Charles University in Prague
Faculty of Social Sciences
Institute of Economic Studies

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

Doctoral Thesis

Author: **Mgr. Lubomír Cingl**
Supervisor: **PhDr. Michal Bauer, PhD.**
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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 paper I attempt to model propensity to herd and infer its relationship to time-pressure by conducting a laboratory experiment. I let subjects perform a simple cognitive task under different treatment conditions and levels of time pressure with the possibility to herd. The order of decision-making is endogenous and the task is not probabilistic. Rather, I impose uncertainty of private signal by different levels of time pressure. This is expected to make participants prone to imitate the behavior of others. 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. The main findings are that propensity to herd was not significantly influenced by different levels of time pressure. Information cascades arose, but never in a perfect form. Personality traits measured by the Big Five protocol contribute considerably to the explanation of the model, but their relationship is not straightforward. Heart-rate increased during performance of a task, but was not correlated to subjectively stated level of stress. Moreover, it significantly influences the propensity to herd, but unexpectedly with a negative sign. The endorsement effect plays an important role in determining the probability to herd, but again unexpectedly with a negative sign.

JEL Classification: C25, C91, D03, D80

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

Author's email: Lubos.Cingl@seznam.cz

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. Za použití laboratorního experimentu se snažím modelovat sklon ke stádovému chování stejně jako sklon k zobrazení informace, která může ke stádovému chování vést. Účastníci experimentu měli za úkol splnit jednoduchou kognitivně nenáročnou úlohu za různých experimentálních podmínek. Úloha není pravděpodobnostní, ale nejistota ohledně vlastního signálu je tvořena různými stupni časové tísně. Očekávám, že tato situace přiměje účastníky k častější imitaci výsledků ostatních. Mezi hlavní výsledky patří, že sklon ke stádovému chování není významně odlišný ani v jedné ze tří úrovní časové tísně. Osobnostní charakteristiky měřené pomocí protokolu Big Five naproti tomu významně vysvětlují model, nicméně ani jejich vztah není vždy intuitivní. Informační kaskády nastaly, nicméně nikdy v perfektní formě. Tepová frekvence narostla v průběhu řešení úlohy, ale nebyla korelovaná se subjektivním údajem stresu. Tepová frekvence navíc významně predikuje sklon ke stádovému chování, nicméně se záporným znaménkem. Efekt reputace hraje významnou roli ve vysvětlení pravděpodobnosti ke stádovému chování, nicméně opět se záporným znaménkem, což jde proti původním očekáváním.

Klasifikace JEL: C25, C91, D03, D80

Klíčová slova: Informační kaskády, stádové chování, experimentální ekonomie, měření tepové frekvence, osobnostní charakteristiky

Autorův email: Lubos.Cingl@seznam.cz

Declaration of Authorship

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Prague, February 15, 2011

Signature

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DOCTORAL THESIS PROPOSAL –

Teze rigorózní práce

Name: Mgr. Lubomír Cingl
Supervisor: PhDr. Michal Bauer PhD.
Proposed name of the Thesis: **Do information cascades arise easier under time pressure? Experimental approach**.

<u>Topic characteristics</u>:

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.

<u>Hypothesis and research question</u>:

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?

<u>Methodology</u>:

