new estimate, it suggests they ignored their own private information thus we consider this to be herding behavior.

[28] The screen containing the information about the estimates of others is further in text referred to as the "public information screen" or in similar way. The most important is that if anywhere in the text I mention "public information", it is this information.

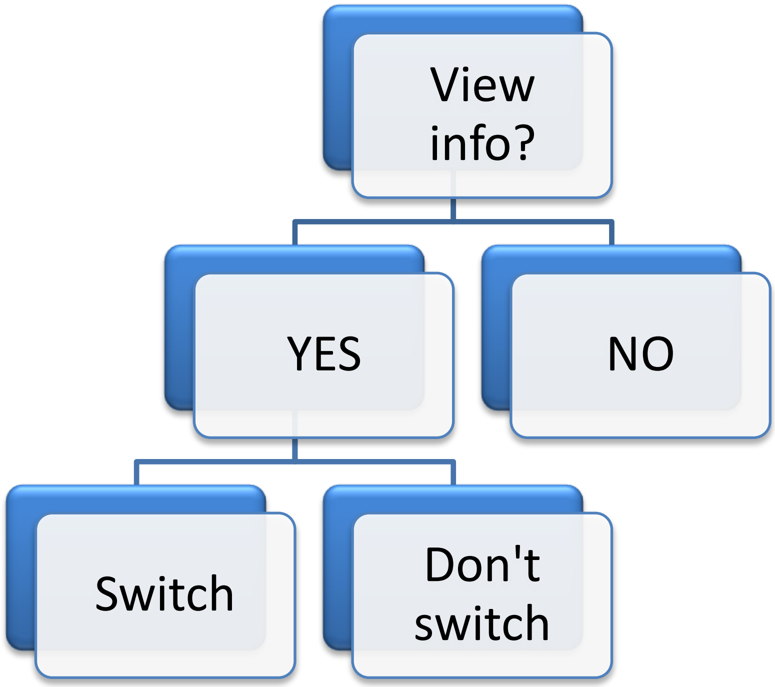


FIGURE 7: SCHEME OF DECISION TREE FACED IN THE TREATMENT 3 AND 4 AFTER SETTING THE ORIGINAL ESTIMATE.

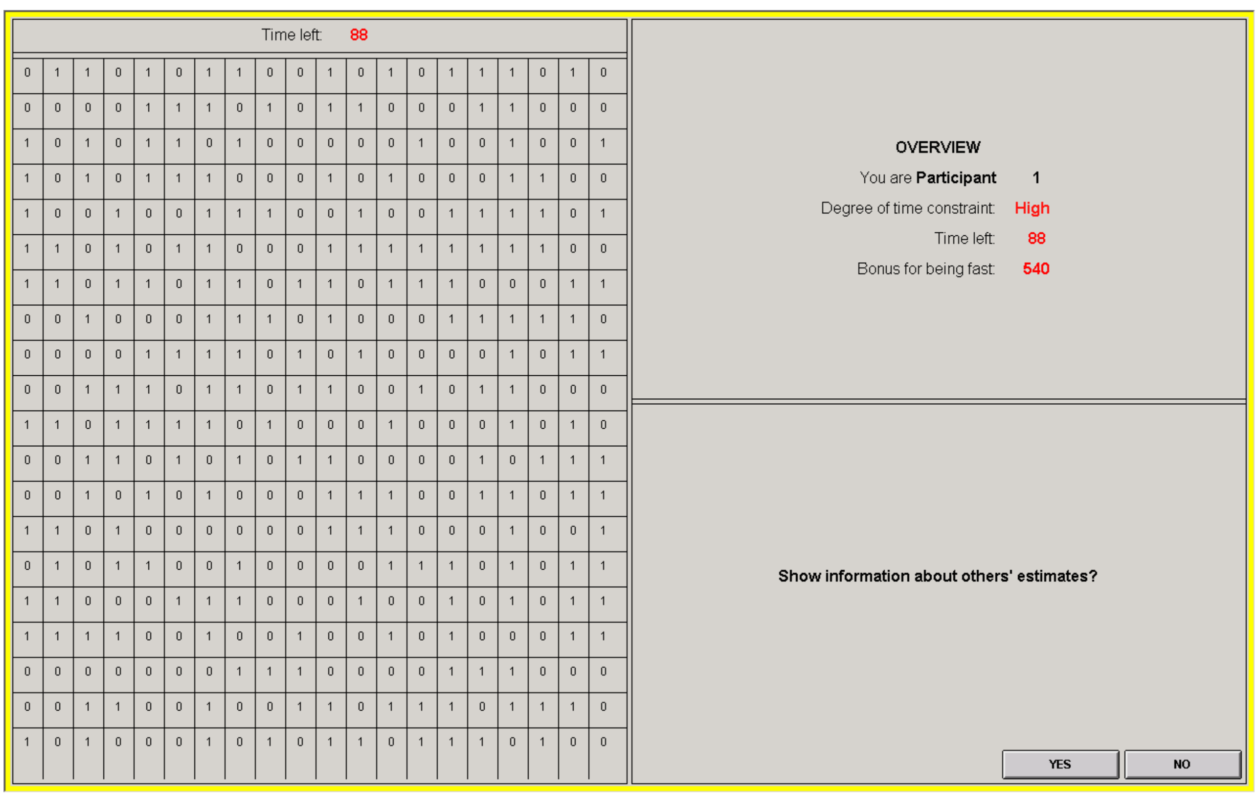


FIGURE 8: DECISION SCREEN

By first entering their own estimation I was able to spot the private signal and infer its accuracy – difference from the correct number of zeros in the sheet.

4.4.5 *The Fourth treatment: Appending past performance to public screen*

This treatment proceeded in the same way as the third treatment with the difference that the information about the choice of others was supplemented by the information about the past performance of participants who had already made their final choice (see Figure 9). The information about past performance was the total cumulative payoff from the second and third treatment, not including the payoff from the current round.

The logic behind is that there may emerge a few leaders with highly accurate guesses and their decisions may have impact on the decisions of others.

FIGURE 9: SCREEN WITH THE PUBLIC INFORMATION (SITUATION OF THE FIRST ESTIMATE SET)

4.4.6 *Questionnaire: Personality traits, social preferences and other*

At the end of the experiment the subjects received an on-screen questionnaire asking the participants their preferences about the kindness of the division of 1,000CZK between them and an anonymous partner exactly as in Falk and Fishbacher (2006) with an additional question on which of the 11 possible divisions they would expect to occur in real life; their personality profile by using 50 personality trait questions and finally on their important demographic characteristics: age, gender, education, field of work/study and a country of origin. Moreover, they had a space for written feedback to the researcher. However, I was unable to incorporate a proper IQ measuring due to low accessibility of the proper material.

4.4.7 CONTROL FOR STRESS – HEART RATE MONITORS

During the experiment participants were controlled for physiological stress-response - the heart-rate, by heart-rate monitors. The heart-rate is taken as a proxy for the real-level of stress the participants have to go through. To be clear, heart rate is the frequency of the contractions of the heart muscle and its unit of measurement is frequency per minute. Changes in heart rate refer to higher levels of arousal, which are often somatically mediated, which suggests that when the heart-rate increases, the body is in a state of increased awareness. However, heart-rate as a psycho-physiological variable is a rather rough measure of stress as stated in Lo and Repin (2002).

I borrowed 17 heart-rate monitors Polar R-400 from the Laboratory of Sport Motor Control at the School of Sports and Physical Education of the Charles University in Prague.[29] These machines measure the heart-rate in 1 second intervals so the heart-rate can be measured very finely. There was another technical complication because the heart-rate monitors simply did not work[30] on some subjects so the data coverage was not full.

I also considered the effect of having the heart-rate monitor on, but as it was the case of a vast majority of subjects and the chest-belt was really compact and comfortable, I omit it from the analysis.

4.4.8 POSSIBLE ISSUES

Unfortunately, it was so silent in the room that everybody could hear the clicking of each other player's mouse and therefore some of the players may have decided to wait until other players started clicking, then set an arbitrary value to see their results and in this way "free ride". I found from feedback that it was not uncommon, but this is also a possible strategy of solving things in everyday life so I do not need to exclude these observations. Apart from that, there were some subjects who were too tired to fully complete the task, but this again did not matter for the validity of the analysis, they just had zero private information. In 20 periods out of 33 there was at least one subject with a "guessing" strategy, who decided not to count the number of zeros and tried her luck.

[29] In Czech: Laboratoř sportovní motoriky FTVS UK

[30] The problem probably was the lack of conductance between the chest-belt and skin, as I realized later.

5 MAIN FINDINGS

5.1 PARTICIPANT SAMPLE DESCRIPTION

There were 90 participants (actually 91, but one computer crashed during the first session) plus 15 participants in the pilot session. The pilot session was too often interrupted by system crashes so I have to exclude all data from it from the analysis. A majority of participants were Czechs (77.8%) followed by Slovaks (12.2%) and other nationalities (10%). There were 62.2% male and 37.8% female participants. The most common field of study was economics and business (75%) and the median age was 22[31]. Participants were paid privately at the end of the experiment, the average payment was 350CZK (app. 13.5€) out of which they had a guaranteed show-up fee of 100CZK (app. 3.80€). The average payment was still about 2 times more than average hourly salary in region.

Due to the low variation in age, education and nationality I did not consider these to be explanatory variables in the model, however it may be important. Generally speaking, I tried *not* to have only undergrad Czech economics students, which would have biased the results, and in the end I had 75% of them, which is enough to remove the bias, but also not enough to focus on variation in these dimensions. They are certainly important and deserve attention: for example Baddeley et al. (2009) show that the propensity to herd across age groups is not homogenous.

5.1.1 DESCRIPTIVE STATISTIC OF MODEL VARIABLES - SUMMARY

In Table 4 you can have a look at the summary statistic of all variables used in the model in section 6. However, in the model only a selected sample was used, so the summary statistics may differ. I would like to point out that all variables with the exception of *A* were on a 1% level of significance found to be normally distributed by using the skewness-kurtosis test.

[31] The standard deviation was 2.72, so the variation was relative small.

variable	label	N	Minimum	Maximum	Mean	Std. Deviation
InfoShown	Decided to see public info	495	0	1	0.58	0.49
InfoUsed	If really used the info	289	0	1	0.42	0.49
score	Score of similarity of others' values among themselves	942	0	74	6.37	11.08
score2	Score of similarity of own estimate to the others' values	495	1	15	3.27	2.71
Reputation	Reputation dummy	495	0	1	0.55	0.50
TimeDeciding	Time spent on screen with public information	942	0	67.38	3.34	6.72
TimeLeft	Time left when original estimate set	760	0	157	43.67	32.44
TP_Medium	Medium Time Pressure	760	0	1	0.33	0.47
TP_High	High Time Pressure	760	0	1	0.34	0.47
O	Openness to Experience	942	-4	20	9.99	5.22
C	Conscientiousness	942	-8	16	3.97	5.38
E	Extraversion	942	-13	18	2.83	6.64
A	Agreeableness	942	-6	18	4.57	4.67
N	Neuroticism	942	-20	8	-4.17	5.16
SubjectiveStress	Stress (Subjective)	760	1	10	5.76	2.45
gender	Male	942	0	1	0.62	0.49
CE	Certainty equivalent	864	2	21	14.68	3.42
RiskAverse	Weakly Risk Averse	942	0	1	0.92	0.28
SelfConfidence	Self Confidence	942	1	5	3.16	1.22
TotalProfit	Total Profit	942	0	2017	347.54	397.71
ExpectedKindness	Expected kindness	942	-100	100	23.22	59.21
HR_DIF	Difference of quiescent to actual HR	677	0	53	16.47	9.82

TABLE 4: DESCRIPTIVE STATISTICS OF THE VARIABLES USED IN THE MODEL

5.1.2 VIEWING AND USING PUBLIC INFORMATION

You can have a look at the crossed frequencies of variables *InfoShown* and *InfoUsed* in the Table 5. You can see that there were 495 cases in total, out of those in 206 cases (42%) the subjects did not decide to view the public information thus they could not even decide whether to use it or not. In 167 cases (34%) they did opt to view it, but they did not change their estimates. Finally, in 122 cases (25%), the subjects did view the information and switched their estimates thus giving up their private information.

		Really used the information (*InfoUsed*)	
		NO	YES
Decided to see public info (*InfoShown*)	NO	206	
	YES	167	122

TABLE 5: RELATIVE FREQUENCIES OF *INFOUSED* VS. *INFOSHOWN*

It is still a little tricky to say that the subject used the public information only if she switched from the original value to a new one (in case of the *InfoUsed* variable) because a subject could use it to reassure herself that she stands on solid ground – that her estimate is not too far from the others. If we count the number of cases when a subject's original estimate was close to the true value, but she decided not to switch because her original value was the one she would switch to, we get 107 more cases of using the public information. If we have a look at the situation when the similarity of their original estimates to the numbers they saw in the screen with the public information was high and probably therefore they did not switch, we get 104 cases of using the information additional to the 122 when they switched.

		Time Pressure			
		Low	Medium	High	Total
If really used the public information (*InfoUsed*)	Mean	**41%**	**40%**	**47%**	42%
	Total number of possibilities	106	91	92	289

TABLE 6: PERCENTAGE OFSWITCHING IN DIFFERENT LEVELS OF TIME PRESSURE.

From the Table 6 it is visible that the percentage of people using the public information is higher in the *High* level of time pressure. This suggests that the subjects tended to use the public information more often when under higher pressure. However, the F-test for the equality of means results in the levels being insignificantly different from each other[32] so statistically there was no real difference which favored the Alternative 1. If in the latter regression analysis the coefficient of the variable *TP_High* proves to be insignificantly different from 0, then we will be able conclude that the Hypothesis 1 is rejected in favor of the Alternative 1.

In the Table 7 you can see the distribution of correct answers – the true number of zeros in the sheets, and you can see that indeed the probability that a random guess would hit the region of +-2 around the correct value looks negligible. The numbers were generated randomly – each number

[32] P-value=0.576

was taken from a standard uniform distribution$U(0,1)$. When summed up 400 times, the mean of 200 was tempting to guess, but its variance was still too high to earn enough just by guessing as the accuracy limit was quite strict. The sample standard deviation was 9.74.

Period number in a session	True number of zeros in the sheet					
	Day					
	1			2		
	Session					
	1	**2**	**3**	**1**	**2**	**3**
1	197	209	197	198	205	204
2	202	208	202	204	200	198
3	207	188	206	211	189	184
4	218	214	196	201	195	199
5	196	213	200	201	208	228
6	*	204	177	205	188	209
7	*	218	217	210	196	192
8	*	199	196	207	203	202
9	208	197	210	203	199	181
10	213	204	185	194	193	202
11	213	196	187	213	183	199

TABLE 7: DISTRIBUTION OF TRUE NUMBER OF ZEROS IN THE TASKS. (*) - EXCLUDED OBSEVATIONS.

5.1.3 Payoffs and achievements among different groups of participants

If we compare the overall achievements of the participants from the tasks (not from the lottery) in different groups and treatments, we can find that there was a significant[33] difference between the groups that performed the third treatment and those which performed the fourth treatment. Most striking was the second group in the fourth treatment (group No.5), which outperformed the groups from the first day by almost 70%.

Profit (ECU)							
Day	Group	Mean total profit from tasks	SD	Mean profit per task	SE	N	SD
1	1	1113.13	714.25	104.41	9.46	123	104.86
	2	1193.33	625.43	108.06	8.65	164	110.83
	3	1107.73	460.43	101.95	10.30	162	131.09
2	4	1444.20	563.68	131.62	8.72	164	111.64
	5	**1918.00**	650.92	174.82	10.52	164	134.74
	6	1374.07	549.84	124.92	9.33	165	119.85
Total		1358.41	646.21	125.21	3.98	942	122.22

TABLE 8: OVERALL GROUP PERFORMANCE

[33] Significant on 1% level; p-value=0.000 for the F-test of equality of means.

During the first day, when only the third treatment was applied, there was no significant[34] difference between the groups. However, during the second day, the second group was significantly better than the other two which implies that it was better than all other groups. The overall performance of the groups is shown in the Table 8. This suggests that the reputation effect, being the only difference between the first and the second day, was significant.

5.2 TREATMENT COMPARISON

5.2.1 *EXAMINING THE ENTRY TASK*

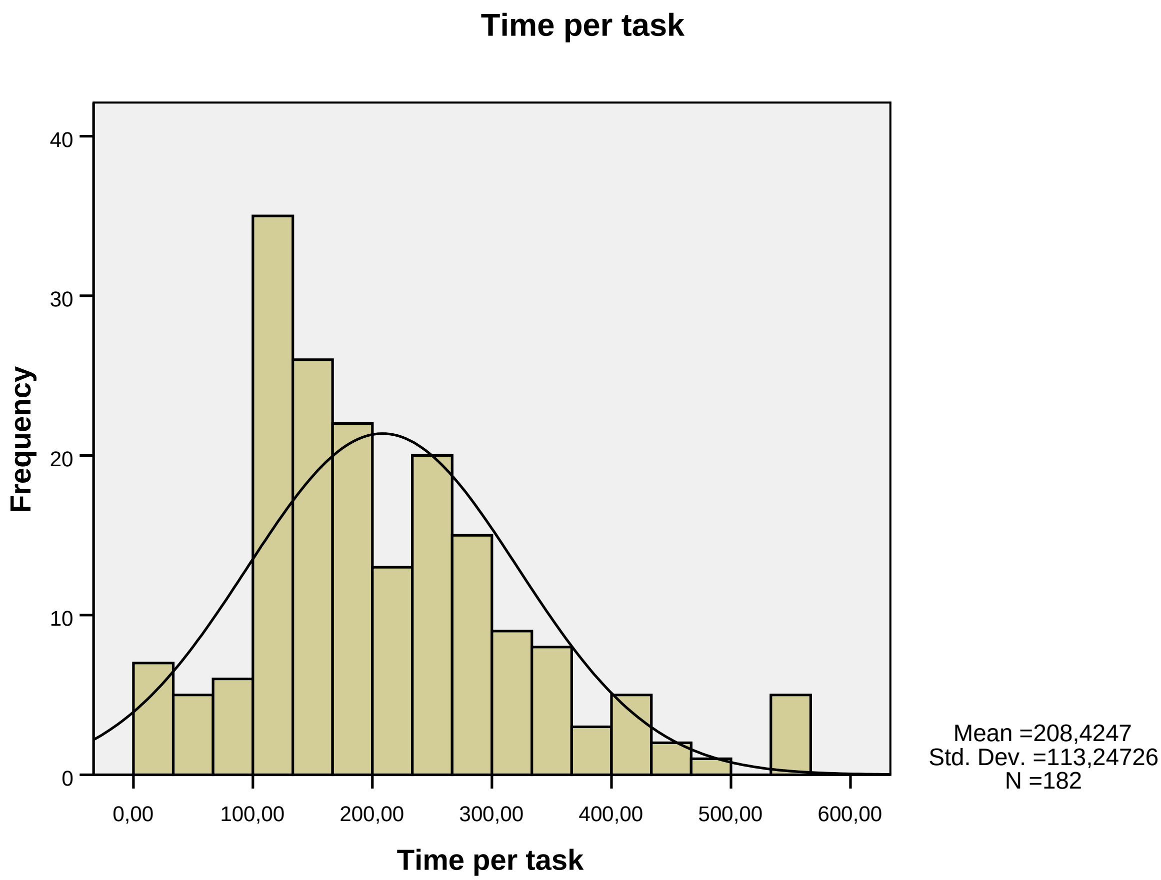
The distribution of time per task in the two rounds of Treatment 1 is in Graph 1. There were 14 subjects in the first period and 4 in the second period trying to guess the number straight, but the mean time per task was 208s.

Period		Inaccuracy of estimates	Time per task (s)	Profit per task	Valid N
1	Mean	**6.25**	**221.18**	**43.38**	77
	SE	(1.44)	(12.21)	(4.72)	
2	Mean	**4.15**	**229.87**	**61.72**	87
	SE	(1.28)	(11.15)	(4.03)	
Total	Mean	**5.13**	**225.79**	**53.11**	164
	SE	(0.96)	(8.22)	(3.15)	

TABLE 9: COMPARISON OF THE FIRST TWO PERIODS. (NOTE: SUBJECTS WHO GUESSED WERE EXCLUDED)

As you can see in Table 9, the first two periods show significant learning effect of subjects as expressed in the way the mean profit per task increased from 39 to 60.4 ECUs as the subjects probably after the first period developed a better strategy of counting the zeros. The mean time per task increased slightly from 221s to 229s if we exclude those who guessed it from the beginning, as you can see in the Table 9, and the inaccuracy of estimates measured as the mean difference of an estimate to the true number of zeros decreased insignificantly from 6.25 to 4.15, so the subjects probably found out they could not guess it randomly or that the task was not as easy as they had imagined. The number of subjects guessing decreased from 14 in the first period to 4 in the second period. If we exclude them from the analysis, the time per task is insignificantly different, whereas the profit stays almost the same: 43.3 ECU in the first and 61.7 ECU in the second period. The accuracy decreases then from 6.25 to 4.15, but the difference is again not significant.

[34] Not significant on the 5% level. P-value =0.909 for the F-test of equality of means.



GRAPH 1: TIME PER TASK IN THE FIRST TREATMENT (WITHOUT TIME PRESSURE)

5.2.2 No info vs. Info vs. Extended Info

In Table 10 I compare the main characteristic variables between the treatments with time pressure. I would like to repeat that the three main treatments of interest differed in the way of how much information the participants had for their disposal. In the Treatment 2, the participants were under time pressure, but they had no chance to get information about the estimates of others. In the Treatment 3, participants had the opportunity to view the estimates of other participants, who were faster than they were and finally, in the Treatment 4, the information about each participant's estimate was supplemented by information about her past performance in the form of the total profit she earned until the preceding round.

Looking at the results, there is a minor tendency that the inaccuracy of original estimates decreased with the treatment, which is however not significant and even if it were significant, it would not be logical, because the original estimates should be unaffected by the additionally revealed information, which can influence only the final estimates. The inaccuracy of final estimates can be, in Treatments 3 and 4, different from the inaccuracy of original estimates because of the possibility to switch from the first value after observing the public information. If the information was valuable in general to the subjects, the inaccuracy should have been lower in Treatment 3 and 4 in comparison with Treatment 2. The result is that the means are again not significantly different, even though the mean of Treatment 4 *is* on a 5% significance level different from the mean of Treatment 2.

Comparison of Treatments	Treatment	2	3	4	Total	p-value
Inaccuracy of *original* estimates	Mean	**8.80**	**7.06**	**5.63**	**7.12**	0.15
	SE	(1.26)	(0.77)	(1.32)	(0.68)	
Inaccuracy of *final* estimates	Mean	**8.80**	**8.50**	**5.03**	**7.33**	0.16
	SE	(1.26)	(1.92)	(1.50)	(0.90)	
Profit	Mean	**112.57**	**135.45**	**206.57**	**153.81**	0.00
	SE	(8.54)	(7.53)	(7.27)	(4.75)	
Time per task	Mean	**108.91**	**97.86**	**104.56**	**103.95**	0.02
	SE	(2.40)	(2.47)	(1.59)	(1.24)	
Stress (Subjective)	Mean	**5.74**	**5.57**	**5.64**	**5.65**	0.77
	SE	(0.15)	(0.17)	(0.14)	(0.09)	
	N	234	216	258	708	

TABLE 10: COMPARISON OF RESULTS IN TREATMENTS WITH TIME PRESSURE. NOTE: P-VALUES INDICATE SIGNIFICANCE OF F-TEST OF EQUALITY OF MEANS.

This finding may be attributed to the fact that the group 3 was remarkably worse in the usage of public information as there were more subjects who guessed the number straight at the beginning (interestingly, they sometimes guessed a very similar number) and some of the other subjects deciding on whether to change or not change to a wrong value (see section 5.5.3 – examination of information cascades for details) However, if we exclude this group from the computation of a mean for the third treatment, the mean even increases to 9.85. We can see that this effect was not the case. After computing means for the different groups of subjects [35] I could clearly identify the source of this leverage: it was group 2, which had a mean of 11.62 compared to the other groups which had a mean of 6.02. With group 2 excluded, the mean of the inaccuracy of final estimates becomes 6.02

[35] To avoid any confusion: here by a group I mean a group of people who attended the same experimental session.

with SE=0.674, which confirms the decreasing tendency of this variable when the public information becomes available.

Apart from examining accuracy, we can have a look at the variable which was the most important for the subjects, the profit per task. Here we can compare the combined profit of the fixed payment from the task with the time-dependent bonus. Because in each treatment there was the same number of periods with the same level of time pressure, we would expect the average profit to be similar or increasing with the availability of information. This time the result is crystal clear that the publicly available information probably caused the significant increase in the profit per task from the base of 112.6 ECU over 135.6ECU to 206.6ECU in the Treatment 4.

5.2.3 *TESTING FOR ORDER EFFECT*

Without randomization of order of levels of time-pressure, the order effect would affect the accuracy of the results either with the subject gaining more experience in the task or, on the contrary, getting tired of the task and looking constantly at the screen. In the Table 11 there you can see that the mean values are insignificantly different from each other and that you can not identify any trend. An interesting observation is that the period 5 was remarkably unsuccessful as in twenty cases the subjects did not manage to finish in time.

Test of order effect	order of a period in a session	**Inaccuracy of original estimates**			Number cases out of time
		Mean (SE)	SD	N	
Treatment 1	1	**7.29** (1.38)	13.19	91	0
	2	**4.07** (1.22)	11.67	91	0
Treatment 2	3	**10.85** (2.58)	23.41	82	7
	4	**8.95** (2.36)	21.26	81	4
	5	**6.25** (1.10)	9.34	71	**20**
Treatment 3 / Treatment 4	6	**9.10** (2.86)	23.81	69	6
	7	**7.84** (2.81)	23.59	70	5
	8	**3.82** (0.70)	6.03	73	2
	9	**6.64** (2.49)	23.52	89	1
	10	**6.27** (1.28)	11.94	86	4
	11	**4.52** (0.61)	5.76	87	3
	Total	6.82 (0.57)	17.16	890	52

TABLE 11: TEST OF ORDER EFFECT. F-TEST FOR EQUALITY OF MEANS IS INSIGNIFICANT ON 10% LEVEL (P-VALUE=0.19; IF PERIOD 3 EXCLUDED, P-VALUE=0.392).

5.3 DISCOVERING EFFECTS OF TIME PRESSURE

5.3.1 COMPARISON OF MAIN CHARACTERISTICS

Time-pressure (TP) is generally expected to increase effort and reduce accuracy when a task is performed as mentioned in the theoretical part earlier in the text. Now we compare only the treatment without TP (Treatment 1) with the treatment with TP, but only the Treatment 2 (i.e. without looking at the public information). If I compare the levels of time pressure to each other, there was an increasing number of those who did not manage the task on time, according to expectations – from 4 in *Low* over 6 in *Medium* to 19 in *High*. What is also in agreement with our expectations is that the time per task is decreasing with the increasing time pressure – from 123.7s in *Low* over 109.8s in *Medium* to 91s in *High* - this is obviously due to the time limit. Another fact which also agrees with our expectations is the subjectively stated level of stress, which is monotonous increasing - significantly higher with each higher level of stress.

However, what is not that straightforward is the behavior of the inaccuracy of their guesses – they are insignificantly different from each other, with means from 8.9 over 10.8 to 6.2, which does not go along with the prediction about lower accuracy during higher stress.

	Time Pressure:	No Pressure	Low	Medium	High	Total	p-value
Inaccuracy of original estimates	Mean	**5.68**	**8.95**	**10.85**	**6.25**	**7.43**	0.09
	SE	(0.92)	(2.36)	(2.58)	(1.10)	(0.82)	
Time per task	Mean	**208.42**	**123.68**	**109.83**	**91.00**	**152.45**	0.00
	SE	(8.39)	(2.91)	(4.54)	(4.06)	(4.59)	
Stress (Subjective)	Mean		**5.10**	**5.84**	**6.34**	**5.74**	0.05
	SE		(0.23)	(0.25)	(0.31)	(0.15)	
	N	182	81	82	71	416	

TABLE 12: COMPARISON OF LEVELS OF TIME PRESSURE IN TREATMENT 2 AND TREATMENT 1. NOTE: STANDARD ERRORS IN PARENTHESES. P-VALUE INDICATES LEVEL OF SIGNIFICANCE FOR THE F-TEST OF EQUALITY OF MEANS ACROSS ALL LEVELS OF TIME PRESSURE. SUBJECTS WHO DID NOT MANAGE ON TIME WERE EXCLUDED.