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

Core Bibliography

- Bikhchandani, S., Hirshleifer, D. Welch, I., “A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades,” Journal of Political Economy, 100(5), 992–1026. 1992
- Anderson, L. and Holt, C.: “Information cascades in the laboratory.” American Economic Review 87, 847–62. 1997
- Anderson, L. and Holt. C.: "Information cascade experiments." The New Palgrave Dictionary of Economics. Second Edition. Eds. Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan, 2008. The New Palgrave Dictionary of Economics Online. Palgrave Macmillan. 28 October 2009
- Bikhchandani, S., Hirshleifer D., Welch, I..: "Information cascades." The New Palgrave Dictionary of Economics. Second Edition. Eds. Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan, 2008. The New Palgrave Dictionary of Economics Online. Palgrave Macmillan. 28 October 2009
- Falk, A., Dohmen, T., Huffman, D., and Sunde, U.: “Are Risk Aversion and Impatience Related to Cognitive Ability?” American Economic Review, forthcoming, 2009
- Camerer, C., Loewenstein, G. and Rabin, M.: "Advances in Behavioral Economics.” Princeton University Press, Princeton, 2003
- Kocher, M.G. , Sutter, M. : "Time is money—Time pressure, incentives, and the quality of decision-making." J. of Economic Behavior & Org. 61, pp. 375–392, 2006
- Ayal,S. and Hochman, G.: "Ignorance or Integration: The Cognitive Processes Underlying Choice Behavior." J. Behav. Dec. Making, 22: 455–474, 2009
- Falk, A., Huffman, D., Mierendorff, K.: “Incentive Effects and Political Acceptability of Workfare”, Working Paper, Institute for the Study of Labour (IZA), Bonn, Germany, 2006
- Falk, Menrath, Kupio and Siegrist: "Unfair pay and Stress." Discussion paper, 2008
- Malik, M., Bigger T. J., Camm, A. J., Kleiger, R.E., Malliani, A., Moss, A.J., and Schwartz P. J. : "Heart rate variability: Standards of measurement, physiological interpretation, and clinical use." European Heart Journal 17(3):354-381, 1996
- McEwen, B. M.: " Physiology and Neurobiology of Stress and Adaptation: Central Role of the Brain." Physiol Rev 87: 873–904, 2007

1 INTRODUCTION

1.1 CONTRIBUTION OF THIS PROJECT – MOTIVATION

In everyday life, we face lots of situations in which we have to make a decision and not always we have enough time to process all information which, furthermore, is not always available or perfectly trustworthy. Mostly 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 available information or 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. In other words, we face uncertainty about our private signal and thus we cannot be sure whether the action we want to make is the proper one or not. In such a case, it is sometimes 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, we become a part of what is called an information cascade. Moreover, people who face the same task after us and see us that we follow the action taken by others have even stronger motivation to believe that the action taken by others is the correct one. As a result, the incentive to herd reinforces. Eventually, there is a cascade of people taking the same action. However, not every time the action followed in the cascade is the correct one – there may emerge also so called reversed cascade, when players follow a wrong signal and subsequently do a wrong action. This situation can lead to an incorrect eventual outcome, as for example in case of smoking, when people get uncertain private information about the adverse effects of smoking but some decide to ignore this information, follow the crowd and smoke.

Apart from that, we often neglect the fact that human behavior heavily depends on the physiological state of the body. If everything goes fine, there is no need to worry about it, but in critical situations even the in-normal-situation-rational decision maker cannot control innate reactions of her body to exogenous stimuli. Lack of time for making decisions is often said to be the cause of stress reaction and the decision maker may behave differently than with the "cool head". A very prominent illustrative example of how the change of human behavior under time pressure can be severe is simply panic, be it in a crowd in a stadium or in financial markets.

The main goal of this paper 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 and the behavioral. 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. (2007)). I assume that both proposed explanations have some merits and flaws and I test whether both are relevant.

1.2 Contribution of experimental economics

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 part of it – of an individual – 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 generally 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 than 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 cannot be attributed to treatment only.

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 et al. (1992) Banerjee (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) Their 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 Bikhchandani et al. (1998)[1], 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[2] in BHW (1998) 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 when they compute[3], 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

[1] Further BHW (1998)
[2] This model is essentially the same as in BHW (1992)
[3] See exact computation in BHW (1998), pp. 153- 156

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. 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. Sharma and Bikhchandani (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" (Sharma and Bikhchandani (2000), pp. 291) and the owners cannot be sure about the true abilities of the portfolio manager. Apart from that, individuals may have concrete intrinsic preferences for conformity so 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. (2007) 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. What we can say with certainty about these natural instincts is that they 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 et al. (2009) for a cross-discipline review, please see Sharma and Bikhchandani (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). Weizsacker (2010) 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 information cascades was done by Anderson and Holt (1997)[4] 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

[4] further "AH"

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

Allsopp 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 PARI-MUTUEL BETTING: ANALOGY TO HORSE RACES

An original simulation of market conditions is in Plott et al. (2003) 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. (2007) 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*

Weizsacker (2010) 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 In (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 (2004) 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 Kogan (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. Kraemer et al. (2000) 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 Bikhchandani et al. (1992). 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 (2002) 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 (2003).

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 et al. (2003) review literature related to emergency-management decision-making under time pressure. They use the definition of stress as in Salas et al. (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,[5] 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

[5] 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.

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 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 then concludes that due to the primitive origin of herding behavior, it cannot 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. (2007)). 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. (2007) 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.

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 cannot 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 STRATEGY SELECTION

The closest paper to the relationship of time-pressure and propensity to herd is Rieskamp and Hoffrage (2008) 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.

3.2.2 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.

3.2.3 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. Sgroi (2003), 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.

3.2.4 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. (2010) 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). 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.

Hypothesis 2: 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.

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), pp.3 provides a very useful overview of the relationship between economics and psychology in the matter of measuring personality traits. Personality traits are defined as "patterns of thoughts, feelings and behavior." I 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[6] by Costa and McCrae (1992). I use

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

an inventory of questions very similar to it, however available for free from IPIP[7]. Formy-Duval (1993), pp. 5–61[8] 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

[7] *International Personality Item Pool: A Scientific Collaboratory for the Development of Advanced Measures of Personality Traits and Other Individual Differences* [Online]. Available: http://ipip.ori.org/ [Accessed].

[8] FORMY-DUVAL, D. L. 1993. Scaling the Adjective Check List for the Five-Factor Model of Personality. *Unpublished master's thesis.* Wake Forest University. As cited in: WILLIAMS, J. E., SATTERWHITE, R. C. & AND SAIZ, J. L. 2002. *The Importance of Psychological Traits,* London, Kluwer Academic Publisher. pp. 33-34.

by the traits artistic, imaginative, insightful, intelligent, original, clever, polished, inventive, sophisticated, and foresighted.

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. (2007) 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 3: Personality traits as part of the behavior-based approach toward herding significantly influence the probability of herding.

3.4 Risk attitudes

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. 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. I expect that risk-averse subjects 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 4: 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.

3.4.1 *VARIABLES SIGNIFICANT FOR RISK-TAKING*

Dohmen et al. (2008) 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[9] serves well as a predictor of the actual elicited risk-taking 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. 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. 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 5: Risk-preferences significantly influence the propensity to herd.

3.4.2 *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 Sharma and Bikhchandani (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

[9] 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."

make other participants follow her investment decisions is called by Hirshleifer and Teoh (2003) the *endorsement* effect. 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 6: Reputation (endorsement) 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.

3.4.3 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 (2007) 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[10].

3.5 MEASURING HEART RATE

Lo and Repin (2001) 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.

[10] If, for example, a subject expected to get 500CZK share and she previously reported perceived kindness over share of 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	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 3	Personality traits as part of the behavior-based approach toward herding significantly influence the probability of herding.
Hypothesis 4	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 5	Risk-preferences significantly influence the propensity to herd.
Hypothesis 6	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 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[11] of counting zeros from a sheet of 400 symbols 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*

[11] for more details see the part Task in section General Description

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. (2007) would interpret it as a sign of Bayesian updating and if significant, this variable would 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 0-1 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 26 dand 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 3 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 5, 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[12]," 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-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

[12] See Figure 9 in the Appendix.

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 have positive sign 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.

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 6. Summary of the expected effect is in the Table 2.

		InfoShown		*InfoUsed*	
VARIABLES	LABELS	Significant?	Expected sign	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)*

3.8 Model Estimation - Technique

Because I assume that the probability to herd or the probability to view the publicly available information is a binary random variable, I decided to use standard logistic regression. It can be shown that the difference between the logit and probit is rather only in computational requirements (e.g. Cameron and Trivedi (2005)). Even though this technique is probably well known to the reader, I rather include in the section 8.1 in the Appendix description of the underlying mechanism of the estimation and the post-estimation techniques that I use later on in the section 6 with the results of the model. Apart from the logistic regression I also apply the Heckman two-stage estimator as the structure of the data fulfills its requirements and due to the possible correlation of residuals of the two equations I may get efficiency gains by the correction for selection bias. Because in both selection and estimation equations the explained variable is binary, I use the modification known as Heck-probit. As this technique is not widely known, I introduce it in the section 8.1.5 in the Appendix.