5.3.2 PERFORMANCE UNDER DIFFERENT LEVELS OF TIME PRESSURE

If we have a look at a comparison of subjects' results under all treatments, the variables we can compare show a little more than the comparison of only Treatment 1 and Treatment 2: The F-test of the equality of means shows that the inaccuracy of original estimates is insignificantly different from each other across all levels of TP. As stated in the preceding paragraph, in the

Treatment 2, there was the Medium TP that was higher than the others, but now this difference disappears. What caused this? We can suppose that part of the effect was that the lower time limit and higher payoff stimulated the effort of subjects rather than distracted.

	Time Pressure	No Pressure	Low	Medium	High	Total	p-value
Inaccuracy of original estimates	Mean	**5.68**	**6.79**	**7.61**	**6.93**	**6.82**	0.73
	SE	(0.92)	(1.22)	(1.27)	(1.00)	(0.57)	
Time per task	Mean	**208.42**	**113.20**	**106.42**	**91.34**	**125.32**	0.00
	SE	(8.39)	(2.00)	(2.20)	(2.03)	(2.43)	
Stress (Subjective)	Mean		**5.14**	**5.65**	**6.46**	**5.76**	0.00
	SE		(0.14)	(0.14)	(0.15)	(0.08)	
	N	182	250	254	256	942	

TABLE 13: COMPARISON OF LEVELS OF TIME PRESSURE IN ALL TREATMENTS. NOTE: STANDARD ERRORS IN PARENTHESES. P-VALUE INDICATES LEVEL OF SIGNIFICANCE FOR THE F-TEST OF EQUALITY OF MEANS ACROSS ALL LEVELS OF TIME PRESSURE. SUBJECTS WHO DID NOT MANAGE ON TIME WERE EXCLUDED.

It is true, that, as you can see in Table 14, there were an increasing number of people who did not manage to answer on time. However, as stated in the Hypothesis 2, the expected behavior is that inaccuracy *increases* with increasing TP, so this result clearly goes against it and we can conclude that **we can not accept Hypothesis 2.**

One possible explanation is connected to the strategies the subjects reported having used: at the beginning, they tried complicated strategies that involved writing down the number of zeros in each row/column and finally adding it together, which was in reality time-consuming and imprecise. The most efficient method seems to be just counting the zeros directly, which all of the subjects were then, due to lack of time to process any other more complicated strategy, forced to adopt and thus they were "forced" to improve their results.

Time Pressure	No Pressure	Low	Medium	High	Total
Not Managed	0	7	14	31	52
Managed	182	243	240	225	890
Total	182	250	254	256	942

TABLE 14: SUMMARY OF CASES IF MANAGED TO ANSWER TASK IN TIME.

5.4 OTHER IMPORTANT ATTRIBUTES

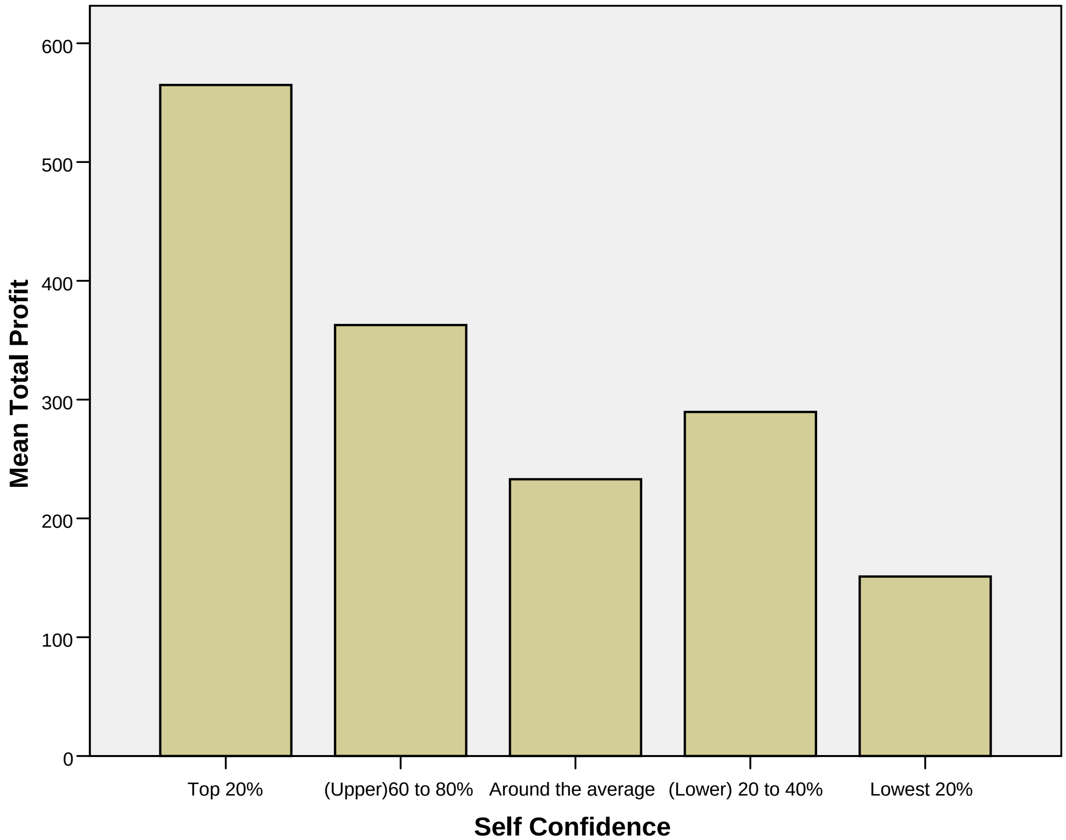
5.4.1 SELF CONFIDENCE: ONLY LESS THAN A THIRD OF SUBJECTS WERE CORRECT

In Graph 2 we can see that the distribution of total profit over stated confidence about the relative ranking of the participant is not monotonously decreasing as may have been expected if the guesses were on average correct.

Self-Confidence	Frequency	Percent
Under-confident	29	31.9%
Realistic	26	28.6%
Overconfident	36	39.6%
Total	91	100%

TABLE 15: REPORTED SELFCONFIDENCE IN CONTRAST WITH REAL RELATIVE RESULTS

In Table 15 there is an evaluation of whether the subjects guessed their relative ranking correctly or not: we can see why the relationship in Graph 2 is not monotonously decreasing: only less than a third of the participants were correct in their estimation. Another third felt less than confident and about 40% of participants felt overconfident. On the other hand, we can see that the highly confident subjects actually accounted for the highest mean total profit (total profit after the end of Treatment 2).

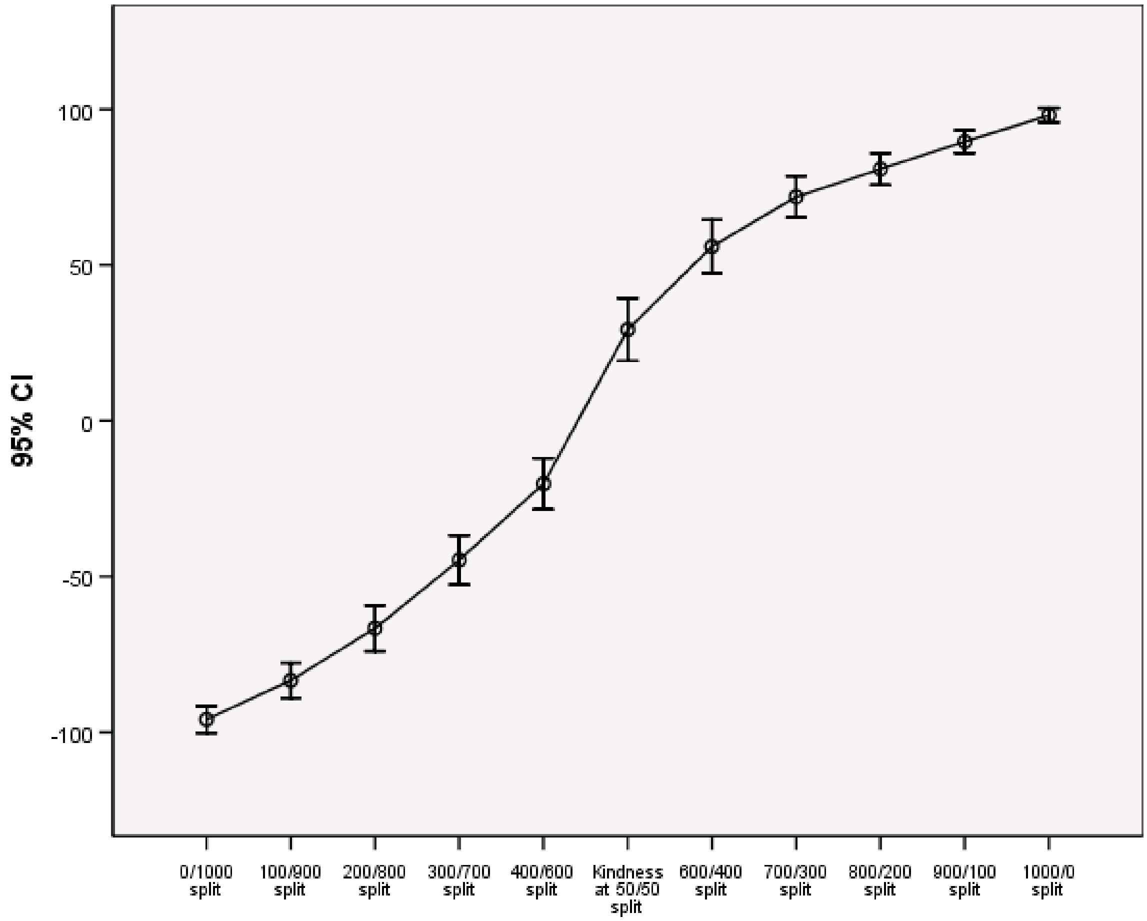


GRAPH 2: REPORTED SELF-CONFIDENCE AND MEAN TOTAL PROFIT

5.4.2 SOCIAL PREFERENCES: PERCEIVED KINDNESS IN A DICTATORIAL GAME

In the questionnaire subjects had to fill in a series of questions that asked for their preferences in the distribution of 1,000CZK in a hypothetical ultimatum game. There were 11 questions on their perceived kindness of distributions that ranged from 0 for them and 1,000 for the anonymous partner to 1,000 for them and 0 for the partner, same as in Falk and Fischbacher (2006). There was an additional question that asked for the expected share on the 1,000CZK if the situation became real.

Apart from this, there can be certain regularities identified in the way subjects assigned values (from -100 to 100) of perceived kindness to the divisions: a majority of subjects assigned a negative value to the unequal distributions with a gradual increase and around the 50/50-point, there was a point where the kindness started to be positive and monotonously increasing until the unequal distribution in favor of the subject (1,000 for subject, 0 for the partner). You can see in the Graph 3 the shape of the resulting curve of this group.



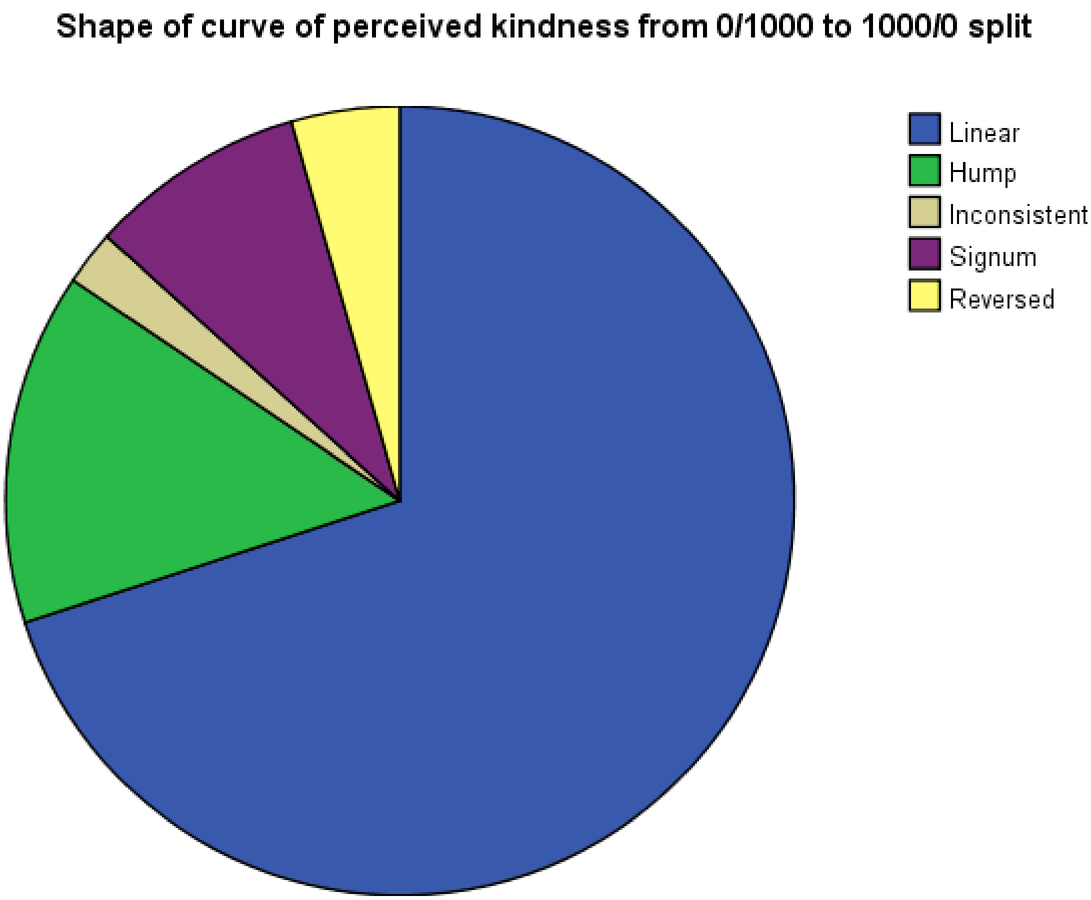
GRAPH 3: PERCEIVED KINDNESS IN A DICTATORIAL GAME.

Then there was another group who perceived the most kind to be the equal split, so there was something like a hump-shape in the curve of their preferences over the divisions. Subjects in this group probably confused the words “kind” and “fair”, but, as there was not a small number of people making that decision (12.3%) we can not attribute it to error.

The regularity of the preferences in the third group can be characterized by the multiplication of a constant by sign-function: there was a stable constant with one value outstanding, for example there were only values of -100 with the exception of the equal 50/50 split. There were 7.5% of subjects who behaved like this.

Subjects in the last group had their preferences reversed – they assigned positive values to the for-them-unfavorable split and the for-them-favorable split was treated in the negative values, in a monotonous manner. There were only 4 subjects like this, constituting 3.8%.

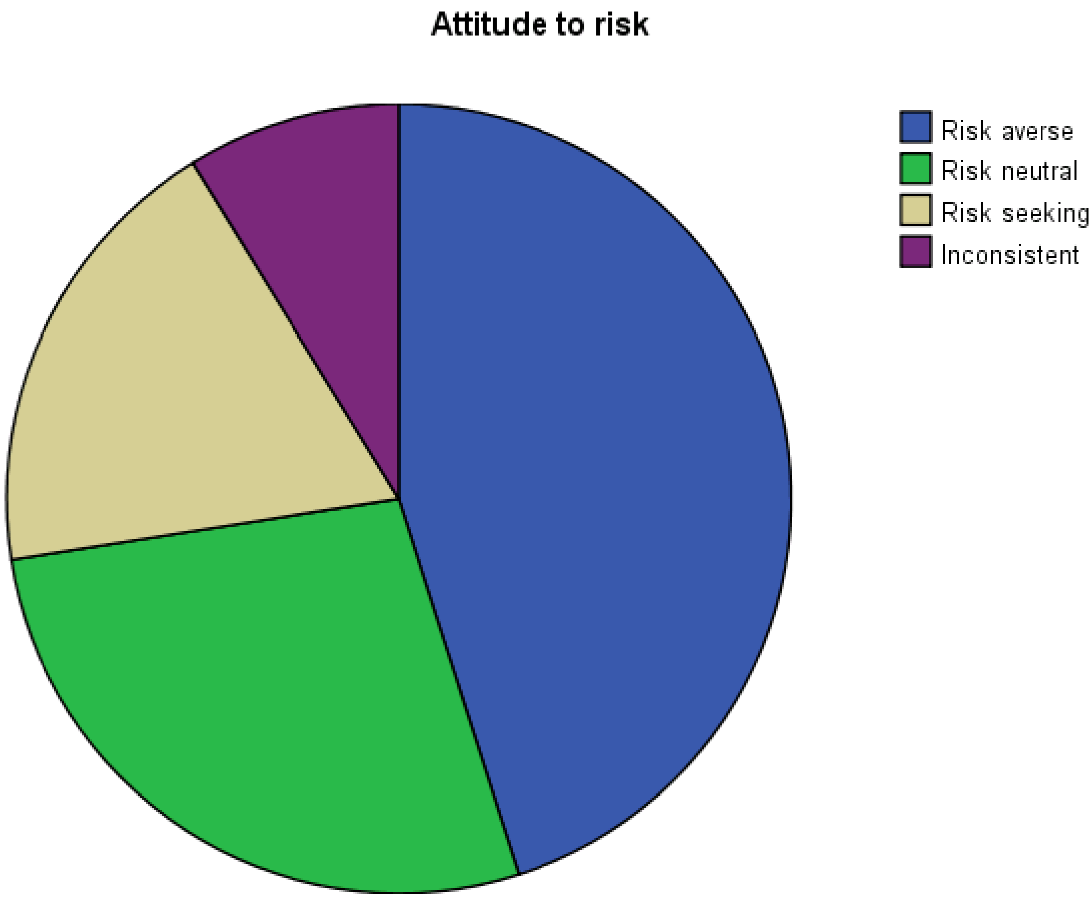
Apart from these, there were 2 subjects inconsistent in the assignment of the values – there was no regularity in the values, and I think they did not understand the task. You can see the distribution of these elicited social preferences in the Graph 4.



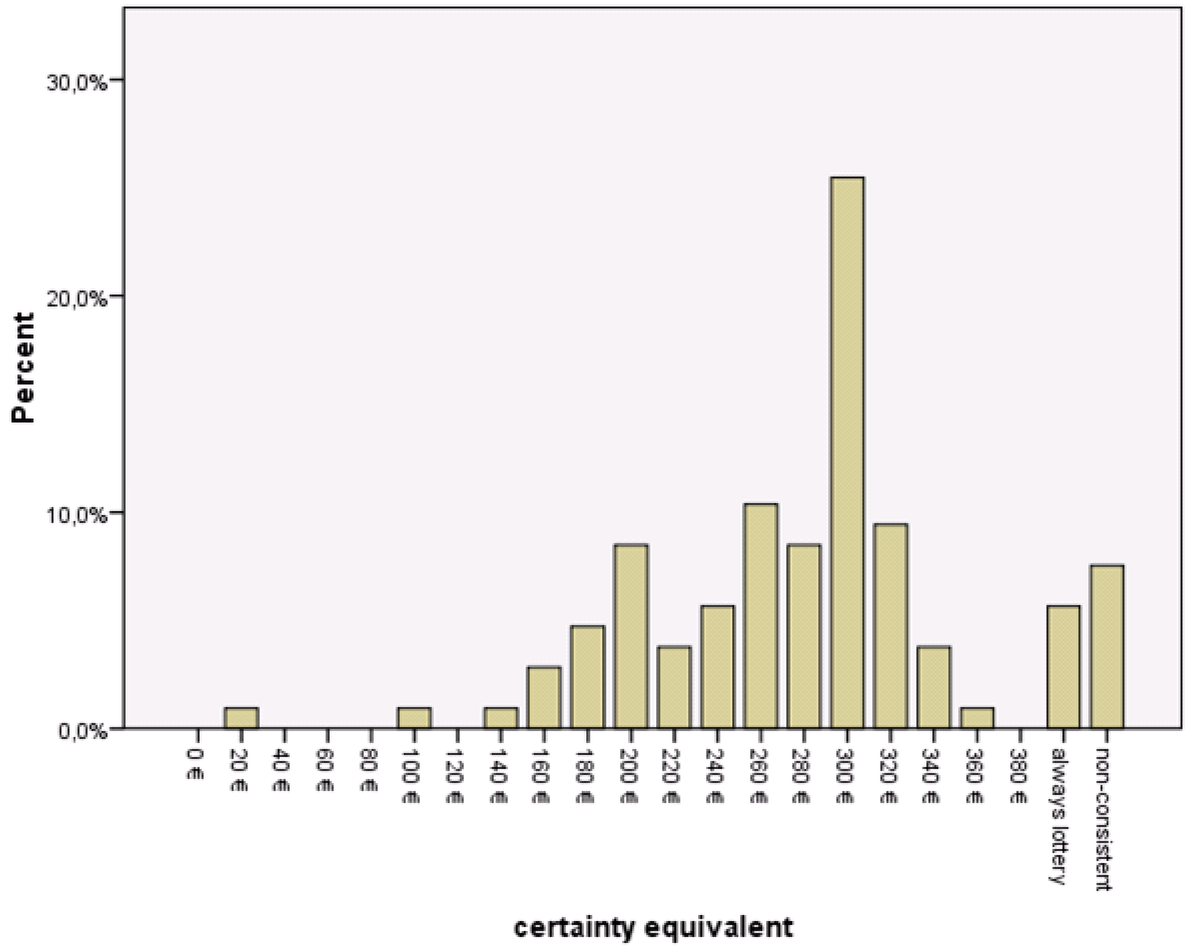
GRAPH 4: DISTRIBUTION OF SHAPES OF THE CURVES OF THE ELICITED SOCIAL PREFERENCES

5.4.3 *Risk preferences: Certainty Equivalent*

The attitude to risk was elicited by the lottery card (see Figure 12 in the Appendix) as mentioned above from Dohmen et al. (2009) and from the stated certainty equivalent we can infer the individual attitude to risk as Dohmen et al. (2009) did. Dohmen et al. (2009) did the research on a large representative sample and they found (to summarize) that about 78% of the population are strictly risk averse; 9% are strictly risk seeking; the females are less willing to take risks in general; with increasing age the willingness to take risks decrease; if the participant's parents have completed high-school there is a positive effect and finally height has also a positive effect on the willingness to take risks. In our sample the subjects were also mostly risk-averse (45%), 27.5% were risk-neutral and 18.7% were risk-seeking, which is much more than in the representative sample above. Apart from these, there were again some subjects who filled the task out in a inconsistent manner – for example switching after each row from preferring the lottery to the certain amount of cash and back. You can see the overview in Graph 5 and the distribution of the stated certainty equivalents in Graph 6.



GRAPH 5: RISK-ATTITUDES



GRAPH 6: DISTRIBUTION OF CERTAINTY EQUIVALENTS

5.4.4 SUBJECTS' "PLAYER" PROFILES

Hypothesis 3 speculates on the different types of subjects; that there will be some that will benefit from the possibility to see the public information, but also that there will be some for whom the information will be useless. The data shows that indeed, both types appeared. Out of 90 subjects, there were 13 subjects who never looked at the public info, and 8 out of them (i.e. 61.5%) performed significantly better than average. This suggests that there was the successful type of subject that would only lose the money by viewing the public info, but not exclusively: there was another type of subject who also never used the information, but this one must have had another motivation as their performance was mostly below average.

On the one hand, there were 33 subjects who did look at the public info each time they had a chance to, but out of those 33 only 5 used always the info, so these curious and imprecise subjects were also not the only type of subjects. On the other hand, there were 8 subjects who looked every time, but never switched. These 8 were mostly highly successful in the task, so they probably just assured themselves that their result was correct.

5.5 INFORMATION CASCADES

There have been two treatments where information cascades could occur – the third and the fourth treatment. They differed in the possibility to see the history of how each participant was successful in the case of treatment 4. In treatment 3, I had to exclude some observations due to technical problems with the computers in the first session. In the end I have 15 full periods in the third treatment and 18 in the fourth treatment, which gives 33 possibilities of getting a cascade. In our setting the cascade occurs when the latter participants switch from their original values and follow the values of players that had been faster. There can be a correct cascade, when all the subjects follow a correct number of zeros; or a weakly correct cascade, when the subjects follow a number that is in the tolerated range +/- 2 around the correct value, and an incorrect cascade, when they follow a completely incorrect number. Of course, there need not be any cascade at all.

5.5.1 OCCURRENCE OF CASCADES

Out of the 33 possibilities, there was *no full cascade* in the sense that *everybody* in the period would look at the public information and switch to the observed value. On the contrary, there were two periods when *nobody* decided to switch. The mean of *InfoUsed* is 42% per period, which indicates that the empirical probability to switch was quite low even if the subject already decided to see the public information. In all possibilities, subjects switched in 24.5% cases, which is even a smaller portion. This favors the theoretical prediction of Lee (1993) and his continuous critique based on information aggregation and not the effect of the endogenous timing of Chari and Kehoe (2002). However, we can observe in *many* cases *quasi-cascades*, sometimes even a reversal of a cascade from an incorrect to the correct one: there were 9 correct quasi-cascades in the sense that we do not consider as a break when a player made a mistake or ran out of time; the most important is that the number followed was the true one. Apart from that, there were 10 weakly correct quasi-cascades when the number followed was not the true one, but is was still in the region +/-2 and the subjects got paid for it.

5.5.2 CLUSTERING OR HERDING

An undisputable advantage of this data is the easy way to distinguish herding from clustering, which is often almost impossible when examining the data from real financial markets. Clustering occurs when more market participants end-up with the same result, but not necessarily by following each other (see Hirshleifer and Teoh, 2003) If we distinguish clustering and herding, we can see more in the data: in many periods the correct outcome was finally followed, but never by the occurrence of a cascade – there were always some subjects who believed more themselves than the crowd – the clustering was mostly mixed with herding.

5.5.3 *WAS PUBLIC INFORMATION USEFUL?*

We can have a look at the rate of "success" of switching: if the new estimate brought a higher payoff than the original one. The percentage of successful changes is shown in the Table 16 – we can see that in most groups the subjects could exploit the information in more than 80% cases. However, one group (group No. 3) was exceptional and had this rate lower than 50%.

Group	1	2	3	4	5	6	Total
Mean	81%	86%	**44%**	88%	82%	85%	76%

TABLE 16: RATE OF SUCCESS OF SWITCHING THE ESTIMATE

5.5.4 *INCORRECT CASCADES*

In this exceptional group No. 3 there were four subjects who mostly guessed the number shortly after the beginning of a period, so they added significant noise to the information seen on the screen to the public information by other subjects. Interestingly, their results were often followed by others: in this group the rate of successful switch was much lower than in the other groups: in other groups, there were on average 3 incorrect switches, but in this group there were 14 incorrect switches. This group is outstanding in this respect: there were even incorrect cascades (or in classical terminology "reverse" cascades) when the number followed was far from the true one: it happened in the first part of a period and it was caused by the subjects who guessed the result who were followed by some (two to three) other subjects. However, in the second half of the period, (three to four) "honest" participants arrived and brought the correct information to light. Then the next subjects mostly either entered correctly the result or did not use the public info at all. This result strongly supports the fragility of cascades in a continuous setting: an incorrect cascade began, but was overrun by the arrival of the information brought by the subjects who counted well and their estimate was precise. In real life, we also cannot distinguish who, when in a cascade, ignores private information and follows the crowd and on the contrary, who accidentally gets the same result and gets into a cluster of subjects with the same results. The results suggest that if subjects expect the arrival of true information, the moment of arrival may, with a high probability, break the cascade.

5.5.5 *TIME PRESSURE AND INFORMATION CASCADES (HERDING)*

The rate of cascade creation was independent of time pressure; the same as the rate of switching from the original estimates (see Table 6). Also the rate of seeing the public information was not significantly different from each other if we simply compared the means as you can see in Table 17 even though the rate seems to be a little higher under Low level of time pressure. This obviously favors the Alternative 1 and the underlying explanatory mechanism of Rieskamp and Hoffrage (2008) who suggest that if people have to work under increasing time pressure, they select faster a smaller amount of information that they consider to be worth it; i.e. they prefer more quality over quantity than in the treatment without time pressure.