3.8.1 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,* is as follows:

$$\log\left(\frac{\Pr[View]}{1-\Pr[View]}\right) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{16} ExpectedKindness + \beta_{17} HR_{DIF} + \epsilon \qquad (3.8.2.1)$$

3.8.2 Model: Probability of herding

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

$$\log\left(\frac{\Pr[Switch]}{1-\Pr[Switch]}\right) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{16} ExpectedKindness + \beta_{17} HR_{DIF} + \beta_{18} score + \beta_{19} score2 + \beta_{20} TimeDeciding + \epsilon \qquad (3.8.3.1)$$

3.8.3 Heckman two stage estimation

In case of the experiment in this thesis, the *selection equation* is specified similarly as the equation where the dependent variable is *InfoShown* (3.8.2.1) and the estimated *probit equation* is similar to the equation for *InfoUsed* (3.8.2.2). 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 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 (3.8.3.1) as the *selection equation* and (3.8.3.2) as the *probit equation*.

Selection equation

$$\Phi^{-1}\,(\Pr[View]) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{17} HR_{DIF} + \epsilon \qquad (3.8.3.1)$$

Probit equation

$$\Phi^{-1}\,(\Pr\,[Switch]) = \alpha + \beta_1 Reputation + \beta_2 SelfConfidence + \beta_3 TimeLeft + \beta_4 TP_{Medium} + \beta_5 TP_{High} + \beta_6 O + \beta_7 C + \beta_8 E + \beta_9 A + \beta_{10} N + \beta_{11} SubjectiveStress + \beta_{12} Female + \beta_{13} CE + \beta_{14} RiskAverse + \beta_{15} lnTotProf + \beta_{16} ExpectedKindness + \beta_{17} HR_{DIF} + \beta_{18} score + \beta_{19} score2 + \beta_{20} TimeDeciding + \epsilon \qquad (3.8.3.2)$$

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 (2007)) except for the task where they had to elicit their risk-preferences[13]. 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, which proved to be very helpful.

4.2 TASK: COUNTING ZEROS

4.2.1 DESCRIPTION OF THE TASK

The participants performed a simple cognitive effort task, which was not supposed to 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.[14] The task is quite tiring and not very interesting, as Falk et al. (2006) 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)

[13] the so-called lottery card, see Figure 12 in the Appendix
[14] However, at every session there was at least one subject who tried it more than once.

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.

4.2.2 PAY-OFF FUNCTION

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[15].

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

4.3 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[16] 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

[15] For the analysis I fortunately have the exact lengths of the participants' performances.
[16] Instructions are available upon request from the author

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.

4.3.1 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.

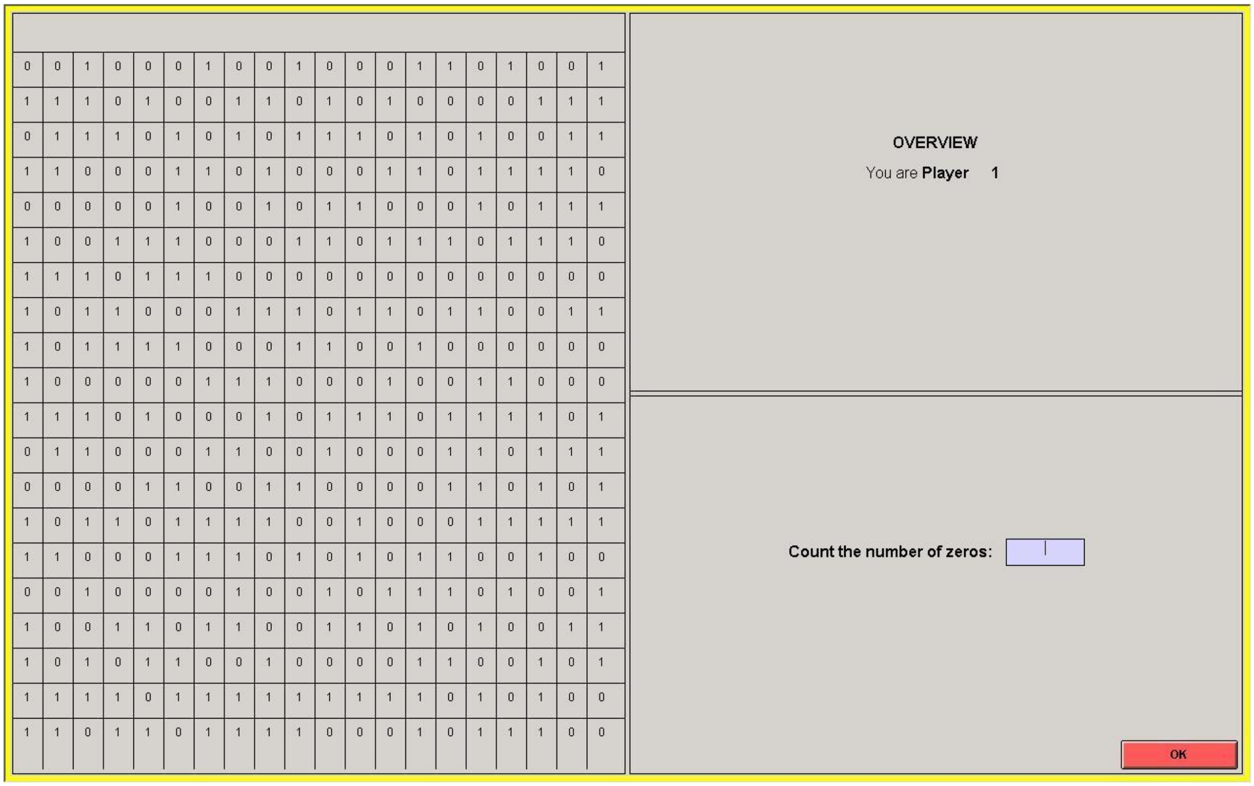


FIGURE 1: TASK SCREEN OF THE TREATMENT 1

4.3.2 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. 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 3) 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. 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 4), 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. 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.

4.3.3 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 9 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.

4.3.4 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 5 in the Appendix). 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[17] (see Figure 6 in the Appendix for the appearance of the decision screen, but without the past performance; and Figure 2 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.

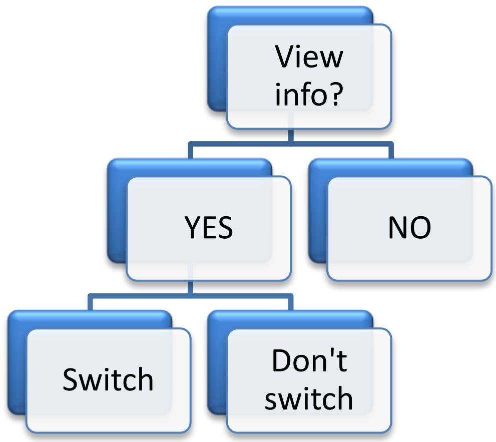


FIGURE 2: SCHEME OF DECISION TREE FACED IN THE TREATMENT 3 AND 4 AFTER SETTING THE ORIGINAL ESTIMATE.

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.

4.3.5 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 6). 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.

4.3.6 Questionnaire: Personality traits, social preferences and other

[17] 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.

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 Fischbacher (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.

4.3.7 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 (2001).

I had 17 heart-rate monitors Polar R-400 for my disposal from the Laboratory of Sport Motor Control at the School of Sports and Physical Education of the Charles University in Prague.[18] 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[19] on some subjects so the data coverage was not full.

4.3.8 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.

[18] In Czech: Laboratoř sportovní motoriky FTVS UK
[19] 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[20]. 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. (2007) 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.

[20] 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[21] so statistically there was no real difference which opposed Hypothesis 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 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

[21] 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	Day 1			Day 2		
	Session 1	Session 2	Session 3	Session 1	Session 2	Session 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

True number of zeros in the sheet

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[22] 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

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

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

During the first day, when only the third treatment was applied, there was no significant[23] 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 NO INFO VS. INFO VS. EXTENDED INFO

In Table 9 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.

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

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 9: 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 5.5.2 – 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 [24] 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 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.

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

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 10: 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.