Decided to view public info *(InfoShown)*				
Time Pressure	Low	Medium	High	Total
Mean	**64%**	**55%**	**56%**	58%
SE	4%	4%	4%	2%
N	165	165	165	495

TABLE 17: COMPARISON OF RATES OF SEEING THE PUBLIC INFORMATION IN DIFFERENT LEVELS OF TIME PRESSURE

5.6 DATA FROM HEART-RATE MONITORS

I had 17 heart rate (HR) monitors Polar RS400 which measure the HR with precision up to 1 second. I extracted the data from the monitors by using specialized software Polar Pro-Trainer 5. During the experiment, there were several points in time when all subjects (once they pressed it all at once, other times separately) had to press the button on the monitor which created time-intervals so that I could synchronize both data-series. I could not force the subject to press the button before and after each task, and I did not even need to because I could compute the exact[36] times when the tasks actually happened and infer the average HR over these time intervals. Unfortunately, with some subjects we could not find the signal from the chest belt at the beginning of a session and with some other subjects the signal kept being lost during the session, which I found out about during the data analysis. In the end, I have 677 reliable observations.

[36] Error of measurement: I can guarantee the precision of my measurement is maximally up to +/- 10s per task, which is in this case appropriate, because if an average task took say 2 minutes, the resulting value of the average HR over the task can differ maximally by 2 points.

5.6.1 VARIABLES

	N	Min	Max	Mean	SE (Mean)	Std. Dev.
Average HR during the Task (*HR_AVG*)	677	59	151	90.94	0.601	15.634
Quiescent Heart Rate (*HR_CALM*)	677	50	98	74.47	0.391	10.179
Difference of quiescent to actual HR (*HR_DIF*)	677	0	53	**16.47**	0.377	9.816

TABLE 18: DESCRIPTIVE STATISTICS OF *HR_AVG*, *HR_CALM* AND *HR_DIF*.

I measured the average HR over the task performed (variable *HR_AVG*); the base rate of the quiescent HR[37] (var. *HR_CALM*) and resulting difference between these two (*HR_DIF*), which should account for the personal differences of different quiescent HR levels. You can see the summary statistic of the HR-variables in the Table 18. Some subjects had an average HR almost the same as when they stayed calm in the end, others had peaks as high as 151, which is equivalent to highly demanding physical activity.[38]

5.6.2 QUALITATIVE ANALYSIS

Generally speaking, there were different kinds of curves in the HR: a majority of them (over 50%) were very legible and fit well to the data (see Figure 10 in the Appendix), i.e. there was a significant and stable increase during the performance of the task and the HR went back to normal levels between the tasks; but some of them were more or less random and similar to white noise (see Figure 11 in the Appendix). Interestingly, some subjects had a steep peak when guessing the number (took only a short time of thinking), but others did not. Many subjects also had a short peak just before a task started and then the normal hump-shape followed, which is a sign of a reaction to the introduction screen of each task. Overall, the HR during task was significantly different to the base rate, which proves the first part of the Hypothesis 9 on 1% level.

5.6.3 ORDER EFFECT

During my examination of the HR-curves I spotted a few qualitative regularities: HR was relatively very high during the first task without any time pressure, which is probably due to the fact

[37] HR measured in a "steady" state when no activity is performed; the interval after completion of a questionnaire and before collecting the money. However, as some of the subjects obviously started to think of other things and maybe they were expecting the reward, I took the average HR instead of from this interval from a part of the questionnaire, when the HR was stable for a longer time.

[38] To illustrate it, the maximum HR of a physically demanding activity is normally computed as 220-age and the higher threshold HR for optimal training of a physical activity like medium-distance jogging is then 80% of the maximum HR; that is by 22 year old subject about 160. Here we got 150, which equivalent to running (Horčic and Formánek, 2003)

that the subjects saw it and practiced for the first time. During the second task the HR was mostly a little lower, but then the first task under time pressure was again associated with very high HR levels (relative to the parts in between the tasks as well as to the base rate). On the other hand, in the latter tasks the HR was generally lower. This proves that the order effect generally plays a significant role and must be treated with a special care – it can best be removed by using a randomized design.

Order of a period in a session	Mean	Std. Error of Mean	N
1	**20.49**	1.27	59
2	**17.69**	1.21	59
3	**20.92**	1.36	65
4	**15.68**	1.07	62
5	**19.80**	1.23	65
6	**17.00**	1.32	57
7	**17.32**	1.43	57
8	**14.27**	1.17	56
9	**12.56**	1.04	66
10	**13.53**	1.12	66
11	**12.31**	0.96	65
Total	**16.47**	0.38	677

TABLE 19: DIFFERENCE OF QUIESCENT TO ACTUAL HR (*HR_DIF*) ACROSS PERIODS

5.6.4 CORRELATION WITH SUBJECTIVELY PERCEIVED STRESS

Hypothesis 9 also stated that there should be a positive correlation between the objectively measured stress and subjectively stated level of stress, in our case between variables *SubjectiveStress* and *HR_DIF*. In Table 20 you can see that indeed there is a significant positive relationship between the *HR_DIF* and subjective stress, but the level is rather smaller than we would expect. However, much more interesting is the negative relationship between *HR_DIF* and the *InfoUsed*, which suggests that the more a person is in a stressful state the less willing she is to use the public information. You can see the proper analysis of the role of the objective and subjective stress in the sections 6.3.6.4 and 6.4.5.

		Difference of quiescent to actual HR (*HR_DIF*)
Average Heart Rate during the Task (*HR_ACT*)	Pearson Correlation	**.773(**)**
	Sig. (2-tailed)	0.000
	N	677
Stress (Subjective)	Pearson Correlation	**.105(*)**
	Sig. (2-tailed)	0.013
	N	559
Self Confidence (*SelfConfidence*)	Pearson Correlation	**.152(**)**
	Sig. (2-tailed)	0.000
	N	677
Decided to see public info (*InfoShown*)	Pearson Correlation	**-0.070**
	Sig. (2-tailed)	0.180
	N	367
Really used the info (*InfoUsed*)	Pearson Correlation	**-.225(**)**
	Sig. (2-tailed)	0.001
	N	205
Gender (Male=1)	Pearson Correlation	**.092(*)**
	Sig. (2-tailed)	0.017
	N	677

TABLE 20: PEARSON CORRELATIONS. NOTE: (*) AND (**) INDICATE SIGNIFICANCE ON 5% AND 1% LEVEL RESPECTIVELY.

5.6.5 SELF CONFIDENCE AND HR

An interesting observation can be made when we take look at the mean of *HR_DIF* with respect to the stated level of confidence: those who felt being more successful than the average also had lower mean of *HR_DIF* in comparison to the average and especially to those who felt rather under-confident. On the contrary, the real ranking shows that the relatively higher *HR_DIF* was the case of those who scored relatively around the average or a little below.

	Reported Self Confidence			Real Ranking		
	Mean	Std. Error of Mean	N	**Mean**	Std. Error of Mean	N
Top 20%	**13.96**	1.258	75	**13.56**	0.716	93
(Upper) 60 to 80%	**15.65**	0.756	133	**14.88**	0.852	93
Around the average	**16.31**	0.666	229	**18.23**	0.744	174
(Lower) 20 to 40%	**16.39**	0.685	165	**20.47**	1.143	130
Lowest 20%	**21.08**	1.224	75	**14.62**	0.662	155
Total	16.47	0.377	677	16.66	0.392	645

TABLE 21: COMPARISON OF MEANS OF *HR_DIF* FOR DIFFERENT LEVELS OF STATED SELF-CONFIDENCE AND OF THE REAL RELATIVE RANKING

5.6.6 RISK PREFERENCES AND HR

A very important part of analysis is to compare the levels of both subjective and physiological stress with respect to the risk attitudes. Table 22 shows us that the means of *HR_DIF* and *SubjectiveStress* are however insignificantly different from each other for the risk-averse and risk-loving subjects and thus we can reject the second part of Hypothesis 5.

		Difference of quiescent to actual HR (*HR_DIF*)	Subjective Stress
Risk loving	Mean	**15.91**	**5.50**
	SE	0.611	0.201
	Std. Deviation	8.955	2.917
	N	215	211
Weakly Risk Averse	Mean	**16.73**	**5.85**
	SE	0.474	0.096
	Std. Deviation	10.192	2.245
	N	462	549

TABLE 22: COMPARISON OF LEVELS OF STRESS WRT RISK ATTITUDE. F-TEST FOR THE EQUALITY OF MEANS DOES NOT REJECT THE NULL FOR BOTH HR_DIF AND SUBJECTIVESTRESS FOR 10% LEVEL OF SIGNIFICANCE.

6 MODEL EVALUATION

As introduced in section 3.7, I model the propensity to herd by using a multiple regression analysis, specifically logit, which means the standard logistic regression. The model has two basic specifications as in 3.7.2 and 3.7.3 that are subject to various modifications, such as when I study exclusion of groups of certain variables of interest. First of all I do a small exercise of comparing the basic techniques; then I move further to examination of possibility of using Heckman's two stage estimator and finally I study the full models for both explained variables in various specifications. As we could see from Table 4, the variance of the *TotalProfit* was really high so to reduce it, I transform it by using a natural logarithm to create variable *lnTotProf*.

6.1 TECHNIQUES COMPARISON: LOGIT VS. PROBIT VS. LPM

6.1.1 EXPLAINED VARIABLE: INFOSHOWN

Following the discussion in 3.8, I compare all three techniques, namely linear probability model (LPM called, which is standard ordinary least squares estimation - OLS), logit and probit, and because the variable *HR_DIF* has some missing values, I check the stability of coefficients when this variable is excluded. The results are in Table 23. From there you can see that the variable *HR_DIF* is clearly a very important regressor as its exclusion in models of all techniques remarkably decreases the log-likelihood function, which happens even if the number of observation in the restricted model increases. I used robust standard errors but the difference to the non-robust model is negligible. First we can have a look at the difference between logit, probit and OLS (that is the linear probability model): all coefficients have the same sign and almost always the same significance, too. The only difference is in the variable *TimeLeft*: it loses “two stars” of significance when the *HR_DIF* is included, so we can conclude that the model is quite stable. Log-likelihood function has the highest value for the full model for both logit and probit (equations 4 and 6), so in this case these two techniques look equivalent. According to Greene (2002), the relationship between logit and probit estimates can be expressed as the probit coefficients multiplied by $\pi/\sqrt{3} = 1.8$.

At this stage of analysis I also check for multi-collinearity problem by using the common indicators variance inflation factor (VIF) tolerance and eigenvalues. All indicators give negative results: the VIF is not greater than 3.12 (if greater than 10 it would indicate a problem); the tolerance are all above 0.32 (0.1 or 0.2 can be problematic) and the highest eigenvalue is 13.4 (eigenvalues above 30 indicate a problem). There are some variables correlated, namely score and score2; RiskAverse and CE; TimeLeft and TP_High and others, but if properly analyzed, this does not cause any problem to the analysis.

Regression comparison: *InfoShown*

VARIABLES	(1) OLS	(2) OLS	(3) Logit	(4) Logit	(5) Probit	(6) Probit
Reputation	0.056	0.065	0.258	0.246	0.140	0.129
	[0.057]	[0.045]	[0.262]	[0.211]	[0.160]	[0.128]
TimeLeft	0.002**	0.001	0.011**	0.006	0.007**	0.004
	[0.001]	[0.001]	[0.005]	[0.004]	[0.003]	[0.003]
TP_Medium	-0.037	-0.073	-0.183	-0.342	-0.111	-0.208
	[0.061]	[0.052]	[0.293]	[0.255]	[0.177]	[0.154]
TP_High	0.004	-0.055	0.022	-0.225	0.020	-0.156
	[0.069]	[0.059]	[0.336]	[0.294]	[0.201]	[0.175]
O	-0.005	-0.005	-0.022	-0.023	-0.013	-0.014
	[0.006]	[0.005]	[0.028]	[0.022]	[0.016]	[0.013]
C	0.013***	0.015***	0.067***	0.073***	0.040***	0.042***
	[0.005]	[0.004]	[0.025]	[0.021]	[0.015]	[0.012]
E	-0.000	-0.001	-0.003	-0.002	-0.003	-0.001
	[0.005]	[0.004]	[0.025]	[0.021]	[0.015]	[0.012]
A	0.019***	0.010**	0.096***	0.060**	0.057***	0.032**
	[0.006]	[0.005]	[0.032]	[0.028]	[0.019]	[0.016]
N	0.018***	0.014***	0.084***	0.069***	0.050***	0.040***
	[0.006]	[0.005]	[0.029]	[0.024]	[0.017]	[0.014]
SubjectiveStress	0.011	0.007	0.056	0.038	0.032	0.023
	[0.011]	[0.009]	[0.053]	[0.045]	[0.031]	[0.027]
Female	0.010	-0.000	0.023	0.066	0.004	0.026
	[0.064]	[0.051]	[0.313]	[0.253]	[0.185]	[0.154]
CE	-0.034***	-0.030***	-0.173***	-0.173***	-0.103***	-0.099***
	[0.010]	[0.008]	[0.055]	[0.049]	[0.032]	[0.027]
RiskAverse	-0.271***	-0.292***	-1.393***	-1.518***	-0.832***	-0.907***
	[0.079]	[0.066]	[0.411]	[0.347]	[0.243]	[0.207]
SelfConfidence	0.135***	0.090***	0.680***	0.460***	0.410***	0.279***
	[0.020]	[0.016]	[0.122]	[0.087]	[0.071]	[0.051]
lnTotProf	0.004	0.006	0.016	0.026	0.008	0.018
	[0.012]	[0.010]	[0.057]	[0.048]	[0.034]	[0.029]
ExpectedKindness	-0.000	-0.000	-0.002	-0.001	-0.001	-0.000
	[0.000]	[0.000]	[0.002]	[0.002]	[0.001]	[0.001]
HR_DIF	-0.010***		-0.050***		-0.031***	
	[0.003]		[0.016]		[0.009]	
Constant	[0.258]	[0.215]	1.526	2.034*	0.940	1.184*
	0.789***	0.851***	[1.290]	[1.117]	[0.772]	[0.660]
Observations	367	495	367	495	367	495
R^2/Pseudo-R^2	0.175	0.155	0.141	0.126	0.141	0.125
Log-Likelihood	-228.6	-310.6	-216.4	-293.6	-216.4	-294.0

TABLE 23: REGRESSION COMPARISON - DEP.VAR. INFOSHOWN. NOTE: STANDARD ERRORS IN BRACKETS; *, ** AND *** DENOTE SIGNIFICANCE ON 10%, 5% AND 1% LEVEL.

6.1.2 Explained variable: InfoUsed

In Table 24 you can see that the *HR_DIF* was not significant in any of (1), (3) or (5) and hence we can focus more on the discussion of the coefficients of the restricted forms of the equations as it has many more observations, namely (2), (4) and (6). The log-likelihood function is much lower, though, as we have different number of observations, it is not crucial and from the McFadden's Pseudo-R^2 we can see that the exclusion of *HR_DIF* either increased the explained part of the model or left it unchanged.

Generally speaking, the coefficients are quite stable: coefficients of variables *SelfConfidence, Reputation, N* and *score* after the exclusion started to be significant on 5% level. This fact (together with other specification tests, such as LR-test and Wald χ^2 tests for significance of regression) tells us that the data behave well so our analysis will have significant explanatory power. The highest log-likelihood function is in case of equation 4, which confirms that the usage of logit is appropriate for further analysis.

Regression comparison: *InfoUsed*

VARIABLES	(1) OLS	(2) OLS	(3) Logit	(4) Logit	(5) Probit	(6) Probit
score	0.006 [0.004]	0.008** [0.003]	0.041* [0.025]	0.048** [0.021]	0.016 [0.013]	0.023** [0.011]
score2	-0.046** [0.019]	-0.065*** [0.016]	-0.317** [0.134]	-0.396*** [0.109]	-0.134** [0.060]	-0.198*** [0.052]
Reputation	-0.153* [0.081]	-0.190*** [0.063]	-1.238** [0.566]	-1.326*** [0.429]	-0.513* [0.287]	-0.610** [0.240]
TimeDeciding	0.021** [0.008]	0.021*** [0.007]	0.166** [0.072]	0.162*** [0.053]	0.059** [0.029]	0.063** [0.027]
TimeLeft	0.001 [0.002]	0.001 [0.001]	0.007 [0.013]	0.009 [0.009]	0.004 [0.006]	0.005 [0.005]
TP_Medium	-0.061 [0.084]	0.026 [0.065]	-0.352 [0.463]	0.122 [0.366]	-0.289 [0.253]	0.001 [0.209]
TP_High	0.088 [0.104]	0.138* [0.082]	0.545 [0.629]	0.755 [0.516]	0.263 [0.331]	0.396 [0.273]
O	0.007 [0.008]	0.007 [0.005]	0.038 [0.039]	0.047 [0.032]	0.030 [0.023]	0.027 [0.017]
C	-0.006 [0.006]	-0.005 [0.005]	-0.047 [0.041]	-0.036 [0.032]	-0.019 [0.021]	-0.017 [0.018]
E	-0.013** [0.006]	-0.015*** [0.005]	-0.095** [0.043]	-0.103*** [0.033]	-0.045** [0.021]	-0.053*** [0.017]
A	0.000 [0.009]	0.001 [0.007]	0.000 [0.051]	0.021 [0.040]	0.008 [0.028]	0.008 [0.022]
N	-0.011 [0.007]	-0.010* [0.006]	-0.085* [0.044]	-0.072** [0.033]	-0.040* [0.023]	-0.039** [0.019]
SubjectiveStress	-0.018 [0.015]	-0.016 [0.012]	-0.106 [0.082]	-0.098 [0.068]	-0.052 [0.044]	-0.046 [0.037]
Female	-0.004 [0.075]	0.015 [0.059]	-0.033 [0.414]	-0.020 [0.353]	-0.057 [0.234]	0.015 [0.194]
CE	0.004 [0.013]	-0.008 [0.009]	0.025 [0.075]	-0.053 [0.052]	-0.002 [0.041]	-0.040 [0.030]
RiskAverse	0.030 [0.096]	-0.121 [0.084]	0.166 [0.507]	-0.718 [0.446]	0.038 [0.299]	-0.472* [0.261]
SelfConfidence	0.020 [0.033]	0.049** [0.022]	0.091 [0.185]	0.274** [0.126]	0.080 [0.100]	0.173** [0.072]
lnTotProf	0.050** [0.020]	0.057*** [0.015]	0.413** [0.180]	0.408*** [0.118]	0.165** [0.078]	0.187*** [0.062]
ExpectedKindness	0.000 [0.000]	-0.000 [0.000]	0.002 [0.003]	-0.002 [0.002]	0.001 [0.002]	-0.001 [0.001]
HR_DIF	-0.003 [0.003]		-0.017 [0.022]		-0.012 [0.011]	
Constant	[0.420] -0.029	[0.341] 0.070	-3.886 [2.563]	-3.036 [1.931]	-1.532 [1.348]	-1.205 [1.133]
Observations	205	289	205	289	205	289
R^2/Pseudo-R^2	0.231	0.273	0.297	0.304	0.247	0.263
Log-Likelihood	-107.2	-150.2	-97.01	-137.1	-103.9	-145.0

TABLE 24: ESTIMATOR COMPARISON - DEP.VAR. *INFOUSED*. NOTE: STANDARD ERRORS IN BRACKETS; *, ** AND *** DENOTE SIGNIFICANCE ON 10%, 5% AND 1% LEVEL.

6.2 HECKMAN'S PROBIT WITH SAMPLE SELECTION

6.2.1 CHECKING ASSUMPTIONS

Following the introduction to the method from the section 3.8.6, this method allows for the correction of the sample selection bias that arises due to the specific structure of the experiment: we observe decisions to switch the estimate only by the subjects who decided to view the public information. The setup of the model in this case is as in the section 3.8.6.4, with the extension that I also check for robustness of the estimator by excluding the *HR_DIF* to get more observations. I would like to repeat that I checked for the presence of multicollinearity as well as the normality of residuals so the assumptions for the correct estimation are set.

6.2.2 RESULTS: WHAT THE …?

The results are as you can see in the Table 25. To assess the quality of the model and the appropriateness of the estimator, we shall first have a look at the p-value of ρ, which indicates the significance of the correlation between the error terms. Therefore, if we reject the null hypothesis that the correlation is significantly different from zero, we shall use this estimator. However, we reject the null only in case of the equation 1, when the full model is considered, but the standard errors are not robust. If we use the White's estimates to obtain the standard errors, situation changes and the correlation looses its significance, which happens also when I exclude the *HR_DIF* to check robustness to addition of observations. In the robust version of this estimation, i.e. in the equations 8 and 9, the p-value gets closer to the threshold of 10%, but still it is too far and we can not accept this model.

6.2.3 CONCLUSION: ANOTHER EXERCISE

So, we can conclude that the Heckman's two stage probit estimator with correction for sample selection is not appropriate for the analysis of the data from this experiment, even though its structure seems appropriate. Why this has happen may be interpreted as follows: the original usage in Heckman (1976) was that each observation was for a different individual, whose wage was either observed or not. Here, we have majority of individuals who both did view and another time did not view the public information, so basically, in the majority of cases we observe decisions of a subject in situations that are very similar to each other. The similarity of these situations was then treated by using the robust variance-covariance matrix estimates. Or, alternatively, the excluded instrument *ExpectedKindness* may have not served its purpose and we estimated only the functional form without structural implications. Put in a different way, also the method may have some bugs, as noted by Puhani (2000). The error terms may be correlated only, say, for positive values of u.

This section could be seen as another exercise to show that checking the validity of the model is essential and fulfilling all the assumptions does not guarantee that a ”fancy” regression technique yields better results than combination of fundamental ones, which I will use in the next two sections.

	Full model				Restricted model (*HR_DIF* excluded)			
	normal		robust		normal		robust	
	(1)	(2)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	***InfoUsed***	***InfoShown***	***InfoUsed***	***InfoShown***	***InfoUsed***	***InfoShown***	***InfoUsed***	***InfoShown***
score	0.012 [0.010]		0.012 [0.011]		0.022** [0.010]		0.022** [0.010]	
score2	-0.126*** [0.041]		-0.126** [0.051]		-0.181*** [0.037]		-0.181*** [0.049]	
Reputation	-0.257 [0.236]	0.091 [0.169]	-0.257 [0.391]	0.091 [0.181]	-0.509** [0.221]	0.115 [0.136]	-0.509* [0.267]	0.115 [0.130]
TimeDeciding	0.037** [0.016]		0.037 [0.049]		0.056*** [0.014]		0.056* [0.030]	
TimeLeft	0.005 [0.005]	0.009*** [0.003]	0.005 [0.005]	0.009** [0.003]	0.005 [0.004]	0.004 [0.003]	0.005 [0.005]	0.004 [0.003]
TP_Medium	-0.314 [0.222]	-0.029 [0.183]	-0.314 [0.216]	-0.029 [0.213]	-0.049 [0.215]	-0.171 [0.159]	-0.049 [0.214]	-0.171 [0.165]
TP_High	0.192 [0.287]	0.088 [0.199]	0.192 [0.266]	0.088 [0.214]	0.340 [0.280]	-0.122 [0.176]	0.340 [0.276]	-0.122 [0.184]
O	0.017 [0.021]	-0.017 [0.017]	0.017 [0.020]	-0.017 [0.017]	0.018 [0.018]	-0.016 [0.013]	0.018 [0.017]	-0.016 [0.013]
C	0.005 [0.019]	0.040*** [0.014]	0.005 [0.021]	0.040*** [0.014]	-0.005 [0.020]	0.041*** [0.012]	-0.005 [0.019]	0.041*** [0.012]
E	-0.037* [0.020]	-0.001 [0.014]	-0.037* [0.021]	-0.001 [0.015]	-0.048** [0.019]	-0.000 [0.012]	-0.048*** [0.018]	-0.000 [0.012]
A	0.033 [0.027]	0.063*** [0.019]	0.033 [0.028]	0.063*** [0.020]	0.012 [0.022]	0.035** [0.016]	0.012 [0.020]	0.035** [0.016]
N	-0.009 [0.022]	0.055*** [0.018]	-0.009 [0.025]	0.055*** [0.019]	-0.025 [0.023]	0.041*** [0.015]	-0.025 [0.021]	0.041*** [0.015]
SubjectiveStress	-0.025 [0.040]	0.035 [0.031]	-0.025 [0.045]	0.035 [0.031]	-0.038 [0.038]	0.025 [0.027]	-0.038 [0.036]	0.025 [0.027]
Female	-0.028 [0.222]	0.067 [0.183]	-0.028 [0.183]	0.067 [0.196]	-0.013 [0.207]	-0.019 [0.161]	-0.013 [0.180]	-0.019 [0.152]
CE	-0.055 [0.042]	-0.100*** [0.032]	-0.055 [0.055]	-0.100*** [0.032]	-0.059* [0.034]	-0.097*** [0.028]	-0.059* [0.031]	-0.097*** [0.027]
RiskAverse	-0.389 [0.321]	-0.796*** [0.253]	-0.389 [0.361]	-0.796*** [0.239]	-0.670** [0.304]	-0.889*** [0.221]	-0.670** [0.270]	-0.889*** [0.205]
SelfConfidence	0.233** [0.097]	0.458*** [0.082]	0.233** [0.094]	0.458*** [0.102]	0.236*** [0.082]	0.293*** [0.058]	0.236*** [0.071]	0.293*** [0.055]
lnTotProf	0.122** [0.054]	0.016 [0.034]	0.122 [0.103]	0.016 [0.034]	0.176*** [0.048]	0.021 [0.030]	0.176*** [0.065]	0.021 [0.030]
HR_DIF	-0.027** [0.012]	-0.030*** [0.009]	-0.027** [0.012]	-0.030*** [0.009]				
ExpectedKindness		-0.002 [0.001]		-0.002 [0.002]		-0.000 [0.001]		-0.000 [0.001]
Constant	-0.992 [1.110]	0.575 [0.800]	-0.992 [1.692]	0.575 [0.896]	-1.249 [0.956]	1.063 [0.704]	-1.249 [1.108]	1.063 [0.710]
athrho	1.344** [0.671]		1.344 [1.685]		0.599 [0.433]		0.599 [0.381]	
Observations	367		367		495		495	
chi^2	46.01		51.02		71.87		57.76	
rho	0.873		0.873		0.537		0.537	
P-value of rho	**0.0451**		**0.425**		**0.301**		**0.116**	

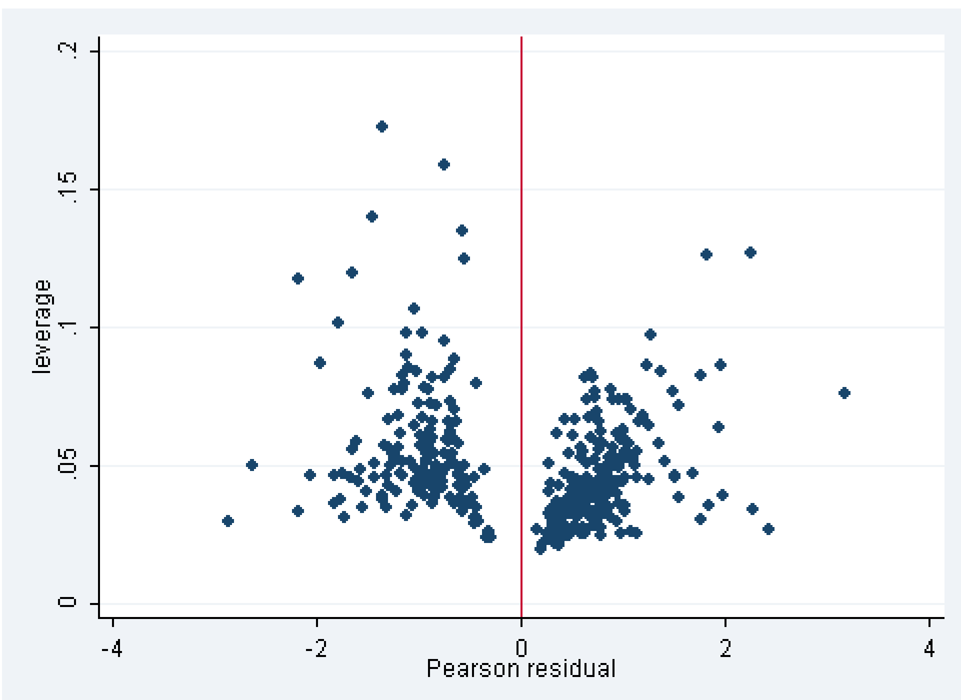
TABLE 25: HECKMAN'S PROBIT WITH SAMPLE SELECTION. NOTE: *, ** AND *** INDICATE SIGNIFICANCE ON 10%, 5% AND 1%, RESPECTIVELY. STADARD ERRORS IN BRACKETS.

6.3 THOROUGH EXAMINATION OF THE MODEL: *INFOSHOWN*

In this part I would like to discuss the model which should help us understand what influences the public to *see* the behavior of others; not if they will follow the information seen, which will be discussed in the latter section. Most researchers have evaluated the propensity to herd, but not many tried to explain, if the people let themselves get into such a situation. Not everybody, for example, reads fashion newspapers and hence can not be influenced by the latest fashion trends.

6.3.1 LEVERAGE POINTS IDENTIFICATION

To identify the influential observations, I plot the Pearson residuals vs. leverage, which gives me Graph 7 , which is interpreted as follows: observations that are close to the bottom axis are low in leverage; scores close to the middle are small. That means that the cases in the top corners are influential cases. We can see that there are very few influential observations; a majority of them are close to the bottom center.



GRAPH 7: PEARSON RESIDUALS VS. LEVERAGE.

6.3.2 TECHNIQUE USED

In Table 26 you can see that using the logistic regression on the full model explains the variation of *InfoShown* quite well: McFaddens' Pseudo-R^2 is 0.141 (if adjusted for number of regressors, we get only 0.069, though) and the whole regression is certainly significant as can be seen on the high χ^2 statistics (p-value=0). I use robust standard errors as there may be some correlation between the residuals either on the level of subjects or on the level of groups. I also considered using the panel estimators or the logistic estimator with standard errors computed using the fact about the clusters, but these were equivalent to the robust estimation, and the results differ negligibly so for the sake of the simplicity of argument, I use only the standard logistic regression.

6.3.3 STABILITY OF COEFFICIENTS – EXCLUSION OF GROUPS OF VARIABLES

As discussed above, if we exclude the variable obtained from the heart-rate monitors (equation 2) in the table), *HR_DIF*, we get a model with more observations, but the Pseudo-R^2 and also the log-likelihood sharply decrease, which tells us that this variable is certainly significant and should not be omitted. If we focus on the discussion from section 3.3 about the personality traits, we could test the power of the model with these variables excluded: it the case of equation (3). We can see that in comparison to (1) Pseudo-R^2 sharply decreases (to 0.09 and the adjusted pseudo-R^2 to 0.047) as does the log-likelihood. Indeed, if we perform the likelihood ratio test[39], it gives us the result that on the significance level 1% we reject the null that the tested models are the same. This strongly supports the general view of Borghans et al. (2008) that the personality profile of a subject is usually very important in predicting her behavior.

However, if I exclude both dummies indicating the level of time pressure (equation 4), the model does not differ as both of them are insignificantly different from zero. This suggests that the pressure subjects were under had no impact on the willingness to see the information about others' estimation.

Another set of variables, *CE* and *RiskAverse* that proxy the individual risk attitude, play a statistically significant[40] role and, as in the case of personality traits, should not be excluded.

Baddeley et al. (2009) also compared two models when one of them included only variables of an informational character and the other one included, on the other hand, only the personal profile. In our case, we could take as the informational variables the *TimeLeft*, level of time pressure, gender of the subject and the log of total profit. This model, as you can see in equation 6, performs much worse than the full model, but still the χ^2 statistic indicates that the model can not be rejected as a whole. The Pseudo-R^2 is only 0.02 when compared to 0.14 of the full model. The

[39] In case of robust standard errors such test is not possible, so I run normal logistic regression, which gives the same results as when the SEs are robust, and from these I run LR test. The Chi2 statistic is 21.21 and p-value=0.000.

[40] The LR-test resulted in Chi2 statistic of 12.57 which gives p-value=0.001

second model of this case (equation 7) consists of personality traits, risk attitudes, social preferences and stress-responses. This model has much better explanatory power, but again it performs worse than the full model. So, we can conclude that both underlying approaches under consideration, the informational as well as the personality-based, are not mutually exclusive and have both some explanatory power.

Thorough Examination: InfoShown

VARIABLES	(1) Full model	(2) HR_DIF excluded	(3) Personality traits excl.	(4) TP excluded	(5) Risk Prefs excluded	(6) Only info	(7) Only personality
Reputation	0.258 [0.262]	0.246 [0.211]	0.260 [0.237]	0.254 [0.262]	0.231 [0.259]	0.342* [0.193]	
TimeLeft	0.011** [0.005]	0.006 [0.004]	0.008* [0.004]	0.011** [0.004]	0.013*** [0.005]	0.005 [0.003]	
TP_Medium	-0.183 [0.293]	-0.342 [0.255]	-0.224 [0.285]		-0.141 [0.294]	-0.308 [0.237]	
TP_High	0.022 [0.336]	-0.225 [0.294]	-0.077 [0.324]		0.097 [0.331]	-0.186 [0.262]	
O	-0.022 [0.028]	-0.023 [0.022]		-0.022 [0.028]	-0.015 [0.027]		-0.017 [0.026]
C	0.067*** [0.025]	0.073*** [0.021]		0.066*** [0.025]	0.063*** [0.024]		0.069*** [0.024]
E	-0.003 [0.025]	-0.002 [0.021]		-0.003 [0.025]	0.002 [0.024]		-0.019 [0.024]
A	0.096*** [0.032]	0.060** [0.028]		0.096*** [0.031]	0.093*** [0.028]		0.072** [0.029]
N	0.084*** [0.029]	0.069*** [0.024]		0.084*** [0.029]	0.092*** [0.028]		0.073** [0.029]
Subjective-Stress	0.056 [0.053]	0.038 [0.045]	0.032 [0.049]	0.058 [0.052]	0.048 [0.053]		0.034 [0.048]
Female	-0.023 [0.313]	-0.066 [0.253]	0.147 [0.281]	-0.027 [0.312]	0.231 [0.281]	0.628*** [0.194]	
CE	-0.173*** [0.055]	-0.173*** [0.049]	-0.146*** [0.049]	-0.173*** [0.055]			-0.167*** [0.047]
RiskAverse	-1.393*** [0.411]	-1.518*** [0.347]	-1.467*** [0.387]	-1.394*** [0.405]			-1.503*** [0.381]
Self-Confidence	0.680*** [0.122]	0.460*** [0.087]	0.532*** [0.109]	0.678*** [0.122]	0.592*** [0.114]		0.693*** [0.119]
lnTotProf	0.016 [0.057]	0.026 [0.048]	0.013 [0.056]	0.018 [0.056]	0.031 [0.055]	0.005 [0.045]	
Expected-Kindness	-0.002 [0.002]	-0.001 [0.002]	-0.000 [0.002]	-0.002 [0.002]	-0.001 [0.002]		-0.002 [0.002]
HR_DIF	-0.050*** [0.016]		-0.033** [0.014]	-0.050*** [0.016]	-0.044*** [0.015]		-0.050*** [0.016]
Constant	1.549 [1.349]	2.100* [1.160]	1.670 [1.204]	1.493 [1.268]	-2.234*** [0.841]	-0.178 [0.413]	2.342** [1.040]
Observations	367	495	367	367	367	495	367
Pseudo R^2	0.141	0.126	0.0986	0.140	0.116	0.0264	0.123
-216.4	-293.6	-227.0	-216.7	-222.7	-327.3	-221.0	
Chi^2	53.05	62.34	45.46	52.06	47.47	18.17	48.51

TABLE 26: LOGISTIC MODEL OF *INFOSHOWN*. NOTE: ROBUST STANDARD ERRORS IN PARENTHESES. *, ** AND *** INDICATE SIGNIFICANCE OF A FACTOR ON 10%, 5% AND 1% LEVEL, RESPECTIVELY.

6.3.4 *EXPLANATORY POWER OF THE FULL MODEL*[41]

As described in the section 3.8, we can judge the model according to certain criteria; here we use the classification table of predicted outcomes vs. actual outcomes, ROC curve, Hosmer-Lemeshow test of goodness of fit and the predicted probabilities vs. sample frequencies.

Let's begin with the classification table of predicted outcomes:

		Predicted classification		
		D	~D	Total
Observed classification	+	**156**	64	220
	-	49	**98**	147
	Total	205	162	367

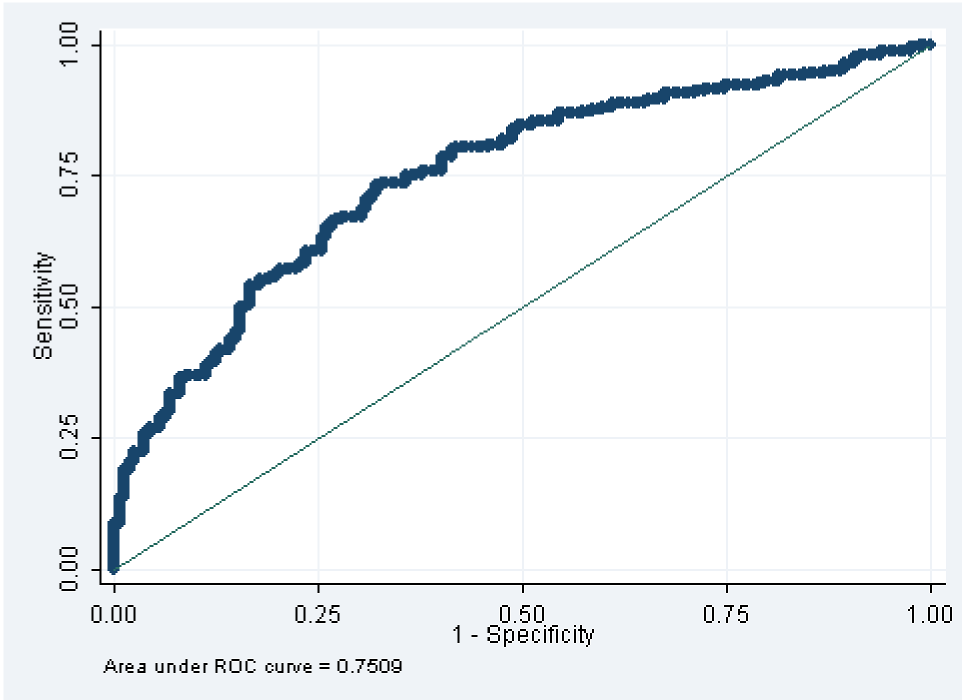
TABLE 27: CLASSIFICATION TABLE OF OBSERVED VS. PREDICTED OUTCOMES. TRUE *D* DEFINED AS INFOSHOWN = 0; CORRECT CLASSIFICATION OF CASE: + IF PREDICTED PROBABILITY > 0.5. CORRECTLY CLASSIFIED CASES: 69.21%

From this table we can see that the predictive power of our model is not great: the overall correctly classified percentage is 69.2% (the correctly predicted numbers are on the diagonal in bold – positive prediction if D is true and negative if D is false) and this number is not much greater that the mean of the sample used of *InfoShown*, which is 55.9%. This table also tells us that if the logistic model has homoskedastic disturbances, the row-percentages of correctly classified cases should be approximately the same: here we have 70.9% in the first row and 66.6% in the second row, which can be considered to be the same.

Another measure of fit is the Hosmer and Lemeshow goodness of fit test as described in detail in 3.8.4: the value of χ^2_8 statistic is 12.78 which gives p-value of 0.121, which is enough not to reject the null hypothesis (in this case that the observed and predicted probabilities do not differ) and so it implies that the models' estimates fit the data well.

If we plot the fraction of correctly classified values against the fraction of incorrectly specified as the cut-off value varies, we get the ROC curve in the Graph 8. It tells us that the further the line from the diagonal, the better the predictive power of our model. In this case, the line looks far enough from the reference line, which is confirmed by the computed value of 0.75 of the area under the ROC curve.

[41] Much of the style of the analysis was inspired by the web resources of UCLA – their Academic Technology Series, which you can find here: http://www.ats.ucla.edu/stat/stata/seminars/stata_logistic/Movies/Stata_Binary_Logistic.html



GRAPH 8: THE ROC CURVE FOR FULL MODEL OF INFOSHOWN.

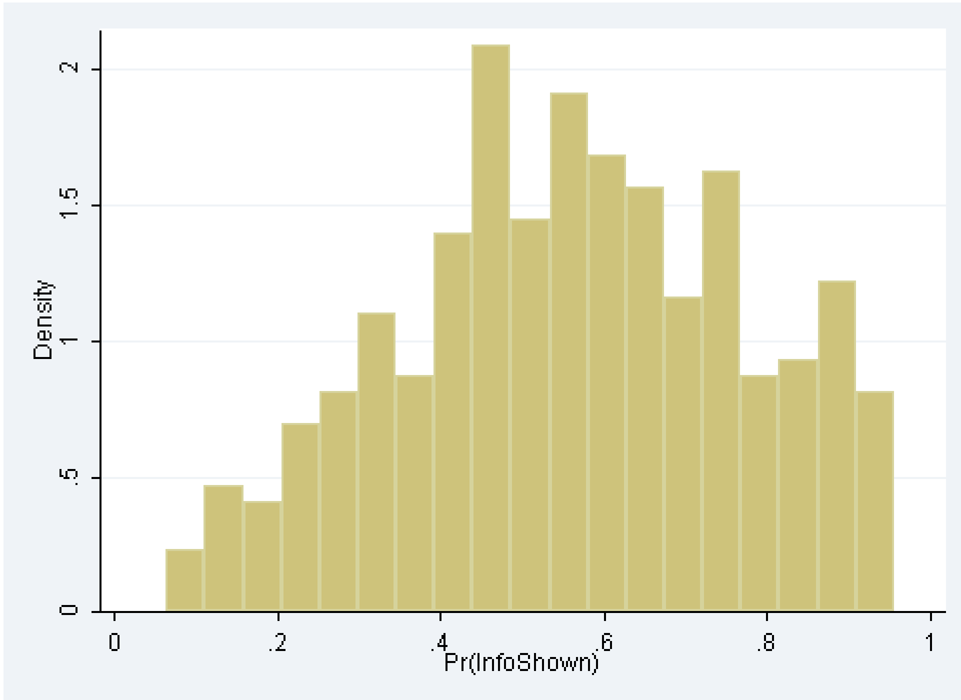
6.3.5 Predicted Probabilities

We can predict the probabilities and summarize as follows in the Table 28.

	N	Mean	SD	Min	Max
Predicted Probabilities	367	0.559	0.209	0.063	0.955

TABLE 28 : SUMMARY STATISTICS OF PREDICTED PROBABILITIES

In the histogram of predicted probabilities (Graph 9) you can see that the shape resembles a normal distribution that is truncated from the right. The fact that most of the predicted probabilities are centered on the mean value tells us that the model does not predict very sharp results: mostly it tells us only that the probability is close to 50/50 and more to one direction; but even with extreme input values the predicted outcome is not (approximately) certain.



GRAPH 9: HISTOGRAM OF PREDICTED PROBABILITIES

6.3.6 COEFFICIENTS – SIGNIFICANCE, SIGNS AND CONFRONTATION WITH PREVIOUS EXPECTATIONS

Before analyzing the magnitudes of the coefficients, I would like to summarize the set of variables that play a major role in explanating the *InfoShown* in the full model. From looking at the equation (1) in the Table 26 we can identify the coefficients that are steadily significant, even after removing some other variables or a different number of observations: these are *C* (Conscientiousness) , *A* (Agreeableness), *N* (Neuroticism), *CE* (Certainty equivalent), *RiskAversion*, *SelfConfidence* and *HR_DIF* (difference of quiescent to actual heart rate). I expected the *lnTotProf* and *Female* dummy would be insignificant, and the *ExpectedKindness*

6.3.6.1 Time dimension

The variable *TimeLeft* is sensitive to the addition of observations and its significance is not stable, but in our model it is, so we can mark it to be marginally significant. It is interesting that the increasing level of time pressure (specified only as a set of dummies) did not have any significant influence on the propensity to view the public information, in any case. I would not be surprised if the relationship was reversed, but the lack of a relationship suggests that the subjects took the task as fixed and either they managed to complete it or they did not; and the level of time pressure did not play any role as suggests the behavior of *TimeLeft*. Being marginally significant, variable *TimeLeft* reveals a positive relationship between the time subjects had left on the screen when entering their original estimate and the probability that they looked at the public information. This behavior was also expected in the model-specification section.

6.3.6.2 Attitude to risk

RiskAversion and *CE* are, of course, correlated[42], so we can only examine these two together. They are both significant on a 1% level and negative as we expected in the theoretical part of the model specification – section 3.4. This fact tells us that the more people are risk-averse, the less willing they were to view the public information. As discussed earlier, the subjects probably perceived the involvement with the public information as a certain kind of a lottery: it was costly and with an uncertain outcome. Some subjects stated in the feedback that they were afraid of being influenced by the other estimates and therefore they did not choose to view them. It is a matter of discussion whether also in real life some people avoid certain activities because they know their will is not the strongest and they would start following others' attitudes. What immediately comes to my mind is the similarity of such reasoning with that of women shopping.

6.3.6.3 Personality traits

Although I expected every trait to be significant, "only" three of them in the end really are. The ones that I personally expected to be most important, Openness to experience and Extraversion, are not. My underlying theoretical discussion was fruitful in the sense that Agreeableness and Neuroticism behave both in the way I predicted: their coefficients are both significant and positive so the mechanism may be the same as I sketched in section 3.7.1.4.

The positive relationship between Conscientiousness, the dimension that can be characterized mostly as being achievement-striving, and *InfoShown* suggests the following: the subjects high in this dimension do want to be successful but what's more, they also want to see the relative position of their estimate in comparison to others (by the way, achievements and victories are mostly relative to others' positions).

6.3.6.4 Stress variables

There are two variables in the model that should serve as a proxy for the stress the subjects feel during the tasks: *SubjectiveStress* and an objective measure *HR_DIF*. They are not correlated and therefore we can analyze each separately. The subjective measure appears to be steadily insignificant, but the objective measure reveals on $\alpha = 0.01$ a stable negative relationship. To remind the reader, *HR_DIF* was constructed as the difference of an average heart rate over the

[42] $\rho = -0.713$

performed task and the base level of heart rate. The relationship to *InfoShown* implies that the higher the level of physical arousal (we may say "stress") the body was in during the task, the lower the probability of viewing the public information. I expected the opposite sign, so this requires more consideration of the underlying reasons: if a subject was in a highly stressful moment, or at least she was exhibiting considerable effort, there may have been a higher chance of being correct than in the opposite case, thus an increased feeling of momentary confidence[43]. Or the solution may agree with the claim of Rieskamp and Hoffrage (2008) that the more people feel under stress, the more selective their strategy becomes: they search for less information, but only for the relevant information. If they perceived their own skill to be more reliable than the public information, this mechanism may be the explanation of this behavior.

6.3.6.5 Confidence

The variable *SelfConfidence* comes from a direct question on the relative perceived position after the fifth period, just before the subjects could see the results of others. The scaling was decreasing: one is for the most self-confident and five for the least self-confident subject. Common sense suggests the connection to *InfoShown* in a way that the more self-confident a subject in the task feels, the less probable it is that she chooses to view the public information because it would most likely be useless for her. Translated into statistics, the sign of the coefficient of the variable should be positive and indeed it is positive and as will be revealed in the next section, it is also one of the most important predictors.

6.3.7 Coefficients – Percentage Changes

The logit coefficients are rather cumbersome to interpret. One way is to analyze odds ratios, if the reported coefficients are transformed as the odds ratio b is e to the power of the coefficient from logit: $b = e^{\beta}$. However, another way to analyze the coefficient is to have a look at percent changes in the predicted probabilities with the change in the predictors. This approach results in much more intuitive and interpretable answers - similar to the marginal coefficients when using probit. Without loss of generality I restrict the analysis only to the significant variables in the full model – see Table 29.

[43] Not to be confused with the variable *SelfConfidence*, which was constructed in a completely different way.

	min->max	**0->1**	**+-1/2**	**-+sd/2**	**Marg. Effect**
TimeLeft	0.3842	0.0028	0.0028	0.0882	0.0028
C	0.3712	0.0166	0.0163	0.0906	0.0163
A	**0.5034**	0.024	0.0235	**0.1096**	0.0235
N	**0.4994**	0.0187	0.0207	**0.1082**	0.0207
CE	**-0.5679**	-0.0084	-0.0423	**-0.1552**	-0.0424
RiskAverse	-0.3131	**-0.3131**	-0.3284	**-0.1573**	-0.3407
SelfConfidence	**0.585**	0.1052	**0.1648**	**0.1893**	0.1662
HR_DIF	-0.5357	-0.0099	-0.0123	**-0.1137**	-0.0123

TABLE 29: PERCENTAGE CHANGES IN PREDICTED PROBABILITIES

6.3.7.1 Minimum to maximum change in predictor

In the first column labeled Min->Max you can see the percent change in the predicted probability of *InfoShown*, if the particular variable increases from its minimum to its maximum while holding other variables on their mean. In case of the *TimeLeft*, if it increases from its minimum of 0, when the subject just ran out of time, to a maximum of 157, which was apparently the case when the subject guessed the number, the predicted probability increases by 38%. The most remarkable change is associated with certainty equivalent, so if a very average subject changed her risk preferences from being totally risk averse to being totally risk-loving, the predicted probability of viewing the public information would decrease by 56% from the variable *CE*. Of course, this would also make a shift in the variable *RiskAverse* from 0 to 1, which is assumed to be constant. It is interesting that the change from minimum to maximum of no variable goes over 60%, which suggests that there is not any one most powerful explanatory variable.

6.3.7.2 0 to 1 change in predictor

The second column marked “0->1” includes the percent change in the predicted probability when the variable changes from 0 to 1, which is logical to apply to all variables but *CE* and *SelfConfidence*, which do not attain 0 in the selected sample. However, an interesting result in this column can be seen only by *RiskAverse* and *SelfConfidence* because only by these variables the 0-1 change is relatively influential. It is obvious that if a variable is a dummy variable, this effect must be the same as in the previous column, as in the case of *RiskAverse*.

6.3.7.3 Half-point change in predictor

The column labeled “+-1/2” contains percentage changes in the predicted probabilities when there is one point change centered on the mean (that is, a half in either direction) of a particular variable. You can see that the biggest change is associated with the variables with the smallest range – *RiskAverse* (dummy variable) and *SelfConfidence* (ranging from 1 to 5). If we focus on the change as big as a half point in *SelfConfidence* from its mean, which is 3.05, we get an increase of 16% in the predicted probability.

6.3.7.4 One standard-deviation change in predictor

The next column indicates the effect of a change as big as one standard deviation in a respective variable centered on its mean, so in fact we get comparable results for all variables. I will focus on this column: the biggest change in the predicted probability of 19% is associated with the variable *SelfConfidence,* so together with being significant on a 1% level, this regressor appears to be the most important variable in the prediction of the probability of *InfoShown*. The second biggest effect is found in both of the variables representing the risk preferences and is almost the same but negative. Apart from these, the rest of variables have almost the same magnitude of effect.

The last column shows the effect of a marginal change in a variable. This change is again centered on the mean and can tell us more about the shape of the probability curve around the mean. For most of the variables it almost equals the effect from the change by half point.

6.3.8 Thorough Model of InfoShown*: Summary*

To sum up, the most important attributes playing a role in explaining the variation in the probability of viewing the publicly available information are the risk preferences and individual confidence. Both of these variables were expected to be significant and they also influence in the expected direction. Apart from these, the important variables were from the area of personality traits, namely conscientiousness, agreeableness and neuroticism, which with the exception of conscientiousness also conform to our expectations. There was only one more variable that behaved "well" and this was the time the subjects had from the moment they entered the first estimate. The individual level of difference of quiescent heart rate with the actual heart rate which serves as a proxy for the real level of physiological stress also proved to be very important variable, but in the opposite direction than was theorized.

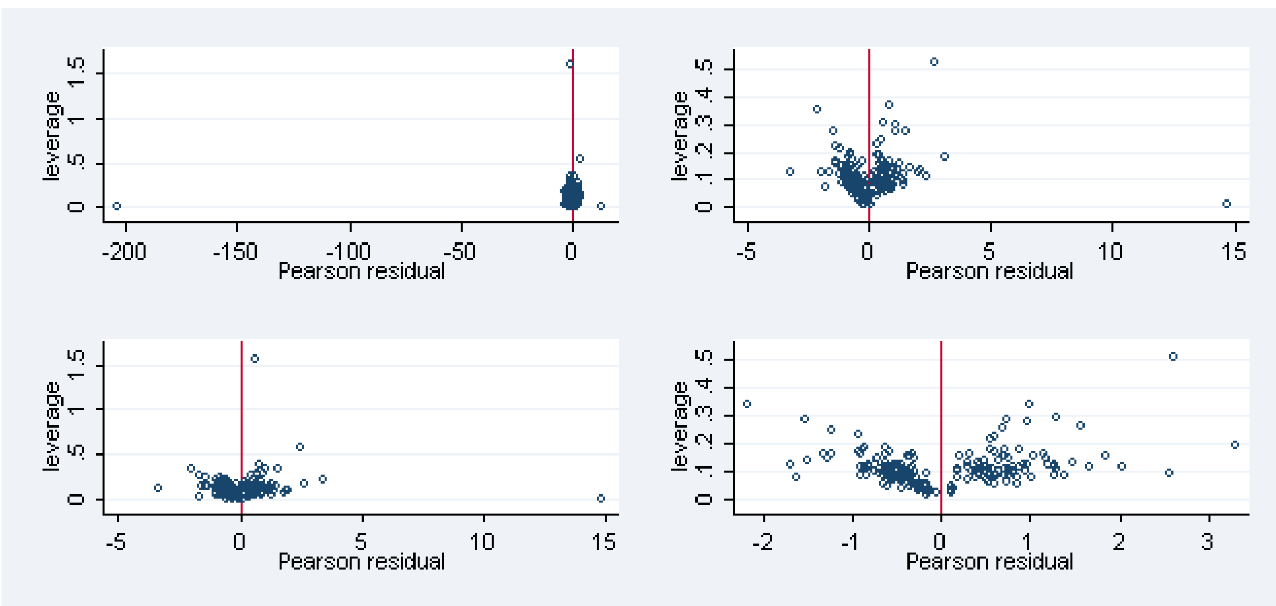
As analyzed at the beginning of this section, the model as such has a satisfactory explanatory power; it was tested for stability of coefficients and the possible heteroskedasticity problem was prevented by using robust standard errors and the leverage points were analyzed in Graph 7: Pearson residuals vs. leverage. where we concluded that no significant leverage points exist. If we consider that we are dealing with micro-data, then pseudo-R^2 of 0.14 also does not seem that small. The model provides overall correct predictions in almost 70% of cases, but as can be seen in Graph 9, the density of predicted probabilities is centered on its mean so the model does not give decisive predictive conclusions when provided with input data

6.4 THOROUGH EXAMINATION OF THE MODEL: *INFOUSED*

Now we can move to the most important part of the analysis, namely the analysis of the probability of herding. I would like to repeat that subjects had the opportunity to switch from their originally stated value of zeros on the sheet after viewing the public information. That means that if a subject decided not to view the information, there was no observation for this model and also that there was some kind of a selection bias – that only those who had decided to observe the crowd could actually follow that crowd. I have 289 observations, but when combined with the availability of data obtained from the heart-rate monitors, there are only 205 left.