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

5.4 OTHER IMPORTANT ATTRIBUTES

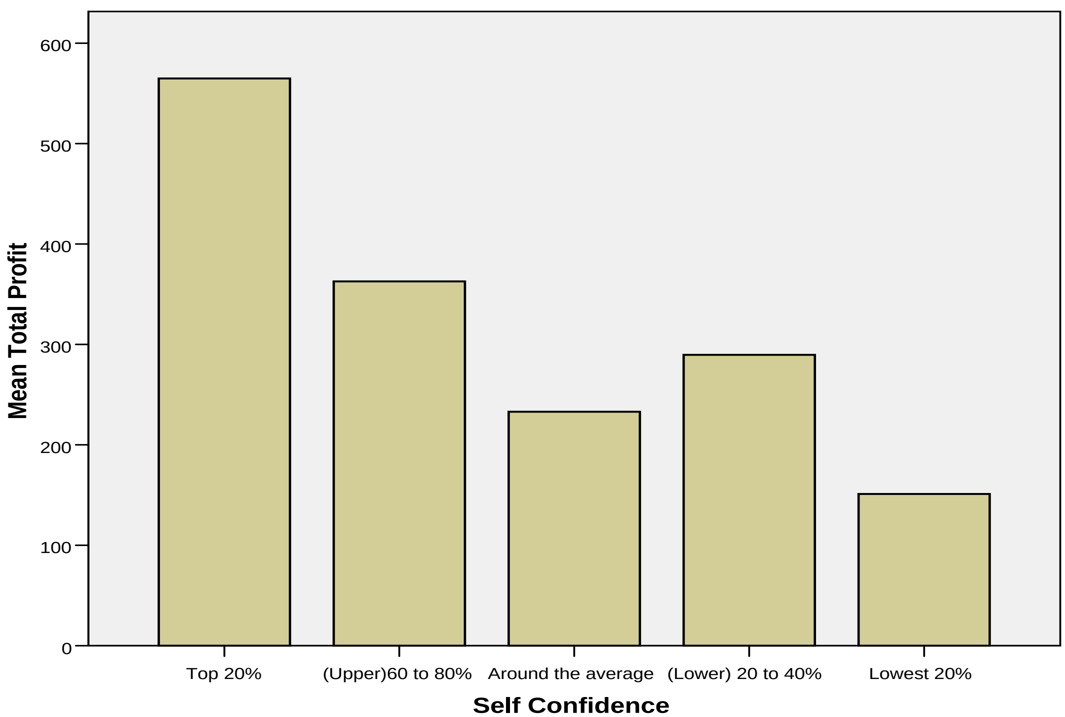
5.4.1 SELF CONFIDENCE: ONLY LESS THAN A THIRD OF SUBJECTS WERE CORRECT

In Graph 1 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 12: REPORTED SELFCONFIDENCE IN CONTRAST WITH REAL RELATIVE RESULTS

In Table 12 there is an evaluation of whether the subjects guessed their relative ranking correctly or not: we can see why the relationship in Graph 1 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).