6.4.1 LEVERAGE POINT DETECTION

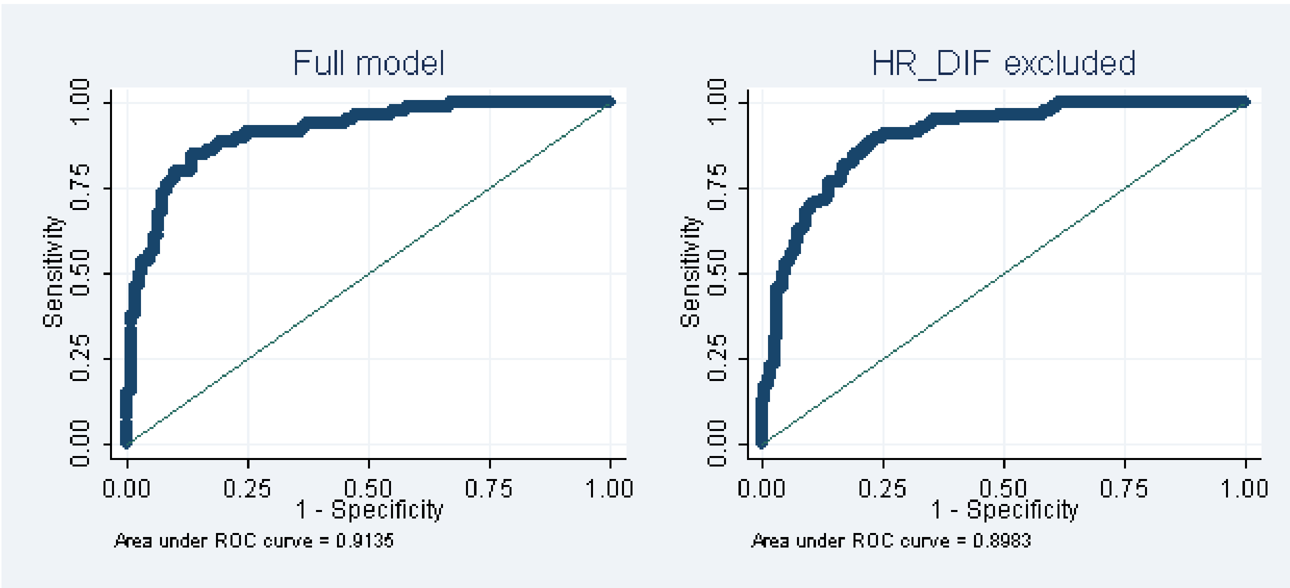
Before choosing the right model, let's exclude the influential observations. By using the predicted Pearson residuals and leverage, I found 4 very influential points, which were the same for both models (with or without *HR_DIF*) and in Graph 10 you can clearly see the effect of their removal. In the end I have only 201 observations for the restricted model. In the bottom left graph it is clear that no single influential points exist anymore. The model results are considerably better when compared to those obtained from the original data set as could be expected.



GRAPH 10: LEVERAGE POINT IDENTIFICATION AND REMOVAL (MIND THE DIFFERENT SCALES OF BOTH X AND Y AXES)

6.4.2 MODEL SELECTION

Choice of a proper specification is then not very clear: as you can see in Table 30, the *HR_DIF* is insignificant, and its removal causes, on one hand an increase in the χ^2 statistic, but, on the other, a decrease in the pseudo-R^2. The coefficients are fairly stable with the exception of *SelfConfidence*, which becomes marginally significant, so the difference may not be that crucial. Also, if we compare the ROC curves, as you can see in Graph 11, the area under the curve is slightly but insignificantly larger in case of the full model.



GRAPH 11: ROC CURVE FOR TWO MODEL SPECIFICATIONS OF INFOUSED: FULL MODEL AND HR_DIF EXCLUDED

Because the models are nested, but not with the same number of observations, we can not use a simple LR ratio or other straight comparison; therefore we shall have a look at the relative values of information criteria: the full model has BIC=256.356 [44] and AIC=186.987 whereas the restricted model's values are BIC=342.217 and AIC=269.168. BIC should compensate for the different number of explanatory variables and thus improve the information obtained with the log-likelihood function. If interpreted as being trivial, then the rule of using BIS in model selection appears thusly: the lower the BIC, then either the better fit of the model, or fewer explanatory variables, or both. According to this attitude, even though we use fewer observations, the full model seems to be more appropriate to use for the detailed analysis.

[44] BIC stands for Bayesian information criterion, which is often known as Schwartz criterion (see Schwartz, 1978), and AIC stands for Akaike information criterion. Both values are as reported by Stata 11.

Thorough examination: *InfoUsed*

VARIABLES	(1) Full model	(2) HR_DIF excluded	(3) Personality traits excluded	(4) TP excluded	(5) Risk preferences excluded	(6) Only information	(7) Only personality
Score	0.068**	0.064**	0.089***	0.048	0.069**	0.068***	
	[0.032]	[0.026]	[0.034]	[0.030]	[0.032]	[0.025]	
score2	-0.506***	-0.531***	-0.475***	-0.502***	-0.526***	-0.492***	
	[0.187]	[0.136]	[0.170]	[0.190]	[0.177]	[0.114]	
Reputation	-1.878***	-1.656***	-1.321**	-1.638***	-1.830***	-1.306***	
	[0.631]	[0.443]	[0.531]	[0.521]	[0.650]	[0.394]	
Time-Deciding	0.301***	0.237***	0.261***	0.315***	0.290***	0.216***	
	[0.093]	[0.056]	[0.079]	[0.098]	[0.088]	[0.052]	
TimeLeft	0.007	0.009	0.016	-0.005	0.008	0.014	
	[0.015]	[0.011]	[0.017]	[0.009]	[0.016]	[0.010]	
TP_Medium	-0.160	0.277	0.002		-0.189	0.376	
	[0.710]	[0.449]	[0.638]		[0.686]	[0.418]	
TP_High	0.899	0.972	1.245		0.978	1.056*	
	[0.757]	[0.610]	[0.773]		[0.763]	[0.554]	
O	0.038	0.058		0.046	0.035		0.046
	[0.047]	[0.038]		[0.048]	[0.049]		[0.038]
C	-0.070	-0.049		-0.062	-0.071		-0.034
	[0.052]	[0.037]		[0.047]	[0.052]		[0.038]
E	-0.151***	-0.128***		-0.164***	-0.152***		-0.051**
	[0.055]	[0.038]		[0.055]	[0.055]		[0.032]
A	-0.021	0.040		-0.042	0.001		0.034
	[0.060]	[0.047]		[0.059]	[0.058]		[0.037]
N	-0.115**	-0.080**		-0.124**	-0.122**		-0.013
	[0.057]	[0.037]		[0.058]	[0.056]		[0.042]
Subjective-Stress	-0.184*	-0.155**	-0.223**	-0.166	-0.180*		-0.196**
	[0.107]	[0.077]	[0.110]	[0.105]	[0.103]		[0.072]
Female	0.253	0.009	0.026	0.313	0.037	-0.178	
	[0.541]	[0.419]	[0.451]	[0.511]	[0.528]	[0.302]	
CE	0.099	-0.038	0.105	0.124			0.098
	[0.095]	[0.062]	[0.077]	[0.091]			[0.073]
RiskAverse	0.317	-0.736	0.342	0.478			0.636
	[0.617]	[0.521]	[0.613]	[0.622]			[0.478]
Self-Confidence	0.037	0.274*	-0.045	0.036	0.048		0.005
	[0.239]	[0.147]	[0.219]	[0.232]	[0.227]		[0.164]
lnTotProf	0.669***	0.536***	0.597***	0.637***	0.658***	0.481***	
	[0.218]	[0.122]	[0.179]	[0.185]	[0.220]	[0.126]	
Expected-Kindness	0.002	-0.003	0.000	0.001	0.003		0.003
	[0.004]	[0.003]	[0.003]	[0.004]	[0.004]		[0.003]
HR_DIF	-0.024		-0.022	-0.014	-0.021		-0.066**
	[0.032]		[0.029]	[0.035]	[0.032]		[0.024]
Constant	-6.643**	-4.283**	-6.521**	-6.415**	-4.915*	-4.880***	-0.901
	[3.079]	[2.093]	[2.960]	[2.664]	[2.772]	[1.361]	[1.433]
Observations	201	285	201	201	201	285	201
Pseudo R^2	0.463	0.409	0.415	0.455	0.459	0.340	0.127
Log-L	-72.49	-114.6	-78.99	-73.68	-73.07	-128.0	-118.0
Chi^2	59.03	87.21	56.05	51.13	59.11	60.98	18.87

TABLE 30: LOGISTIC MODEL OF INFOUSED. NOTE: ROBUST STANDARD ERRORS IN BRACKETS. *, ** AND *** INDICATE SIGNIFICANCE OF A FACTOR ON 10%, 5% AND 1% LEVEL, RESPECTIVELY.

The full model is without doubt significant as indicated by a high result of χ^2 test on 1% level of significance. One of the measures used to indicate the power of the model is the pseudo-R^2, which is in our case 0.463, which is relatively high value compared to other micro-models. However, after adjusting for number of predictors, it shrinks to 0.308, which is still not a bad result.

The Hosmer-Lemeshow test produces value of χ_8^2 statistic of 2.25which gives p-value of 0.9725, which results in a strong rejection of the null hypothesis that the observed and predicted probabilities do not differ and so it implies that the model's estimates fit well to the data.

		Predicted classification		
		D	~D	Total
Observed classification	Yes	**64**	12	76
	No	16	**109**	125
	Total	80	121	201

TABLE 31: CLASSIFICATION TABLE OF OBSERVED VS. PREDICTED OUTCOMES. TRUE D DEFINED AS INFOSHOWN = 0; CORRECT CLASSIFICATION OF CASE: + IF PREDICTED PROBABILITY > 0.5. CORRECTLY CLASSIFIED CASES: 86.07%

The comparison of predicted versus observed classification which you can see in Table 31 tells us that in almost 86% of cases the model provided a correct prediction. The mean of *InfoUsed* is 0.4, so the model performs better than another model of simply predicting only NO, which would give 60% of correct predictions. This table also tells us that if the logistic model has homoskedastic disturbances, the row-percentages of correctly classified cases should be approximately the same: here we have 84.2% in the first row and 87.2% in the second row, so there is no difference.

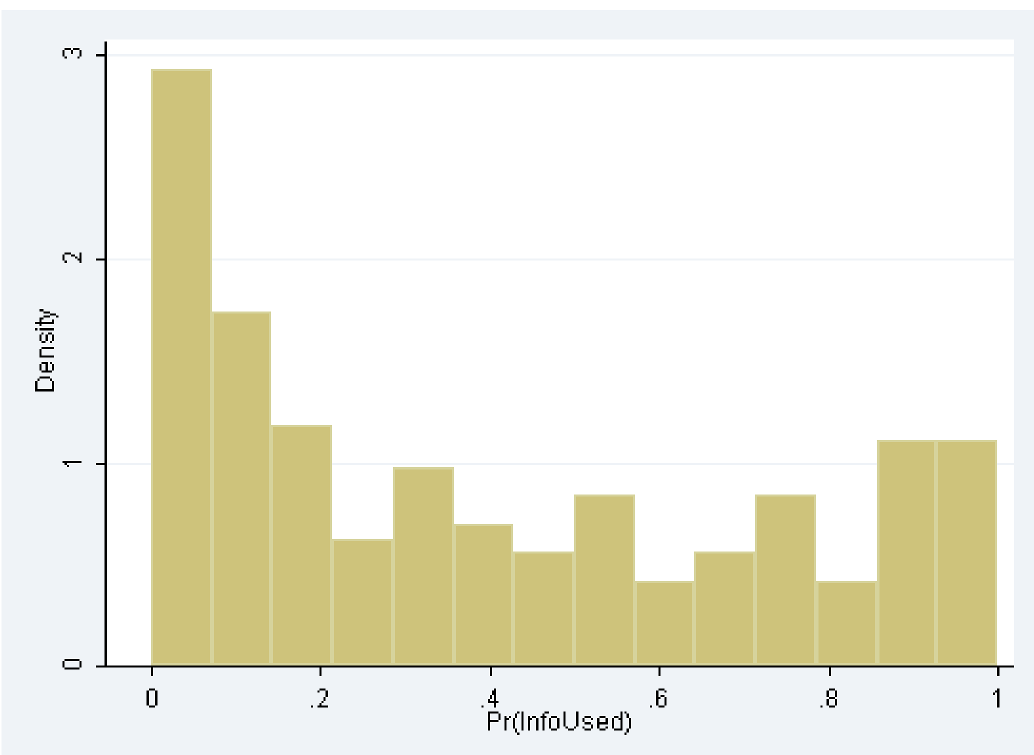
6.4.3 STABILITY OF COEFFICIENTS – EXCLUSION OF GROUPS OF VARIABLES

Table 30 provides an overview of different specifications of the model with certain modifications. We can see that the exclusion of *HR_DIF* in the equation 2 does not change the situation too dramatically; the only difference being that the coefficient of *SelfConfidence* starts to be significant. On the other hand, if we exclude the personality traits, which we did in equation 3, all coefficients keep their original significance levels. This exclusion can be tested by looking at the LR test, if we run the non-robust versions of both models, and the resulting p-value[45] is 0.02 so on the 5% level of significance we reject that the models are the same. We can conclude that the personality traits play an important role in the model and its magnitude will be discussed later.

[45] The value of LR Chi2(5) =12.99.

The second imposed restriction was the exclusion of dummies indicating time pressure in equation 4. LR test for this restriction did not reject that the models are the same so we conclude that the simple fact of being under increasing time pressure does not play any important role in determining the probability of switching from the original value to a new value.

Exclusion of variables indicating the risk-preferences yields the same result (equation 5) – these variables obviously played a major role at the stage of making the decision whether to view the publicly available information or not – in the previous model. The last imposed restrictions are again comparing the exclusive information-based (equation 6) and personality-based (equation 7) approaches. When we compare these two models, we can see that the information-based model that includes only the variables not accounting for any non-observable differences performs considerably better in comparison with the personality-based one. The comparison is obvious from the χ^2 statistics or from the pseudo-R^2. Interestingly, in equation 6 the dummy variable indicating high level of time pressure becomes marginally significant. The differences that occurred in equation 7 in comparison with the full model are not worth commenting on as the whole model is not significant on a 5% level.



GRAPH 12: HISTOGRAM OF PREDICTED PROBABILITIES OF *INFOUSED*

6.4.4 *PREDICTED PROBABILITIES*

If we predict the probabilities implied by the full model, we can summarize the resulting variable as follows in Table 32.

	N	Mean	SD	Min	Max
Predicted Probabilities	201	0.398	0.332	0.0002	0.999

TABLE 32: SUMMARY STATISTIC OF PREDICTED PROBABILITIES OF INFOUSED

Histogram of the predicted probabilities (Graph 12) tells us by its shape that the model predicted much more of the extremely low probabilities than others.

6.4.5 *COEFFICIENTS – SIGNIFICANCE, SIGNS AND CONFRONTATION WITH PREVIOUS EXPECTATIONS*

First of all, I would like to summarize which coefficients were significant in explaining the variation of the variable *InfoUsed*: both variables indicating the information seen on the screen (*score* and *score2*), dummy indicating the fact that in the round it was possible to view, apart from the actual estimates, also the past performance of the subjects (*Reputation*), the time subjects spent on the screen with the public information (*TimeDeciding*), personality traits extraversion and neuroticism (variables E and N), and finally the log of total profit earned up to that time (*lnTotProf*). I expected that variables *TimeLeft*, *Female* and *ExpectedKindess* would not be important, but apart from them, the insignificant variables were also the dummies indicating the level of time pressure *TP_Medium* and *TP_High*, variable indicating the stress subjects were under *HR_DIF*, both variables indicating subjects' risk attitudes, and the reported level of confidence (remember, the scale is reversed). The insignificance of both time pressure dummies then rejects hypothesis 1.

6.4.5.1 Time dimension

The variables that in any way indicated the time dimension of the task reaped mixed results. Both dummies indicating the level of time pressure are not significant as well as the time the subjects had to make a decision, but the time they spent on the screen with the public information is the most important variable with a positive relationship to the explained variable. The logic may be thus (as already outlined earlier): the subjects did have a look at the others' results, decided quickly whether they needed to change the coefficient or not, and then either left or started to think of the new value they should switch to, which was time consuming. Therefore, the causality may not be in the way that the longer time a subject stays, the more probable it is that she switches her estimate; but rather the opposite: if a subject wants to switch from her value, it will take her some time. On the other hand, this result can be interpreted also in the way that in case we observe somebody staying longer on the public info screen, then the probability that this subject is changing her estimate is very high.

6.4.5.2 Level of publicly available information

I constructed two indices of the level of information that was contained on the screen with the others' estimates: the first one, *score*, measures the similarity of the guesses of other's estimates among each other and the second one, *score2*, measures the level of similarity of subject's estimate to the estimates of others. Both variables turn out to be steadily significant and thus it proves that the subjects behaved rationally in the sense that the additional information provided to them in this form influenced their decisions in the correct way. The positive sign of the coefficient of the *score* means that the more similar the coefficients of others, the higher the probability of switching. On the other hand, the negative sign of the *score2* means that the more similar the subject's estimate to the estimates of the others' was, the lower the reason she had to change it (and the lower the probability that she did).

6.4.5.3 Personality traits

I happened to predict the expected significance of the psychometric variables correctly: as expected, the traits openness to experience, agreeableness and conscientiousness were not important in this model whereas extraversion and neuroticism were both significant. However, my prediction was not perfect, because both extraversion and neuroticism have an opposite sign to that expected: negative. By the extraversion dimension the negative sign of its coefficient in the regression suggests that the more a subject scored in this dimension (which is normally associated with personal attributes like sociable, adventurous, energetic, frank and enthusiastic) the less likely she was to switch her estimate and follow the crowd. The same reasoning is applied to neuroticism: if a subject scores high, she should be an emotionally unstable, nervous personality, and the coefficient in our model implies that such a person is less likely to follow the results of others.

6.4.5.4 Total profit

The variable *lnTotProf* was computed by taking natural logarithm from the variable *TotalProfit*, which was the amount of ECU earned and whether a subject had viewed this piece of information on the summary screen just before the round in progress. I expected it to be significant and with a positive sign due to the simple underlying logic: if a subject had already earned some ECU, it might have increased her confidence and she may have had greater incentives to risk and try to switch from her value because this, according to the loss-aversion principle, may lead to greater losses as well as greater gains, which normal risk-averse subjects are willing to risk when they can not go into red numbers. However, if I run a model extended by an interaction of *RiskAverse* and *lnTotProf* and test for its significance, it is not.

6.4.5.5 Reputation

A very important variable is the dummy indicating if on the screen with the public information included by the subjects' reputation. I expected this coefficient would have a positive sign, but the opposite is true. The dummy is a very rough indication of the additional information, but we can believe that the more precise the information was, the more selectively the subjects analyzed the information and decided to follow the others only if an estimate worth following was both similar to other estimates and its author's reputation was reasonably high. I suggest that the data can be considerably analyzed in this way in a future research.

6.4.5.6 Subjective stress and self-confidence

The last variables that help to explain the propensity to herd are the subjectively reported level of stress and the reported confidence. Both are marginally significant and as we will see in the next section, they have a very low impact on the explained variable. I expected them to be in a positive relationship to *InfoUsed*, which is not the case of *SubjectiveStress,* but of *SelfConfidence* is.

6.4.6 Coefficients – percentage changes

6.4.6.1 General description of the method

As I noted in the same section for the *InfoShown*, coefficients of logistic distribution are not easy to interpret and therefore I apply the approach of analyzing the respective percentage changes. In Table 33 you can see the summary of changes in the predicted probability of *InfoUsed* with the respective change in variable while holding all other variables fixed to their means. Please see section 6.3.7 for a more detailed general description of how this table functions. I would like to repeat that the different columns indicate the magnitude of change in a variable, which is indicated in the row, and finally, the cells contain the resulting percentage change in the predicted probability. The "min->max" column indicates the change of a variable from its minimum to the maximum, the "0->1" column indicates the difference from zero to one; the "+-1/2" indicates difference of one point centered on its mean, i.e. a half point in both directions; the "+-sd/2" is a change of one standard deviation centered on the mean and finally, the "MargEffct" column reports the smallest possible change in the predictor centered on its mean.

	min->max	0->1	+-1/2	**+- sd/2**	MargEfct
score	**0.7671**	0.01	0.0151	0.1963	0.0151
score2	-0.6173	-0.1103	-0.1123	-0.2979	-0.1127
Reputation	-0.4147	**-0.4147**	-0.3987	-0.2042	-0.4187
TimeDeciding	**0.9574**	0.0073	0.0671	**0.4526**	0.0672
E	**-0.8011**	-0.037	-0.0337	-0.195	-0.0337
N	-0.6225	-0.0205	-0.0256	-0.1219	-0.0256
lnTotProf	**0.6879**	0.0134	0.1483	**0.3212**	0.1492
SubjectiveStress	-0.3626	-0.0449	-0.041	-0.0965	-0.0411
SelfConfidence	0.0328	0.0079	0.0082	0.0089	0.0082

TABLE 33: PERCENTAGE CHANGES IN PREDICTED PROBABILITY OF INFOUSED WRT TO CHANGE IN PARTICULAR VARIABLE.

6.4.6.2 "Min to max" change

Table 33 tells us the relative importance of each variable from the regression analysis. Without loss of generality I again restrict the table items only to the significant coefficients. The first column tells us that the resulting change in the probability if a variable increases by the maximal amount, ceteris paribus. We can see that the highest number is in the row of *TimeDeciding*, which means that if a subject had instead of a minimum of 2.3 seconds, a maximum of 49.8 seconds, it would increase the probability of switching by 95.7%. As I have mentioned, however, the causality seems to be reversed in this case so we can not really take this result seriously.

6.4.6.3 *Score* and *score2*

The second highest number in this column is in the row of the variable *score*, which is intuitively correct: if there was the same situation, but instead of having no information (e.g. in the case of being the first to set the estimate), having many estimates the same, increases the probability by 76.7%. Conversely, if one's estimate changes from being very dissimilar to others' to very similar (as indicated by the variable *score2)* the probability of switching decreases by 61.7%. An interesting situation may occur when we fix the *score* at zero, which is the situation of having no similar estimates on the public screen: the change in the probability of *score2* changes from min to max is much lower: only (-)40%, (see Table 34)which is logical because if there is no certain value to switch to, why should one switch? Only if one's own estimate is far too different from all of the rest then it may seem reasonable to risk it and switch.

	score = 64	*score* = 0	*score* = mean
score	0.7671	0.7671	0.7671
score2	-0.9388	-0.4055	-0.6173
Reputation	-0.0971	-0.3014	-0.4147
TimeDeciding	0.4087	0.9815	0.9574
E	-0.3647	-0.6847	-0.8011
N	-0.1513	-0.5093	-0.6225
lnTotProf	0.6643	0.4924	0.6879

TABLE 34: CHANGE IN PREDICTED PROBABILITIES OF INFOUSED WITH RESPECT TO CHANGE IN PARTICULAR VARIABLES. *SCORE* IS FIXED.

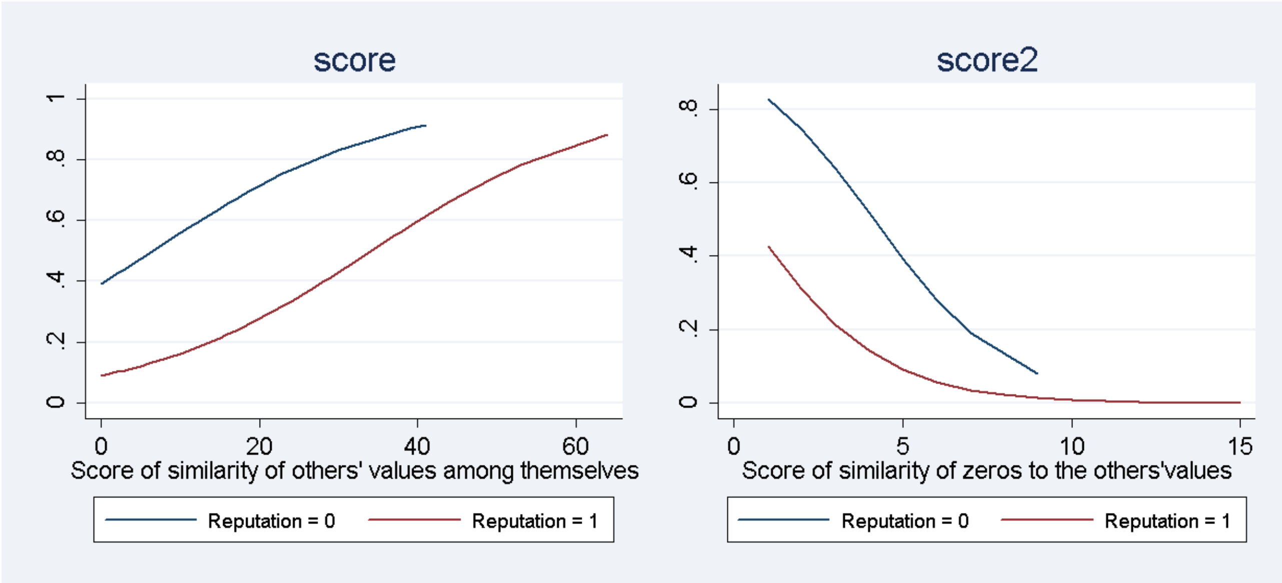
On the other hand, if we set the *score* to be the highest value, 64, the difference in the predicted probability becomes to be (-) 93.8%, which is again intuitively correct. If there are only similar estimates on the public screen, then if one's own estimate changes from totally unlike to totally alike, there is no point in switching. In this situation (*score* is maximal) all other variables reveal relatively much lower predicted change than in the initial situation when it was fixed to its mean except of the variable *lnTotProf*. Generally speaking, this exercise reveals that the subjects behaved relatively rationally and used the information wisely.

6.4.6.4 Personality traits

We analyze only extraversion and neuroticism, and in the sense that if in the same situation, ceteris paribus, was the same person, but with a different score in a particular dimension. If in the decision situation was instead of a subject who scored the least, another subject who scored the most, it would change the predicted probability of following the crowd by 80% in case of extraversion and by 62% in case of neuroticism.

6.4.6.5 Reputation

The effect of presence of the reputation of others can be well seen in Graph 13 where the two graphs indicate the variation in the predicted probability with changes in the variable – we have *score* and *score2* – and the two curves indicate the state of *Reputation*: the blue line indicates the probability if the *Reputation* is zero and the red line if it is one; or put differently, whether the additional information was shown or not. Indeed, the two lines are remarkably different, which proves the significance of the Reputation dummy.



GRAPH 13: VARIATION OF CHANGE IN THE PREDICTED PROBABILITY (THE Y-AXIS) WITH RESPECT TO CHANGES IN *SCORE* AND *SCORE2*.

6.4.6.6 Relative importance: difference of ½ SD

If we go back to Table 33, we can see that what happens with the predicted probability after a change of a half of a standard deviation in a variable. This measure should be roughly comparable across the variables and thus this column can tell us more about the relative importance of the variables. The biggest change in probability is associated with the variable *TimeDeciding* so this one is probably the most important in the regression. We have to expect the causality in a different way: if a subject spends significantly longer time (by one SD, which is in this case 7 seconds) on the screen with the public information, there is much higher probability (by 45%) that she switches. However, if we force a subject to spend the time on the screen, there is no guarantee that she will switch. The second most influential variable is the log of total profit. If a subject had by *exp*(2.2) = 9.02 ECU more of total profit earned, the predicted probability would increase by roughly a third – by 32%. The third most important is the *score2*-measure of the similarity of one's estimate to the estimates seen on the screen. If it increases again by one SD, the probability decreases by almost 30%. The rest of the variables follow. It is very clear that the variables which were labeled "marginally significant", namely *SubjectiveStress* and *SelfConfidence* have a very minor to no influence at all on the change in the predicted probabilities.

6.4.7 Thorough model of InfoUsed: Summary

To sum up, the model I am using for the explanation of variation in the variable InfoUsed, which is a binary variable approaching one if a subject decided (after viewing the publicly available information about the estimates of other subjects who were faster then she was) to switch from her original value to a new value, which was possibly influenced by the information seen. Overall, the model explains the variation pretty well, which can be seen from the indicators such as adjusted pseudo-R^2 of 0.3 or the high ratio of 86% of correctly predicted cases. That the model fits data well was also confirmed by the Hosmer-Lemeshow test. There are a number of insignificant predictors included in the model, but the inclusion of an irrelevant variable can not destroy the consistency of the model, it can only decrease the efficiency (Greene, 2002), which in our case is satisfactory.

Overall, I made mostly correct predictions about the behavior of explanatory variables, but some of them surprised, such as the significant personality traits or the indicator of availability of information about the reputation of subjects who made them, which had the opposite sign than assumed. The most important variable was identified to be the time subjects spent on the screen with the publicly available information, but the causality is in this case probably reversed. Both variables capturing the information contained in the others' estimates are significant, behave as expected and have a considerable predictive power. Another important predictor is the transformed total profit the subjects had acquired. This variable behaved again as expected. A certain disappointment is the insignificance of variables indicating the level of time pressure as well as the level of stress subjects perceived themselves to be in, but because the model is relatively well constructed, we can take this result seriously and try to find answers on why it is the case. I propose the mechanism based on the Rieskamp and Hoffrage (2007) who found that under increasing time pressure, people tend to focus less on quantity of information and more on its quality. If they perceived the information about others as unimportant, they might with increasing time pressure more often ignore it and believe only in their own skills. The results also agree with Borghans et al. (2008) in their general recommendation that new studies should incorporate validated personality measurements, because they can reveal interesting results as here they prove to be significant, but the relationship to the explained variable is rather unintuitive.

7 MODEL SUMMARY AND OVERALL CONCLUSION

7.1 ORIGINAL AIM OF THIS THESIS

The main purpose of this thesis is that I attempted to model the individual propensity to herd with a special concern to the effect of time pressure. To do this, I designed and carried out a laboratory experiment, where the subjects performed a simple cognitive task under various conditions. The task was to count the number of zeros from a sheet of 400 symbols in a given time. There were four different treatments of the task: in the first treatment the subjects were not restricted by time and had two tasks only to try-out the task. In the second treatment I introduced three levels of time pressure, which was represented by a strict time constraint and a time-dependent bonus to motivate the subjects to be fast. The third and fourth treatments followed the second one, but only one of them was done per group. The third treatment introduced the core idea of the opportunity to (after setting the first estimate) look at the results of others who were faster than the subject and then switching from the originally set value to a new one. The fourth treatment was different to the third one only in that the publicly available information about the estimates of other subjects was improved by including the information about the past performance of a respective subject.

The fact that a subject switched from her value to the new one served us as a proxy for indication of occurrence of herding. Hence by using a logistic regression I can model the probability of switching and the results should be able to generalize to herding in general. Apart from that, I also model the propensity that the subject even let herself be influenced by the others' decisions, namely the propensity to look at this publicly available information.

I tracked not only the information directly revealed during the task, but also the individual attributes such as risk attitude, social preferences, task-specific confidence, personality traits and subjective as well as objective level of stress. These attributes play a major role in the regression model and their respective behavior can be seen in the Table 35, where also the theoretically expected behavior is included.

Originally, the motivation of this experiment was to examine the occurrence of information cascades, expressed in the experiment as the full ignorance of one's own information in favor of the prevalent public information. The results show that no full information cascade happened, although there were a number of quasi-cascades and in a few cases even a reverse cascade started, but was disconnected by the "honest" subjects who revealed the true information. This result actually supports the continuous critique as in Lee (1993) and fragility of cascades in general. If only this result were true also in case of fads such as smoking or other dangerous habits.

		InfoShown				***InfoUsed***			
		Expectations		***Real behavior***		***Expectations***		***Real behavior***	
VARIABLES	LABELS	Signif	Sign	Signif	Sign	Signif	Sign	Signif	Sign
score	similarity of others' values					yes	+	yes	+
score2	similarity of zeros to the others'					yes	-	yes	-
Reputation	1 if reputation shown	yes	+	no		yes	+	yes	-
TimeDeciding	Time spent on screen with public information					yes	+	yes	+
TimeLeft	Time left when original estimate set	yes	+	yes	+	no		no	
TP_High	1 if High Time Pressure	yes	+	no		yes	+	no	
O	Openness to Experience	yes	+	no		no		no	
C	Conscientiousness	yes	-	yes	+	no		no	
E	Extraversion	yes	+	no		yes	+	yes	-
A	Agreeableness	yes	+	yes	+	no		no	
N	Neuroticism	yes	+	yes	+	yes	+	yes	-
SubjectiveStress	Stress (Subjective)	yes	+	no		yes	+	no	
Female	1 for female	no		no		no		no	
CE	Certainty equivalent	yes	-	yes	-	yes	-	yes	+
RiskAverse	1 if Weakly Risk Averse	Yes	-	Yes	-	Yes	-	no	
SelfConfidence	Self Confidence	yes	+	yes	+	yes	+	no	
lnTotProf	Ln (Total Profit)	no		no		yes	+	yes	+
ExpectedKindness	Average perceived kindness	Yes	+	no		no		no	
HR_DIF	Difference of quiescent to actual HR	Yes	+	Yes	-	Yes	+	no	

TABLE 35: SUMMARY OF PREDICTED AND ACTUAL BEHAVIOR OF VARIABLES IN THE REGRESSION MODELS.

7.2 HYPOTHESES EVALUATION

In section 3.6 you can see an overview of the tested hypotheses. Now we will repeat their respective results, which can be found in the text of the preceding sections.

Hypothesis 1

Hypothesis 1 stated that the occurrence of information cascades is more frequent under time pressure. Translated into statistical language, the coefficient of the variable indicating a high level of time pressure, the *TP_High*, should have been significant and positive. However, as you can see in the analysis in section 6.4.5, both dummies indicating the time pressure are not significantly different from zero, and this result is fairly stable across various specifications. On the other hand, the time dimension played an important role in both models – in the first model there was the time subjects had left when setting the original estimate and in the second model the time they spent looking at the public information – and both must have been implicitly influenced by the total available time that varied with the level of time pressure. Therefore I recommend further research focusing on finer resolution of time pressure levels, such as gradually reducing the time subjects have for making their decisions.

Hypothesis 2

Hypothesis 2 touched the issue that has been extensively researched – the dependence of individual performance on the level of time pressure. I found decisive evidence that performance does not decrease with increasing time pressure as you can see in the section 5.3.2, where I discover by using simple mean comparison that performance even increased in the high level of time pressure and so I confirm the results of Ariely et al. (2005) that this relationship is more complicated than just linear and depends on the nature of the given task. The proper regression analysis of explanation of performance under pressure was not the aim of this thesis, though, and was subject to many papers already.

Hypothesis 3

Hypothesis 3 was more theoretically oriented when it stated that the behavior of subjects with respect to viewing and using the information about others' results will be such that some subjects *will* use it whereas others will not. Section 5.5.1 shows that this was indeed the case, as there were some subjects who never looked at the information as well as some who used it almost every time. This heterogeneity in approach to using the information about the behavior of others shows that the neoclassical view of self-centered rationality is not exclusive and while there may be some people who never let themselves be influenced by others' behavior, they are more or less a rarity and a majority of people strategically use this information for their own benefit. Section 6.4.6.3 showed that the information was mostly used wisely and in an intuitive way and also the simple comparison of means in the respective treatments shows that the earnings were significantly higher when the public information was available.

Hypothesis 4

This hypothesis was aimed at the relative importance of the personality profile of a subject – how it affects her probability of letting herself be influenced by others. The personality dimensions sometimes called the "Big 5" (see section 3.3 for details) were measured with a standard psychometric questionnaire which had 50 questions – 10 per each dimension, which should provide a relatively accurate measure of each trait involved. Indeed, the 5 dimensions proved to be significant as a group in both examined models, but of course only alone did not play the most important part in the explained variable. Even if some of them were significant, they mostly did not behave in the way expected. The underlying psychological mechanisms may thus be much more complicated and I recommend them to be subject to further interdisciplinary research of economists and psychologists.

The importance of personality measurements in the regression analysis also constitutes another piece of evidence against the neoclassical idea of people being selfish, rational calculation machines – the concept of *homo economicus.* The propensity to herd is thus not solely an informational phenomenon as originally thought by BHW (1992).

Hypotheses 5 and 6

These two hypotheses focused on the role of risk-attitudes in the models and differentiation of attitudes of risk-averse and risk-loving individuals: Hypothesis 5 stated that the risk-averse subjects would have a higher propensity to look at the public information i.e. the variables *RiskAverse* and *CE* would be significant in the model of *InfoShown* and would have a positive sign. The second part of the hypothesis was connected to behavior under stress: if the hypothesis was true, the risk-averse subjects would state significantly higher levels of perceived stress and moreover the measure of their physiological stress would also be higher than for the risk-loving. Hypothesis 6 then stated that risk preferences would play a role in the model of explaining the probability of switching from the original estimate.

Risk preferences indeed play a significant role in the model of explaining the propensity to look at the public information, as you can see in part 6.3.6 but the direction is the opposite: the propensity to look at the public information is negatively influenced by the risk-aversion. In section 5.6.6 you can see that the means of both reported and physiological levels of stress were the same for both risk-averse and risk-loving subjects so we have to reject the second part of Hypothesis 5. Similarly, we have to reject Hypothesis 6 because risk preferences do not significantly influence the propensity to switch from the original estimate.

Hypotheses 7 and 8

The seventh hypothesis concerned the role of the reputation effect (or endorsement effect as originally called). In section 3.4.5 I discussed that the expected effect on the probability of switching should be significantly positive. In section 6.4.5.5 I showed that the effect is significant and this variable indeed plays a very important role, but the effect is negative. On the other hand, section 5.2 shows that the performance was indeed higher in the case of the fourth treatment, where the only difference to the third treatment was the displayed reputation of others, which speaks in favor of hypothesis 8. The underlying explanation may be that the rate of switching was lower due to greater selectivity of provided information – switching only in the important cases.

I admit that only a dummy indicator of the additional information is rather rough and I suggest more research is needed in this way, possibly using the same dataset.

Hypotheses 9

The last two tested hypotheses focused on the role of the physiological stress in the analysis of the propensity to switch / propensity to look at the public information. I used the variable indicating the difference of average heart rate over the performed task and the base quiescent level. The basic message of hypothesis 9 is that the task really induced stress and it is possible to measure it using the proxy of variability in the heart rate.[46] The result is that even though the task was performed while sitting in front of the computer and not doing any physical activity, the average difference of the heart rate to the base (quiescent) level was 16.47 so this variable looks like a good

[46] Do not confuse with the heart rate variability, which is a specific variable with a different meaning.

measure of the induced stress. Of course, the heart rate of some subjects was overall not different to the white noise, but the majority had very clearly identifiable periods of performance in comparison to the base level with some subjects reaching as high as 150 beats per minute.

I expected this variable to be correlated to the subjectively reported level of stress in each round, but as you can see in the deeper analysis in section 5.6.4, this correlation was significant on a 5% level but rather small – only 0.1. This shows a clear discrepancy between the reported and revealed/directly measured variable. For the next analyses concerning the behavior under stress or anything connected, I recommend using at least the heart rate monitors to get the real physiological level of stress, including possibly extending the testing to include the level of hormones associated with stress (the andrenocorticotropic hormones). Hypothesis 9 then expected a higher level of stress during the higher level of time pressure, but on the 1% significance level we can conclude that the difference was insignificant.

Interesting is, that the variable *HR_DIF* is important in predicting the probability of looking at the public information, but not in the model of using the public information. The effect on the probability of looking at public information was however negative, which is consistent with the behavior of coefficients of risk preferences.

7.3 Discoveries made

Put into nutshell, the most important results are as these: **time pressure** indicated by a set of 0/1 indicator variables **played no** significant **role** in either of the models of herding. Nevertheless, the **time** dimension **is significant** and very important in both cases and thus the time pressure needs to be further examined by using finer resolution than a set of indicators. **Information cascades did not arise** in their pure form, implying their fragility and dependence on the specific setting of the task. However, **herding was** relatively **common** and only in two out of 33 cases nobody used the public information. **Personality traits contribute considerably** to the explanation of both models, but the behavior is not straightforward and may need further research. Their significance is however very important result suggesting more intense future cooperation between psychologists and economists. Moreover, this result constitutes a new piece of evidence against the traditional conception of *homo economicus*. **Subjectively** perceived **stress** was **not correlated to** the **objectively** measured **indicator** which indicates a certain discrepancy between the stated and objectively measured dimensions. Again, this result needs further explanations and research, whether it is systematic or was an effect of the specific task. **Performance** of subjects **was** even **better under time pressure** if expressed as the accuracy of subjects' estimates and this effect probably stems from a specific nature of the given task. The effect of **reputation** (also called the endorsement effect) played a very important and positive role in determination of the performance of subjects. It was also important in the prediction of the probability of switching, but this time the effect was unexpectedly negative. Subjects mostly used the information in a logical and rational way, however

Generally speaking, this experiment has provided a very important insight into the state of analysis of behavior under time pressure, especially in connection to the propensity to herd. Apart from that, it has also given rise to many important new questions, such as the relationship of the propensity to herd and personality traits or the relationship of the subjectively reported and objectively measured levels of stress. Future research on the deeper examination of effects of time pressure is suggested as well as further research on the endorsement effect. However, the results from this experiment have to be treated with care due to the specific nature of the given task and to the non-representative sample of subjects.

8 APPENDIX

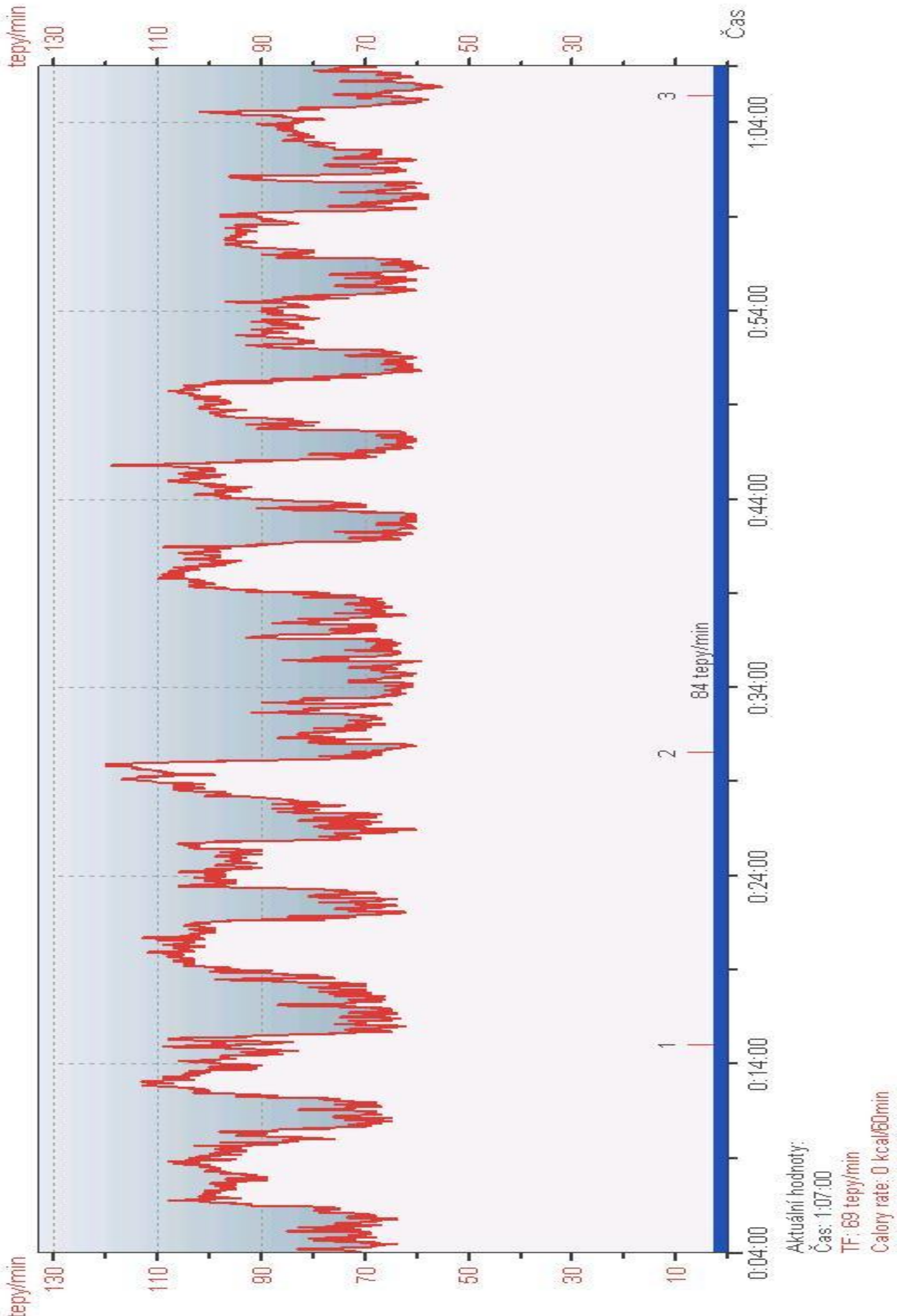


FIGURE 10: CURVE OF HEART RATE FROM THE HR-MONITORS.

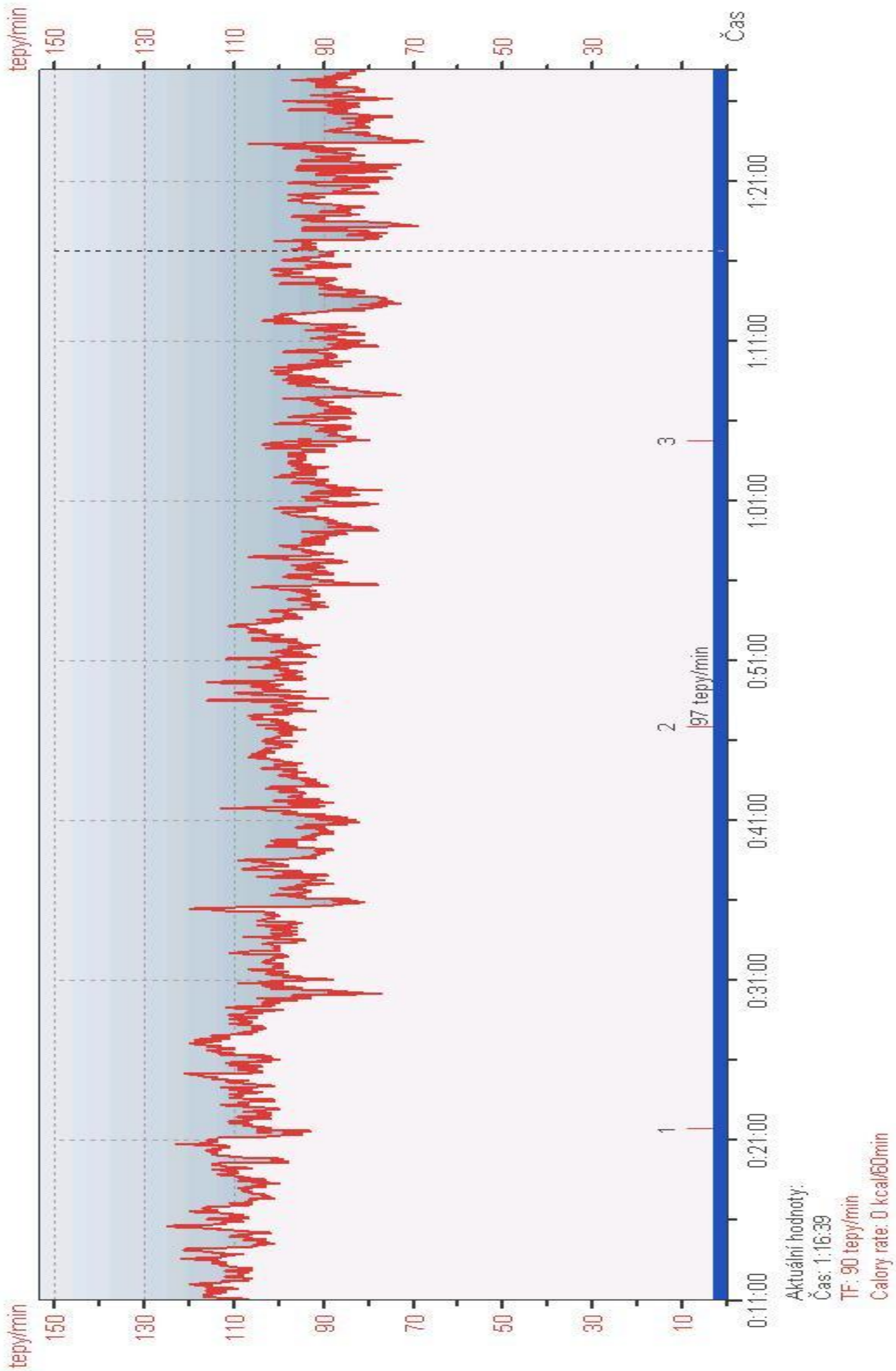


FIGURE 11: CURVE OF HEART RATE FROM THE HR MONITOR.

8.1 ECONOMIC EXPERIMENT: INSTRUCTIONS (A)

Introduction

Today you are participating in an experiment with focus on behavior under time restrictions. These instructions describe how the experiment will be conducted and the decision task you will undertake. You will see the important part of instructions before each part of the experiment again on the screen. Your payoffs in this whole experiment will depend only on the choices made by you, and will not depend on choices made by other participants. You will be given 100 CZK for coming on time and completing a questionnaire in the end. This 100 CZK and any money that you earn during the experiment will be paid to you, in cash, at the end of the experiment. It is impossible to lose money in this experiment. You should feel free to make as much money as possible. Money for this experiment has been provided by the J&T Bank a.s..

Experimental Currency

All experimental payoffs are denominated in experimental currency units (ECUs). Your ECU earnings will be converted to CZK at the end of the experiment at a conversion rate of 10 ECUs equal to 1 CZK. You will be paid at the end of the experiment privately, and no other player will be told what you earned for the experiment. If you have any questions while these instructions are being read, please raise your hand and we will attempt to answer your questions.

Please do not talk to the other participants during the experiment, or else your participation in the experiment will be terminated without any payment.

Task

The decision task constitutes of several rounds. Your task should substitute the real routine concentration effort you normally make in a real life. In each round, your task will be to **count zeros** from a table shown on the screen on the left and type in your **estimate** of this number. All parts of the experiment are based on this task and differ only in some additional features. In any given round, the task is identical across all participants.

In all parts of the experiment, you will be paid for the **accuracy** of your estimate:

If you estimate the number exactly, you get 100 ECU.

If you miss by one, you get 80 ECU.

If you miss by two, you get 50 ECU.

If you miss by more than two, you get 0 ECU.

The table with the zeros and ones has 20 rows and 20 columns and the numbers are generated randomly. Figure 1 (or later Figure 4) provides an example.

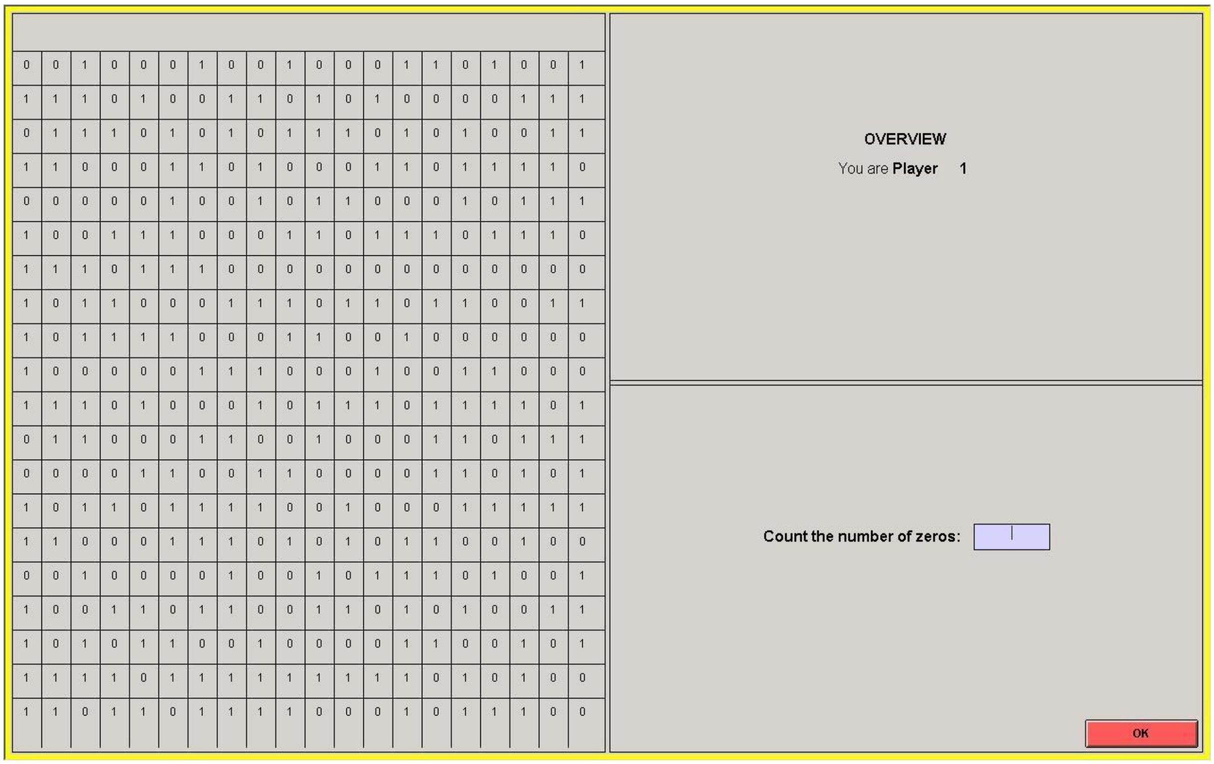


FIGURE 1

After each round, you will see the summary with the following information: your estimate, the true number of zeros, and your payoff (Figure 2). To begin with the next period, you will have to wait for others to complete the task. Please, always click “Continue” so that the experiment can continue.

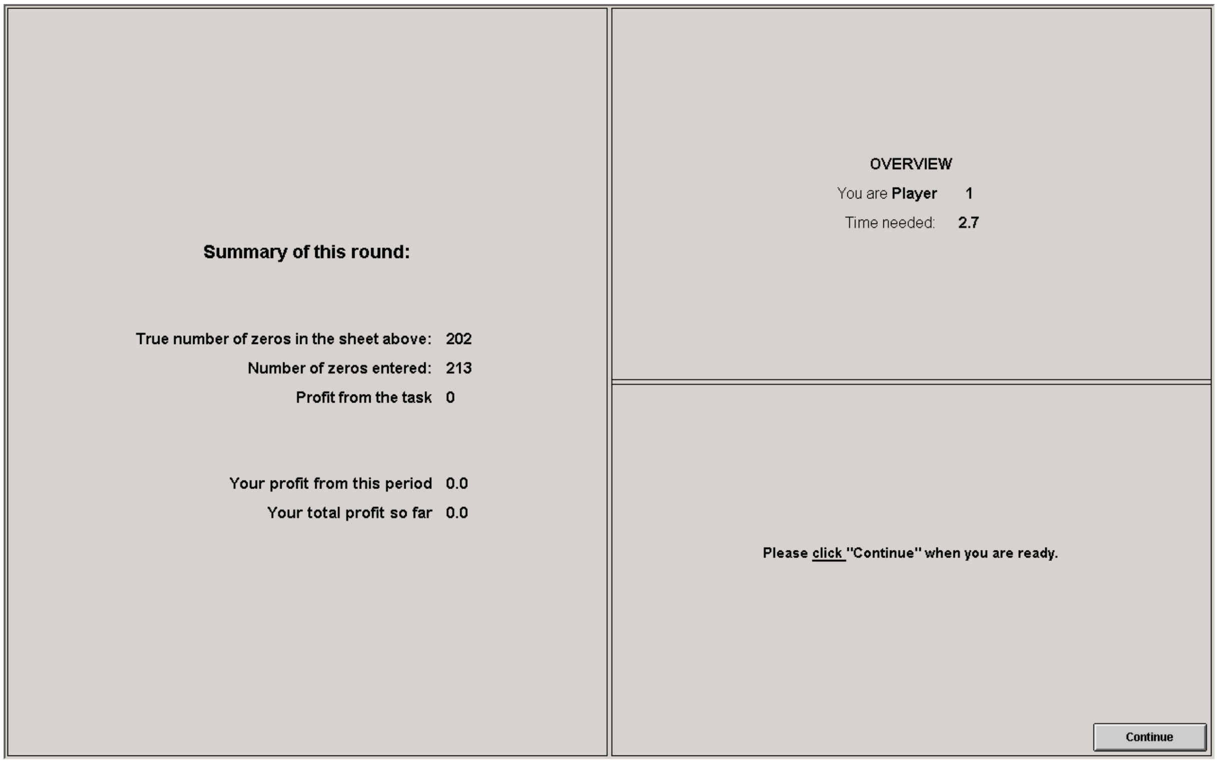


FIGURE 2

The parts of the experiment (treatments)

The first part of the experiment is intended for you to practice the task. There will be two rounds without any time restrictions.

The second part of the experiment will proceed under **time constraint** and will last for 3 rounds.

There will be three levels of time constraint - "Low", "Medium" and “High", out which one gets randomly selected. For completing the task, you will have 150 seconds in the “Low” time constraint, 130 seconds in the “Medium” and 100 seconds in the “High” level of time constraint.