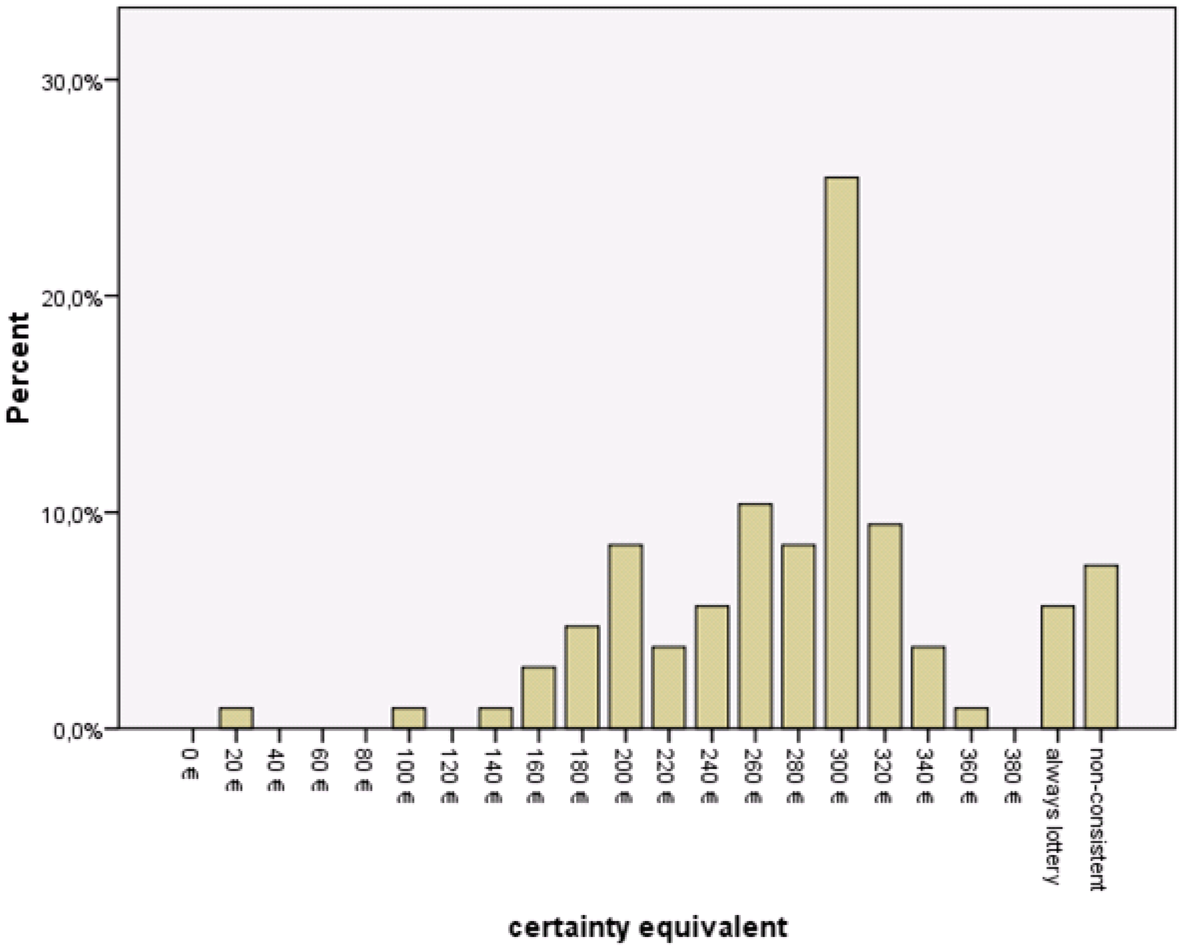
GRAPH 1: REPORTED SELF-CONFIDENCE AND MEAN TOTAL PROFIT

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.

5.4.3 *RISK PREFERENCES: CERTAINTY EQUIVALENT*

The attitude to risk was elicited by the lottery card (see Figure 9 in the Appendix) and from the stated certainty equivalent we can infer the individual attitude to risk as Dohmen et al. (2009) did. They did the research on a large representative sample and they found 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 and with increasing age the willingness to take risks decrease. 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. The distribution of the stated certainty equivalents is in Graph 2.



GRAPH 2: DISTRIBUTION OF CERTAINTY EQUIVALENTS

5.4.4 *SUBJECTS' "PLAYER" PROFILES*

Hypothesis 2 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 In (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 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 13 –

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 13: RATE OF SUCCESS OF SWITCHING THE ESTIMATE

5.5.3 *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.

5.5.4 *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 14 even though the rate seems to be a little higher under Low level of time pressure. This obviously opposes Hypothesis 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 14: 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 (further on 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.

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 15: 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[25] (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 15. 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.[26]

[25] 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.

[26] 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

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 7 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 8 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 AND RISK-PREFERENCES

During 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 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 16: DIFFERENCE OF QUIESCENT TO ACTUAL HR (*HR_DIF*) ACROSS PERIODS

maximum HR; that is by 22 year old subject about 160. Here we got 150, which equivalent to running HORČIC, J. & FORMÁNEK, J. 2003. *Triatlon: Historie, trénink, výsledky,* Praha, Olympia.

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 17 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 6.2.5.4 and 6.3.4.

		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 17: 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 18: COMPARISON OF MEANS OF *HR_DIF* FOR DIFFERENT LEVELS OF STATED SELF-CONFIDENCE AND OF THE REAL RELATIVE RANKING

A very important part of analysis is to compare the levels of both subjective and physiological stress with respect to the risk attitudes. Table 19 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 4.

		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 19: 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 0 and 3.8.2 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*.

I first compared 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 checked the stability of coefficients when this variable was excluded. Results were merely the same: all coefficients had the same sign and almost always the same significance, too. At this stage of analysis I also check for multicolinearity 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.

6.1 HECKMAN'S PROBIT WITH SAMPLE SELECTION

6.1.1 CHECKING ASSUMPTIONS

Following the introduction to the method from the section 8.1.5, 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 3.8.3, 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 multicolinearity as well as the normality of residuals so the assumptions for the correct estimation are set.

6.1.2 *RESULTS*

The results are as you can see in the Table 20. 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 loses 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 cannot accept this model.

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.