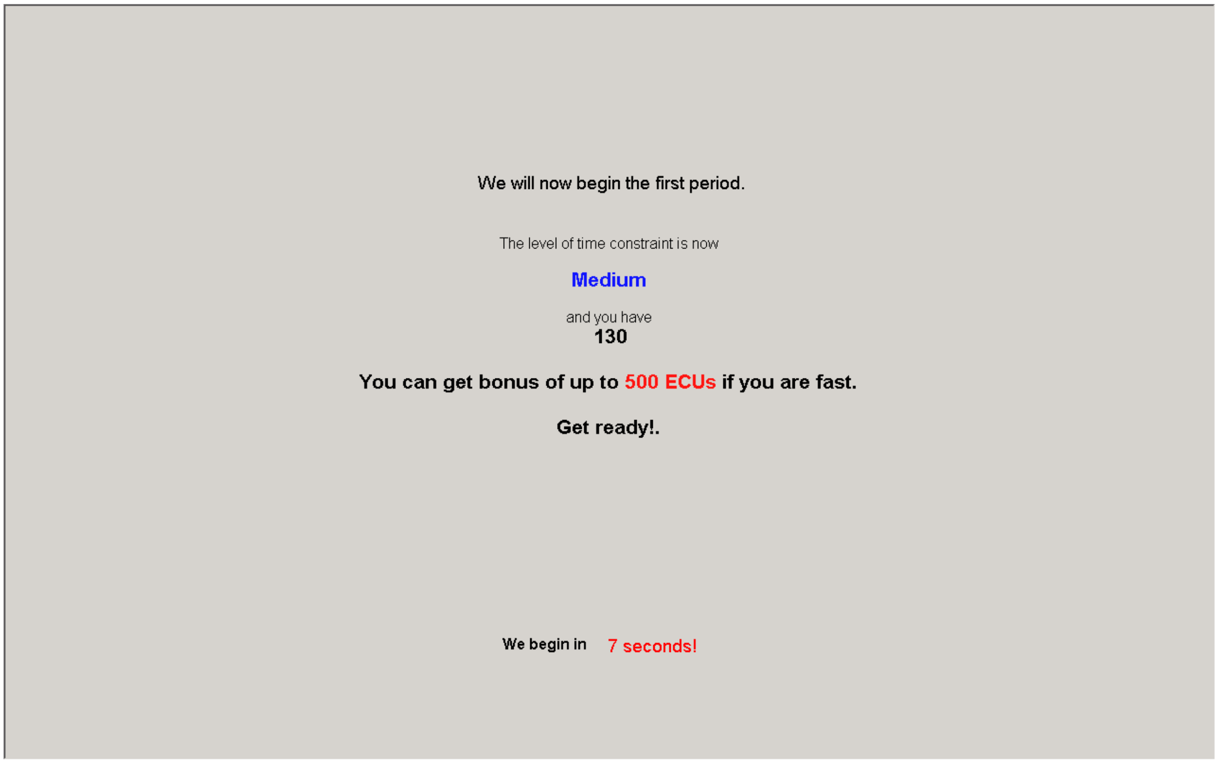


FIGURE 3

You will get a **bonus** for being fast. The bonus will **decrease with time**. In “Low” time constraint, the bonus starts at 400 ECUs at the beginning of a period and decreases by 3 ECUs with each second; in “Medium” time constraint, the bonus starts at 500 ECUs and decreases by 4 ECUS with each second; in “High” time constraint, the bonus starts at 600 ECUs and decreases by 5 ECUs with each second. You will get the bonus **only** if you do not miss it by more than 2. Otherwise your bonus wil be 0.

Information about the level of time constraint for the period, time for the task and the bonus will appear on the **welcome screen (Figure3)** before you start a round.

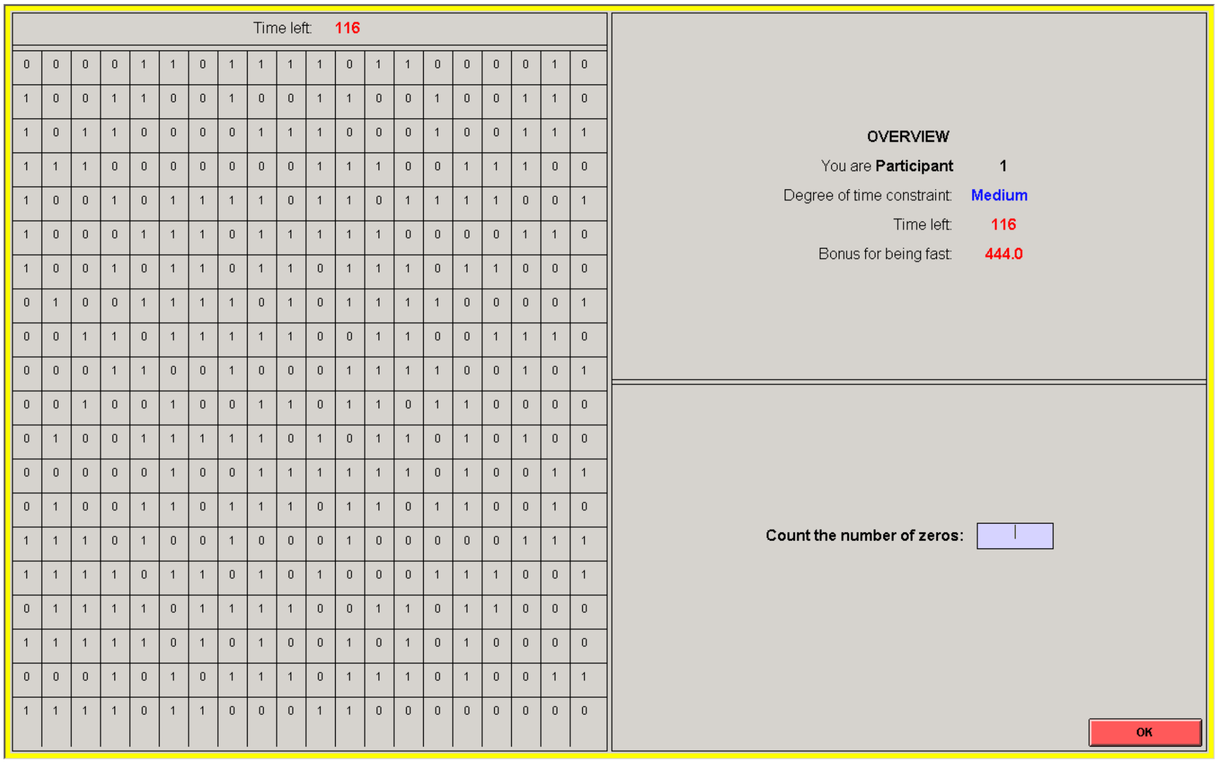


FIGURE 4

After you enter your estimate, the summary screen (Figure5) appears. There is one question in the bottom left corner on the level of pressure you subjectively felt during the task that you have to answer.

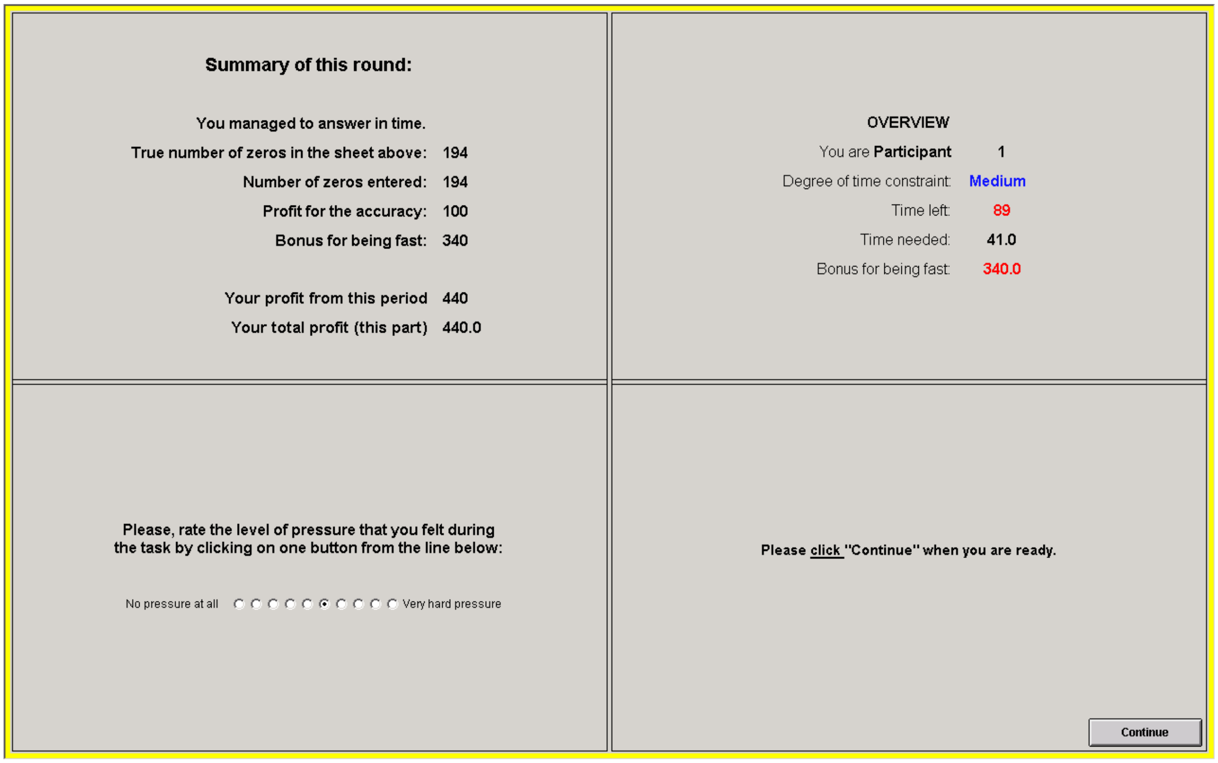


FIGURE 5

The third part

This part will last for 6 rounds and you will have the option to **see the estimates of the other participants** made in the current round and change your mind according to new information. To see it, you have to first type in your guess, click “OK” and then you can click "YES" or "NO” as to whether to see estimates of other participants.

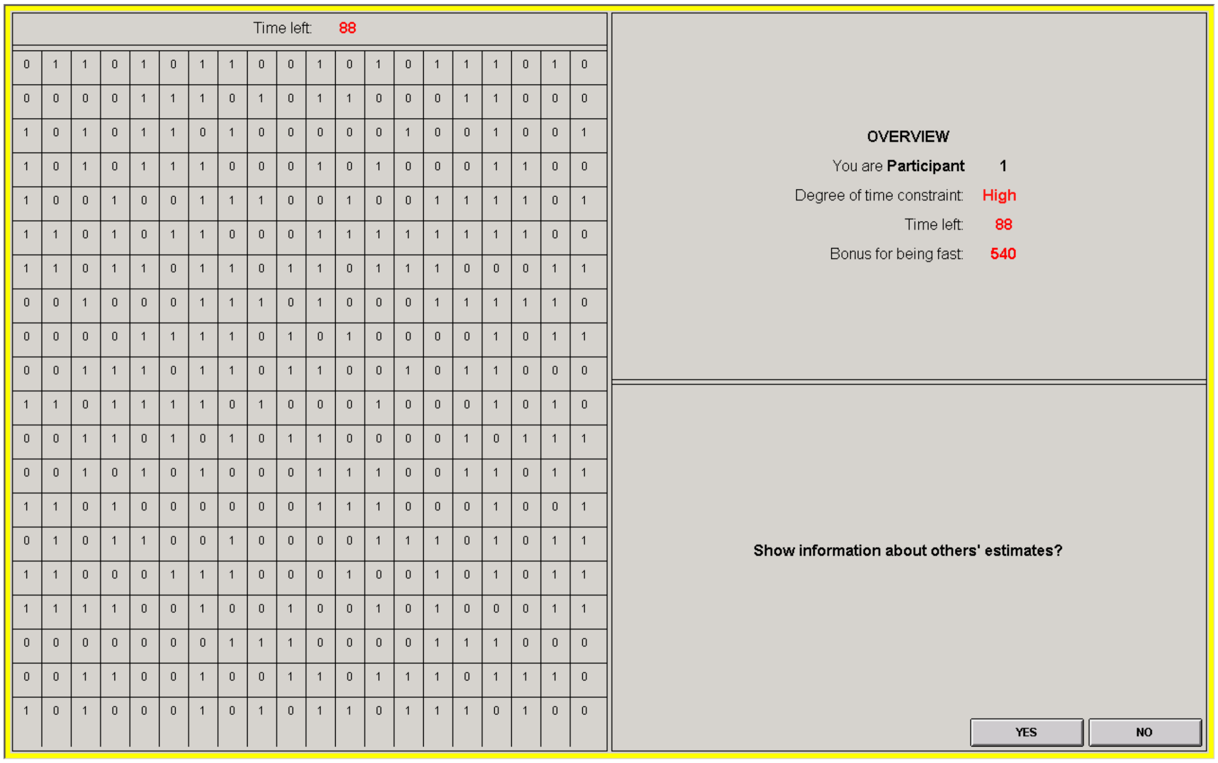


FIGURE 6

If you click “NO”, the experiment will proceed as in the previous parts– the estimate will be set and you will see the summary of the round.

If you click “YES”, you will see a table with the **original** estimates typed in by the other participants that entered them **before** you clicked on "YES". The estimates will be arranged in a table with a fixed order of participants, including you. You will see your own Participant number in the "Overview" part of the screen. While examining these estimates, your **time** will still be **running** out, so be careful.

In the screen with the estimates of the others (Figure 7), you will have a chance to enter **a new estimate**. If you want to use your own first estimate, click on “NO (Keep my original estimate)”. If you want to enter a new estimate, click on “OK (enter a new estimate)”. There is no penalty for changing your estimate.

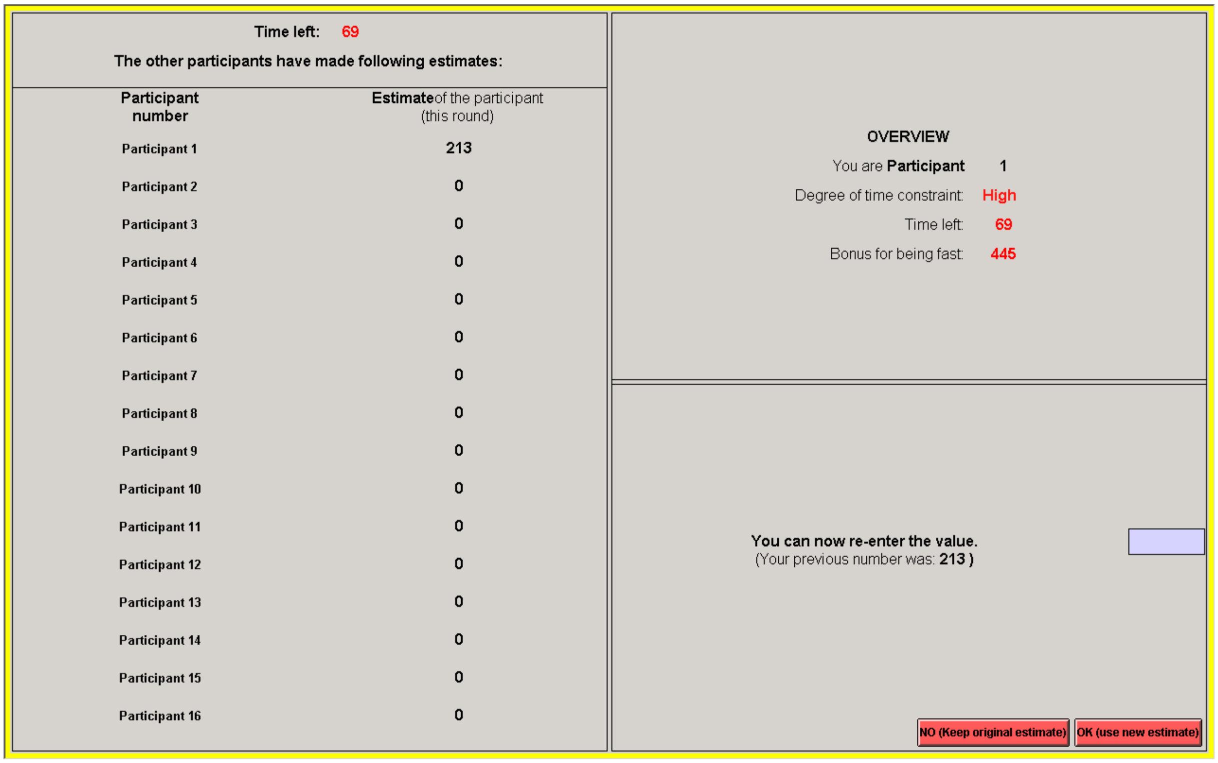


FIGURE 7

Questionnaire

After concluding the decision tasks, you will fill out questionnaire asking you about:

your preferences about **fairness** of division of 1000 CZK between you and an anonymous partner

your **personality profile**

your important **demographic characteristics** such as gender, field of work/study, etc.

Answers to these questions will be kept strictly confidential and will be used exclusively for research purposes.

There will also be a space for your feedback – please provide comments, suggestions, describe your strategy of solving the task, or comment on how you felt during the experiment. You can get extra bonus if we find the feedback outstanding.

Apart from these, on your table there is a **sheet of paper** with an additional task – choosing between a risky **lottery** and an amount of **cash** received for certain. Each line requires one choice. After you fill this piece of paper out, then me or my assistant will come, throw a dice and will write you the result on the paper. You will get signal when is the time to fill it out.

Summary

The experiment will consist of three parts, each with several rounds and different conditions, followed by a questionnaire at the end. You will be paid in cash at the end of the experiment. All information about your choices and payoffs in this experiment will be kept strictly confidential.

Please do not talk to the other subjects at any point during the experiment, even to ask questions about the instructions. If we hear you talking at any point during the experiment other than talking with me or one of my assistants, your participation in the experiment will be terminated without any payment. If you have any questions about any part of the instructions, please raise your hand now. We want everyone to understand the instructions before we begin the experiment.

8.2 ECONOMIC EXPERIMENT: INSTRUCTIONS (B)

Introduction

Today you are participating in an experiment with focus on behavior under time restrictions. These instructions describe how the experiment will be conducted and the decision task you will undertake. You will see the important part of instructions before each part of the experiment again on the screen. Your payoffs in this whole experiment will depend only on the choices made by you, and will not depend on choices made by other participants. You will be given 100 CZK for coming on time and completing a questionnaire in the end. This 100 CZK and any money that you earn during the experiment will be paid to you, in cash, at the end of the experiment. It is impossible to lose money in this experiment. You should feel free to make as much money as possible. Money for this experiment has been provided by the J&T Bank a.s..

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In all parts of the experiment, you will be paid for the **accuracy** of your estimate:

If you estimate the number exactly, you get 100 ECU.

If you miss by one, you get 80 ECU.

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If you miss by more than two, you get 0 ECU.

The table with the zeros and ones has 20 rows and 20 columns and the numbers are generated randomly. Figure 1 (or later Figure 4) provides an example.

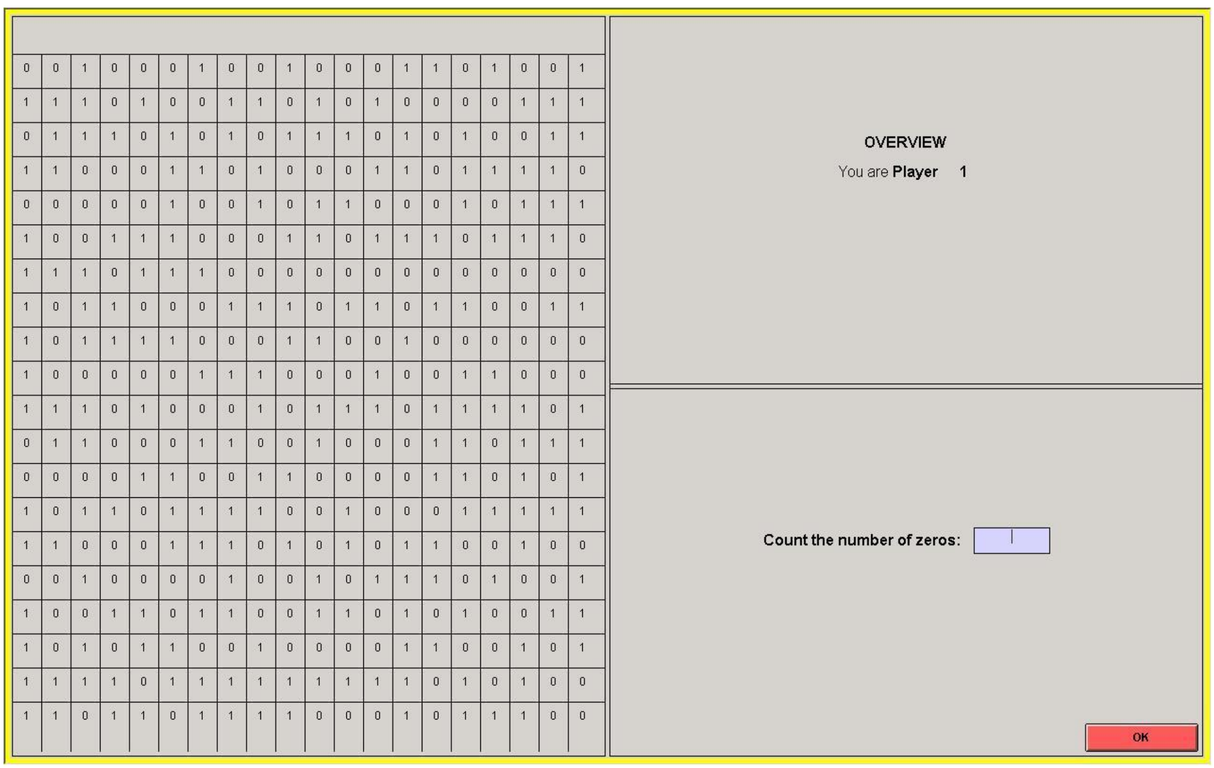


FIGURE 8

After each round, you will see the summary with the following information: your estimate, the true number of zeros, and your payoff (Figure 2). To begin with the next period, you will have to wait for others to complete the task. Please, always click “Continue” so that the experiment can continue.

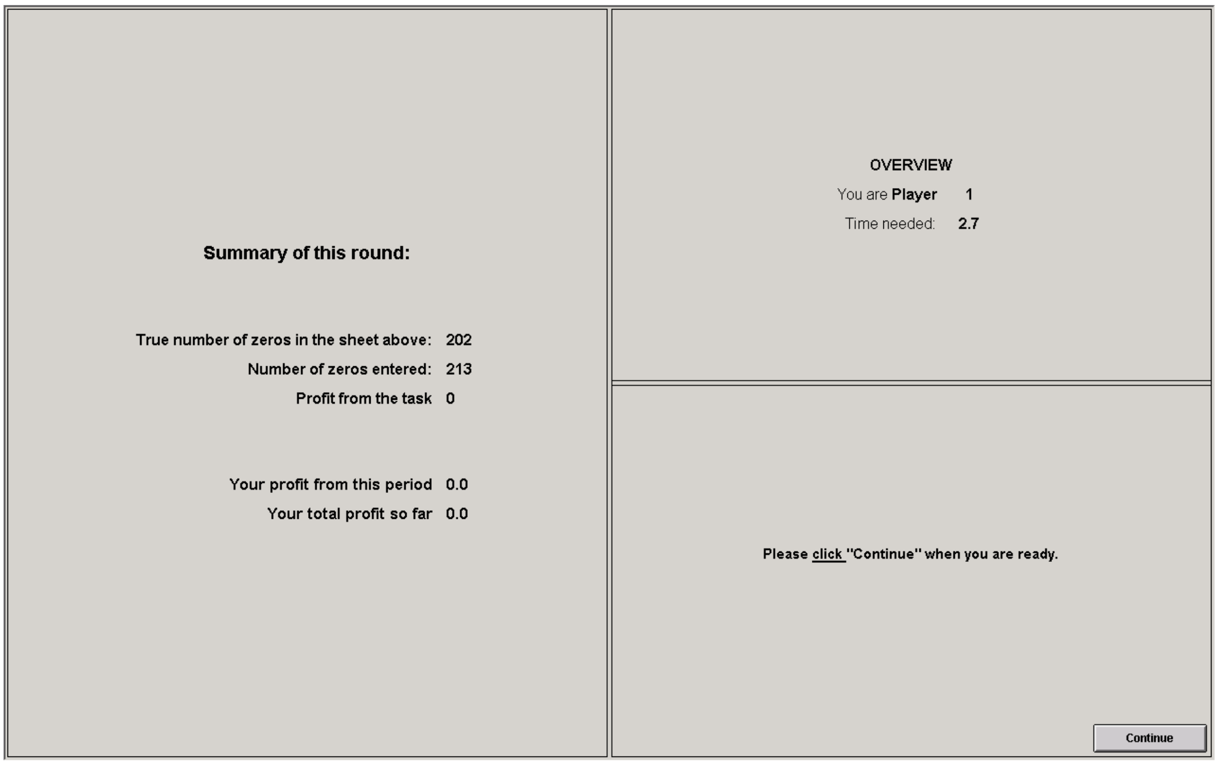


FIGURE 9

The parts of the experiment (treatments)

The first part of the experiment is intended for you to practice the task. There will be two rounds without any time restrictions.

The second part of the experiment will proceed under **time constraint** and will last for 3 rounds.

There will be three levels of time constraint - "Low", "Medium" and “High", out which one gets randomly selected. For completing the task, you will have 150 seconds in the “Low” time constraint, 130 seconds in the “Medium” and 100 seconds in the “High” level of time constraint.

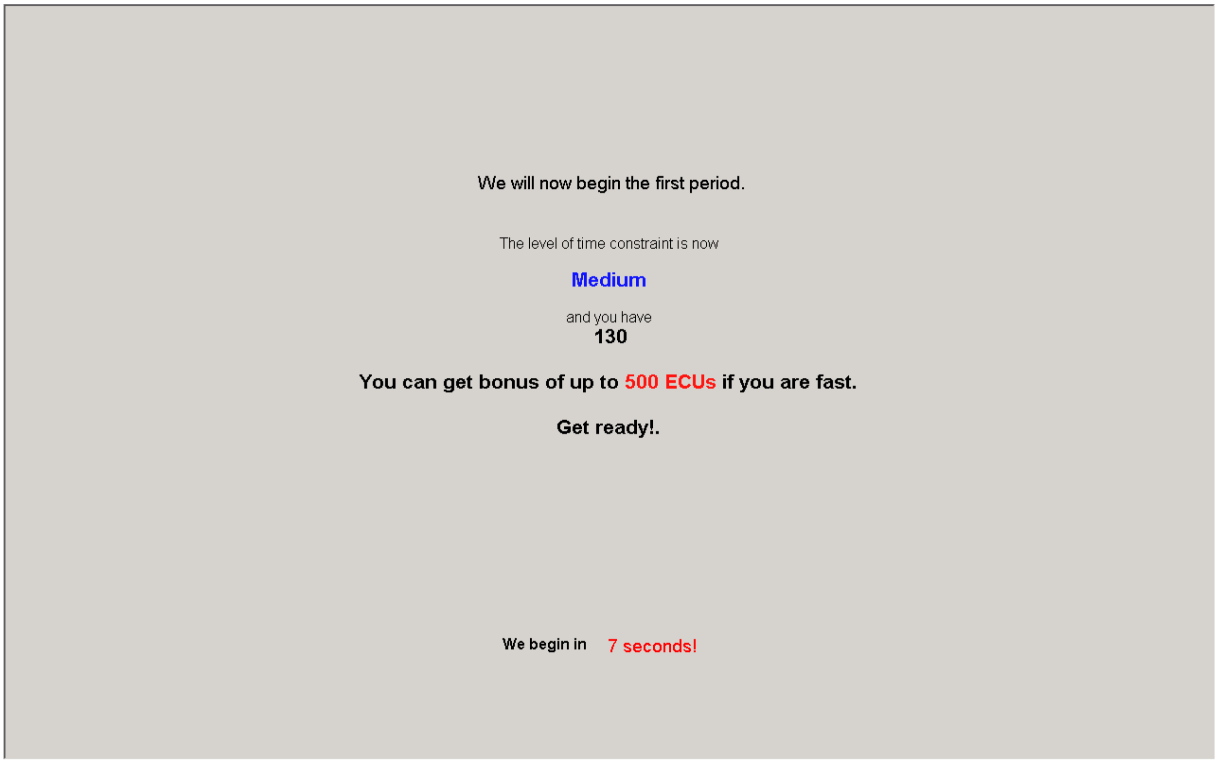


FIGURE 10

You will get a **bonus** for being fast. The bonus will **decrease with time**. In “Low” time constraint, the bonus starts at 400 ECUs at the beginning of a period and decreases by 3 ECUs with each second; in “Medium” time constraint, the bonus starts at 500 ECUs and decreases by 4 ECUS with each second; in “High” time constraint, the bonus starts at 600 ECUs and decreases by 5 ECUs with each second. You will get the bonus **only** if you do not miss it by more than 2. Otherwise your bonus wil be 0.

Information about the level of time constraint for the period, time for the task and the bonus will appear on the **welcome screen (Figure3)** before you start a round.

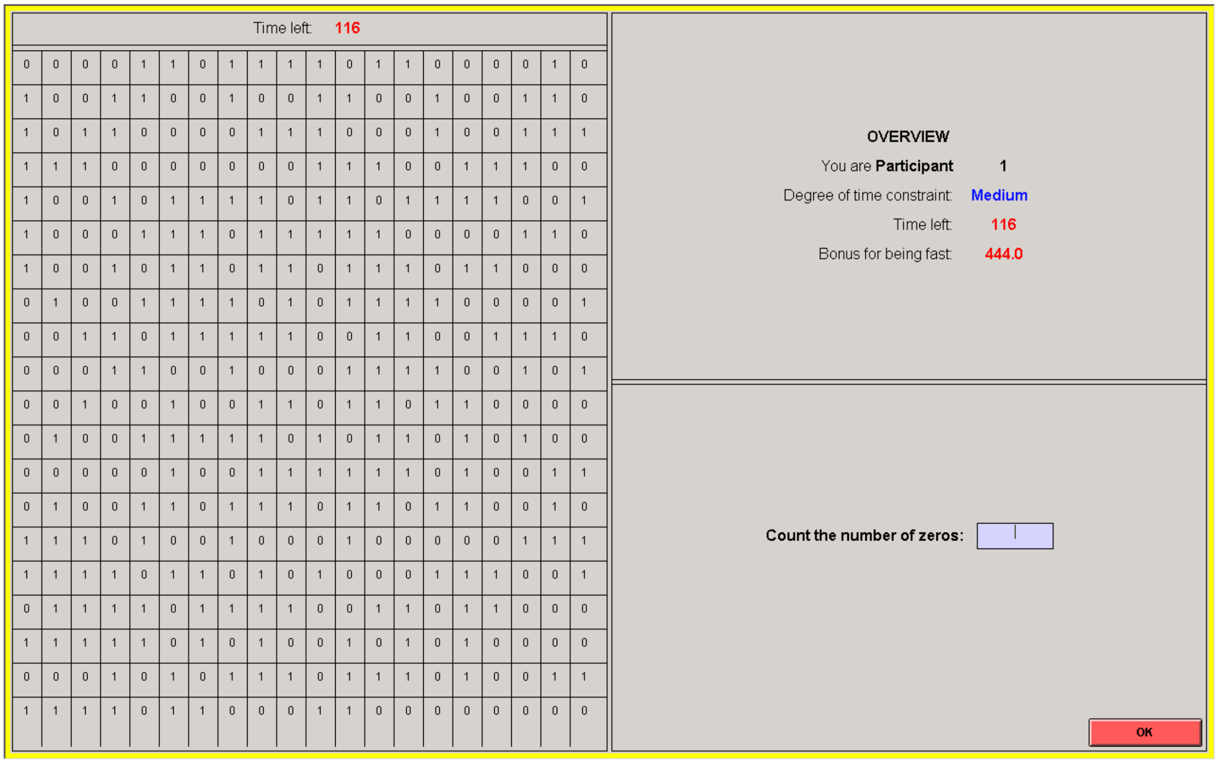


FIGURE 11

After you enter your estimate, the summary screen (Figure5) appears. There is one question in the bottom left corner on the level of pressure you subjectively felt during the task that you have to answer.

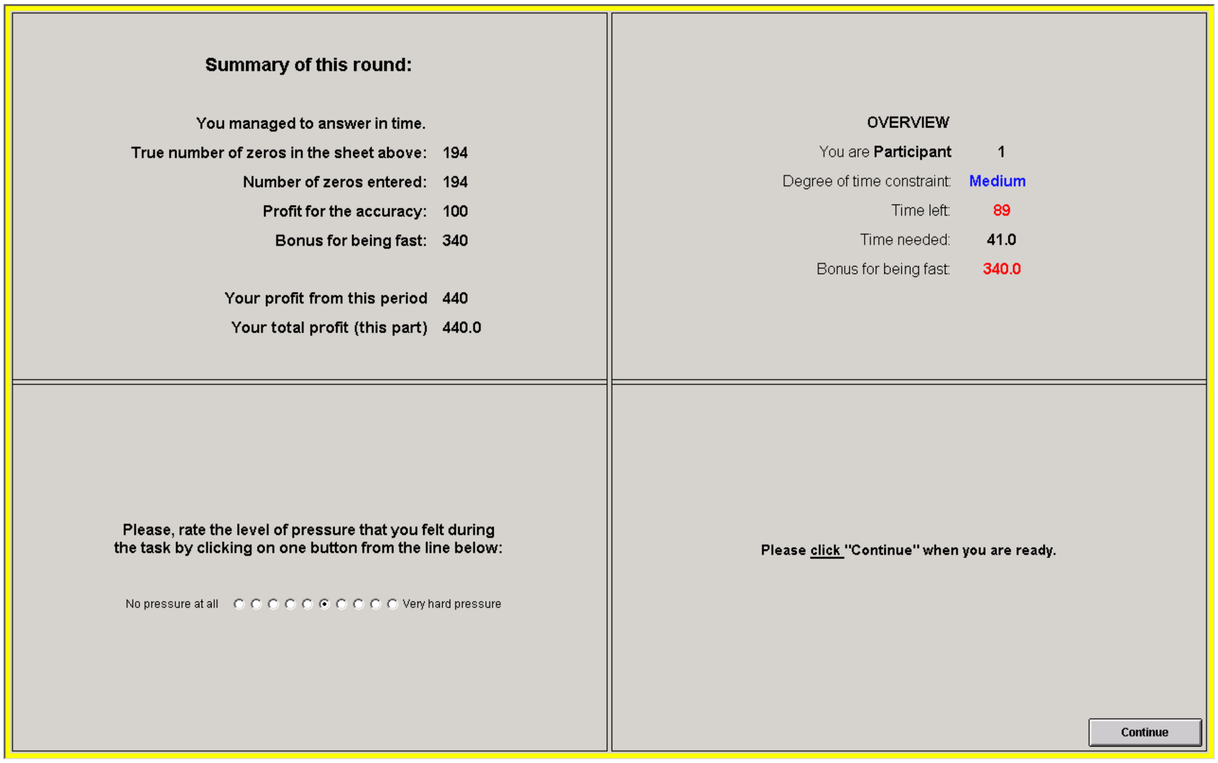


FIGURE 12

The third part

This part will last for 6 rounds and you will have the option to **see the estimates of the other participants** made in the current round and the **total payoff of each participant** from the previous rounds (not from the current one) and change your mind according to new information. To see it, you have to first type in your guess, click “OK” and then you can click "YES" or "NO” as to whether to see estimates of other participants.

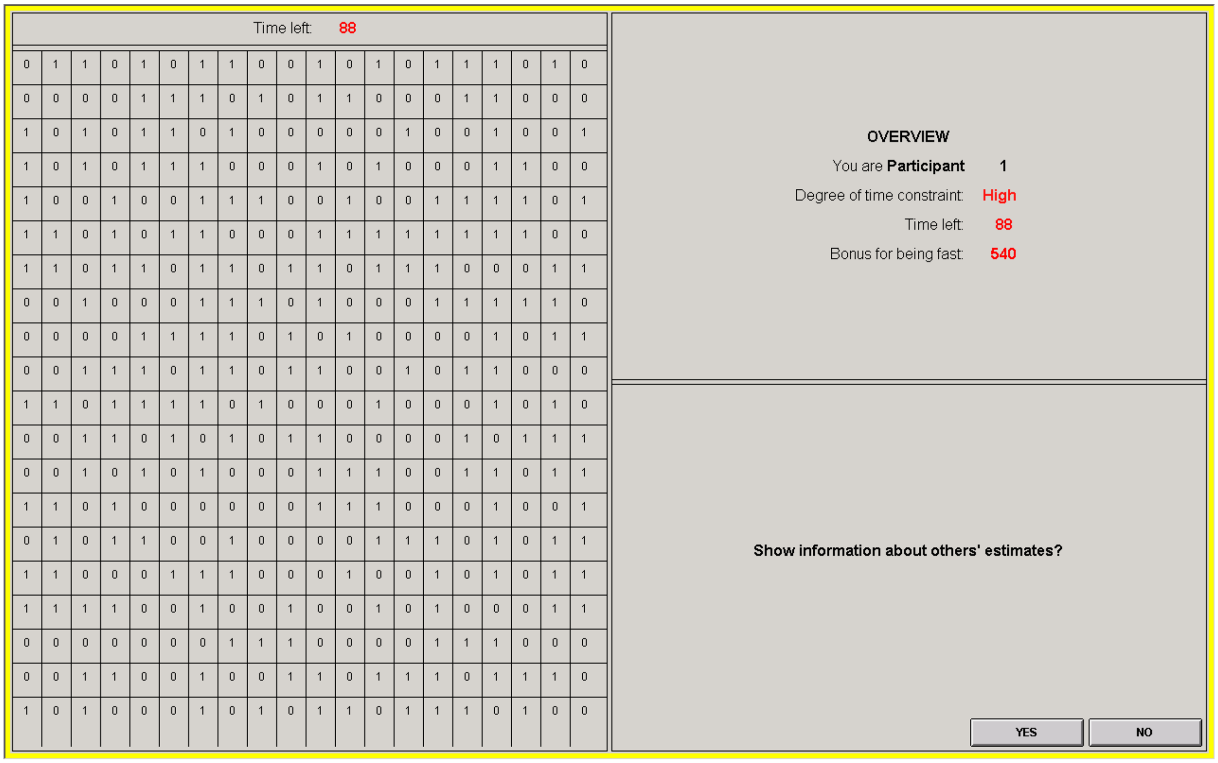


FIGURE 13

If you click "NO", the experiment will proceed as in the previous parts– the estimate will be set and you will see the summary of the round.

If you click "YES", you will see a table with the **original** estimates typed in by the other participants that entered them **before** you clicked on "YES". The estimates will be arranged in a table with a fixed order of participants, including you. In the right column, there will be the **total** cumulative **payoff** from all preceding rounds of this part and also from the previous part of the game. You will see your own Participant number in the "Overview" part of the screen. While examining these estimates, your **time** will still be **running** out, so be careful.

In the screen with the estimates of the others (Figure 7), you will have a chance to enter **a new estimate**. If you want to use your own first estimate, click on "NO (Keep my original estimate)". If you want to enter a new estimate, click on "OK (enter a new estimate)". There is no penalty for changing your estimate.

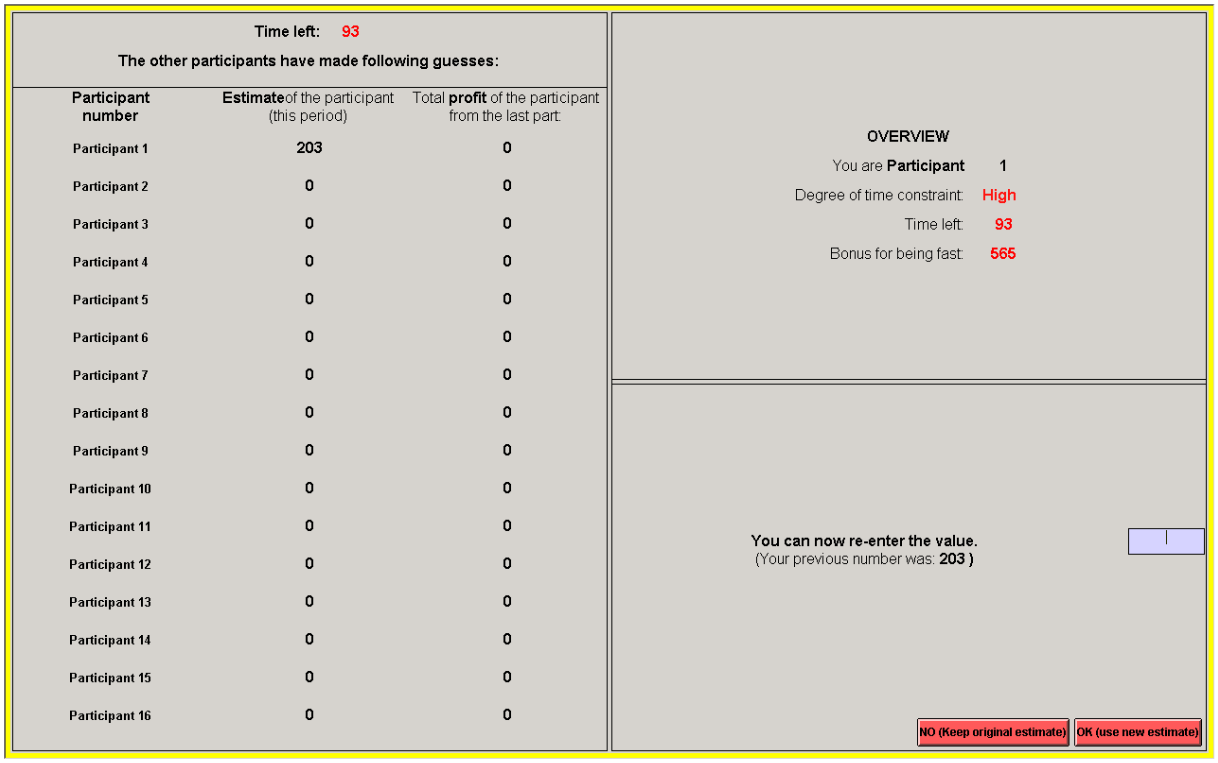


FIGURE 14

Questionnaire

After concluding the decision tasks, you will fill out questionnaire asking you about:

your preferences about **fairness** of division of 1000 CZK between you and an anonymous partner

your **personality profile**

your important **demographic characteristics** such as gender, field of work/study, etc.

Answers to these questions will be kept strictly confidential and will be used exclusively for research purposes.

There will also be a space for your feedback – please provide comments, suggestions, describe your strategy of solving the task, or comment on how you felt during the experiment. You can get extra bonus if we find the feedback outstanding.

Apart from these, on your table there is a **sheet of paper** with an additional task – choosing between a risky **lottery** and an amount of **cash** received for certain. Each line requires one choice. After you fill this piece of paper out, then me or my assistant will come, throw a dice and will write you the result on the paper. You will get signal when is the time to fill it out.

Summary

The experiment will consist of three parts, each with several rounds and different conditions, followed by a questionnaire at the end. You will be paid in cash at the end of the experiment. All information about your choices and payoffs in this experiment will be kept strictly confidential.

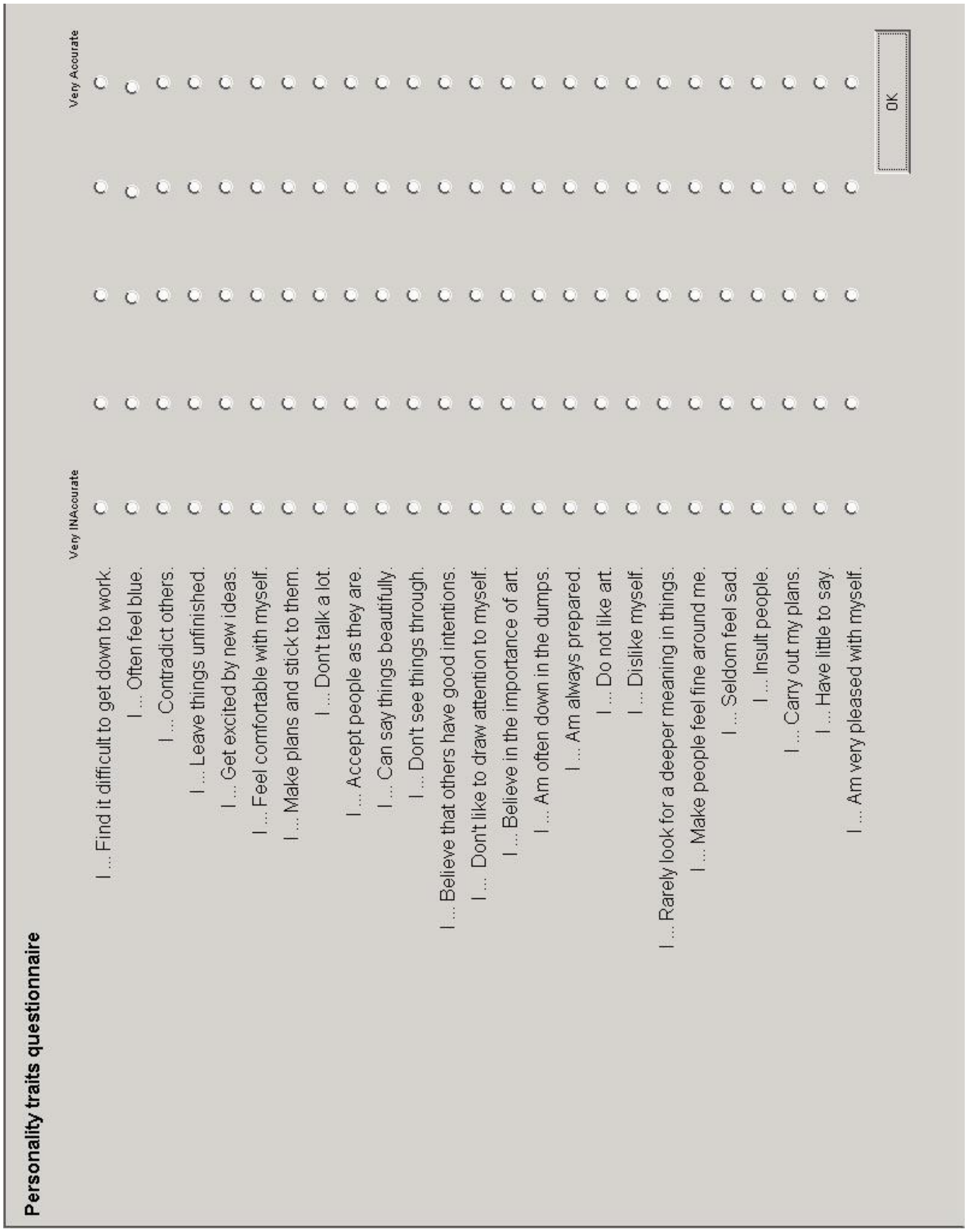
Please do not talk to the other subjects at any point during the experiment, even to ask questions about the instructions. If we hear you talking at any point during the experiment other than talking with me or one of my assistants, your participation in the experiment will be terminated without any payment. If you have any questions about any part of the instructions, please raise your hand now. We want everyone to understand the instructions before we begin the experiment.

What alternative would you prefere: an amount of cash or a lottery?

1	0 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
2	20 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
3	40 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
4	60 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
5	80 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
6	100 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
7	120 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
8	140 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
9	160 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
10	180 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
11	200 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
12	220 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
13	240 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
14	260 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
15	280 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
16	300 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
17	320 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
18	340 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
19	360 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%
20	380 ECU for sure	○	○	or lottery where you can win 600 ECUs with a chance of 50% or win 0 with chance of 50%

FIGURE 12: LOTTERY TASK

8.3 PERSONALITY TRAIT QUESTIONS USED IN THE EXPERIMENT



Personality traits questionnaire

Very INAccurate — Very Accurate

I ... Find it difficult to get down to work.
I ... Often feel blue.
I ... Contradict others.
I ... Leave things unfinished.
I ... Get excited by new ideas.
I ... Feel comfortable with myself.
I ... Make plans and stick to them.
I ... Don't talk a lot.
I ... Accept people as they are.
I ... Can say things beautifully.
I ... Don't see things through.
I ... Believe that others have good intentions.
I ... Don't like to draw attention to myself.
I ... Believe in the importance of art.
I ... Am often down in the dumps.
I ... Am always prepared.
I ... Do not like art.
I ... Dislike myself.
I ... Rarely look for a deeper meaning in things.
I ... Make people feel fine around me.
I ... Seldom feel sad.
I ... Insult people.
I ... Carry out my plans.
I ... Have little to say.
I ... Am very pleased with myself.

OK

FIGURE 13: PERSONALITY TRAIT QUESTIONS USED IN THE EXPERIMENT. THE FIRST PART.

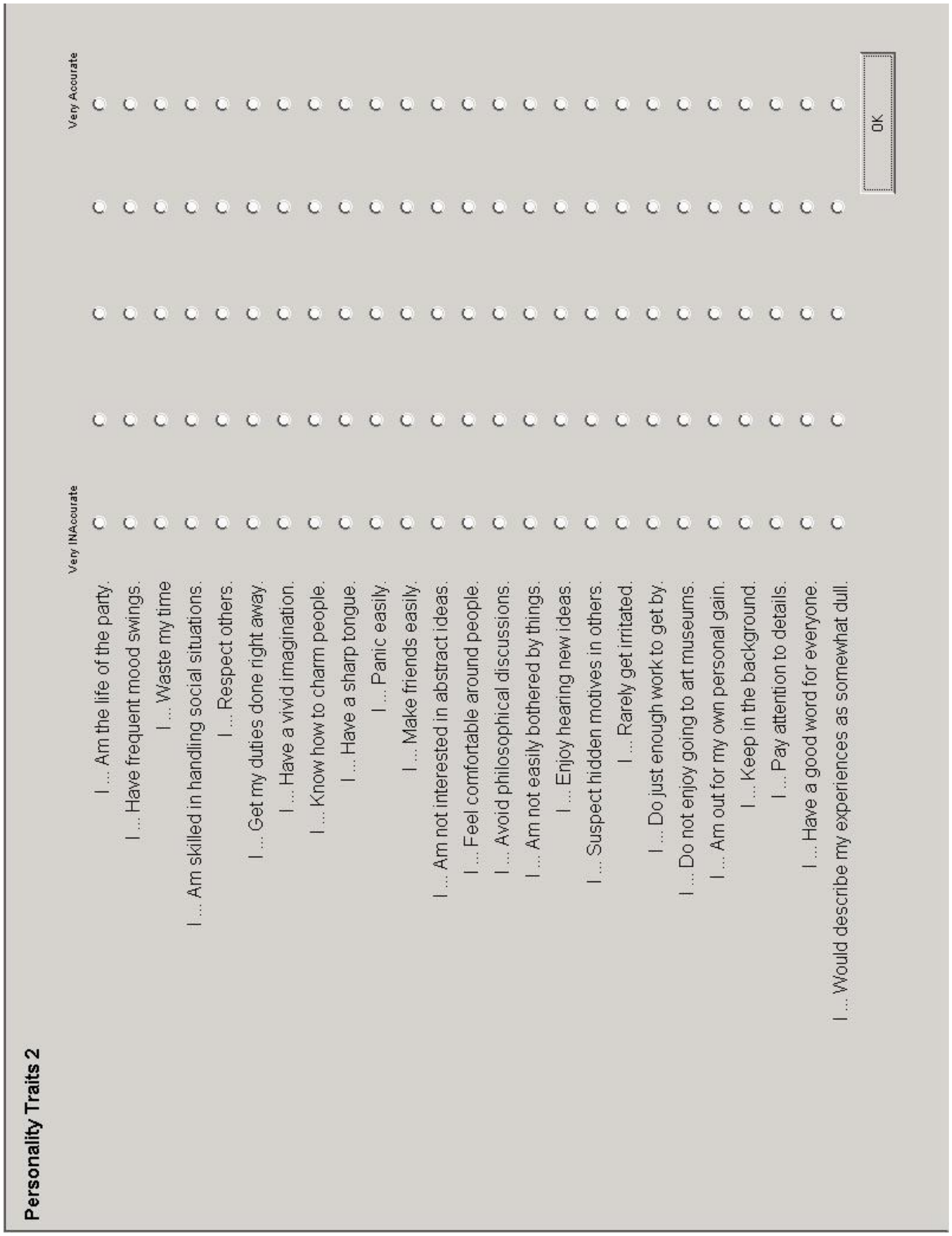


FIGURE 14: PERSONALITY TRAIT QUESTIONS USED IN THE EXPERIMENT. THE SECOND PART.

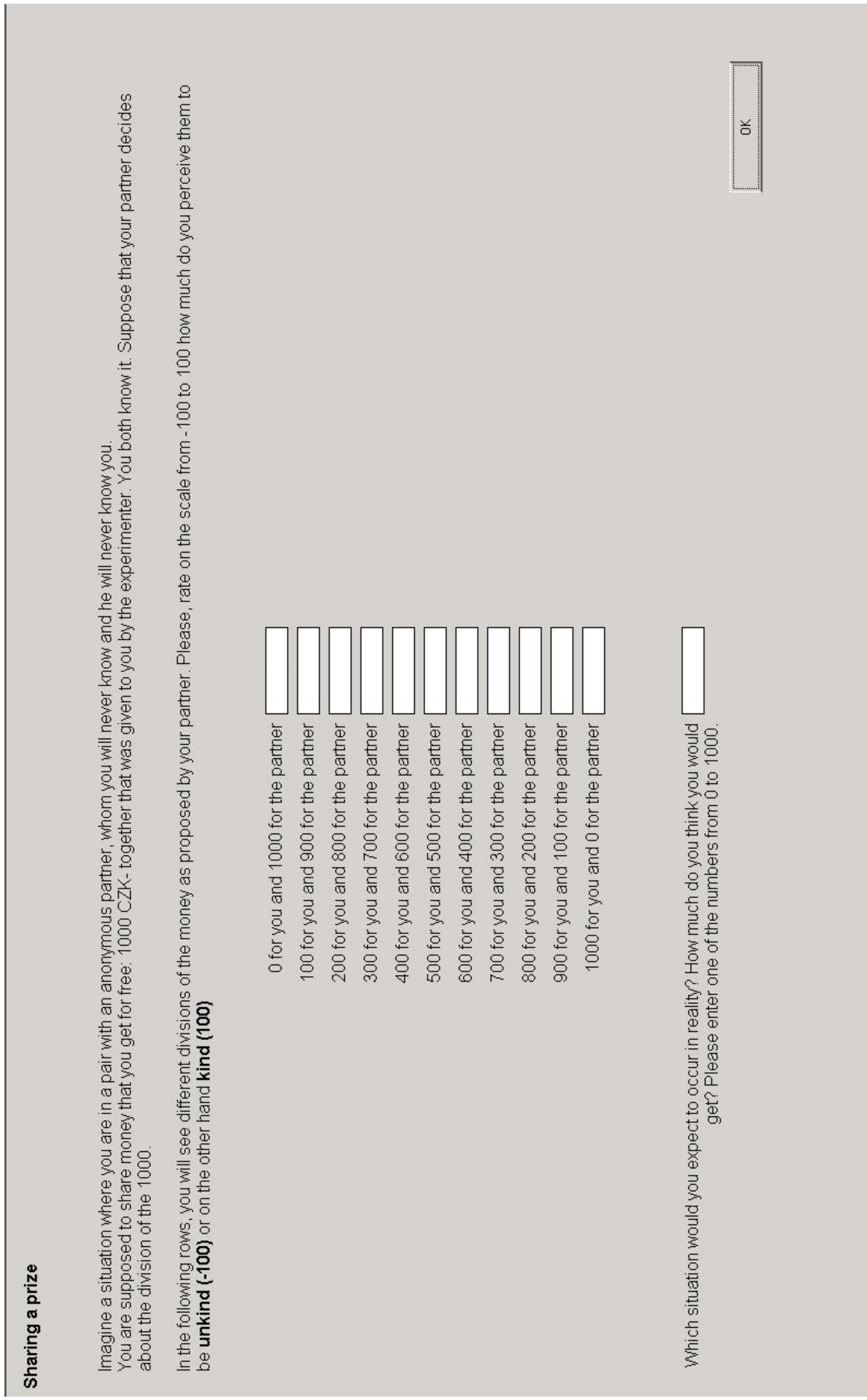


FIGURE 15: SCREEN WITH THE TASK OF EVALUATING KINDNESS OF DIVISION OF 1000CZK BASED ON FALK ET AL (2007).

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