	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**	

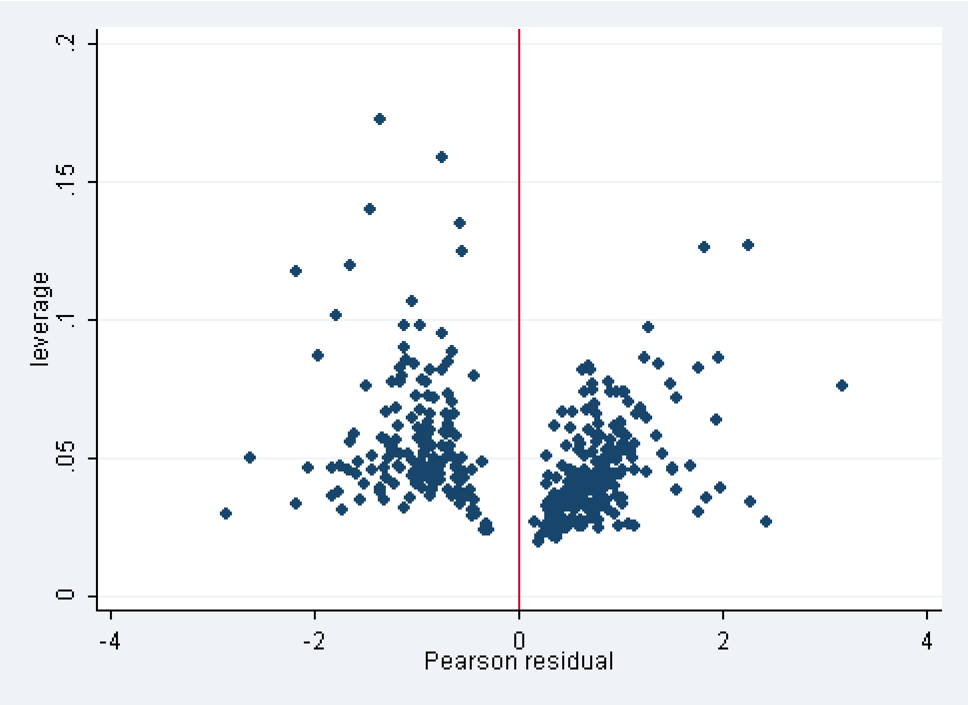
TABLE 20: HECKMAN'S PROBIT WITH SAMPLE SELECTION. NOTE: *, ** AND *** INDICATE SIGNIFICANCE ON 10%, 5% AND 1%, RESPECTIVELY. STADARD ERRORS IN BRACKETS.

6.2 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 cannot be influenced by the latest fashion trends.

6.2.1 LEVERAGE POINTS IDENTIFICATION

To identify the influential observations, I plot the Pearson residuals vs. leverage, which gives me Graph 3 , 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 3: PEARSON RESIDUALS VS. LEVERAGE.

6.2.2 TECHNIQUE USED

In Table 21 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.

6.2.3 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[27], 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[28] role and, as in the case of personality traits, should not be excluded.

Baddeley et al. (2007) 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

[27] 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.

[28] 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	0.246	0.260	0.254	0.231	0.342*	
	[0.262]	[0.211]	[0.237]	[0.262]	[0.259]	[0.193]	
TimeLeft	0.011**	0.006	0.008*	0.011**	0.013***	0.005	
	[0.005]	[0.004]	[0.004]	[0.004]	[0.005]	[0.003]	
TP_Medium	-0.183	-0.342	-0.224		-0.141	-0.308	
	[0.293]	[0.255]	[0.285]		[0.294]	[0.237]	
TP_High	0.022	-0.225	-0.077		0.097	-0.186	
	[0.336]	[0.294]	[0.324]		[0.331]	[0.262]	
O	-0.022	-0.023		-0.022	-0.015		-0.017
	[0.028]	[0.022]		[0.028]	[0.027]		[0.026]
C	0.067***	0.073***		0.066***	0.063***		0.069***
	[0.025]	[0.021]		[0.025]	[0.024]		[0.024]
E	-0.003	-0.002		-0.003	0.002		-0.019
	[0.025]	[0.021]		[0.025]	[0.024]		[0.024]
A	0.096***	0.060**		0.096***	0.093***		0.072**
	[0.032]	[0.028]		[0.031]	[0.028]		[0.029]
N	0.084***	0.069***		0.084***	0.092***		0.073**
	[0.029]	[0.024]		[0.029]	[0.028]		[0.029]
Subjective-Stress	0.056	0.038	0.032	0.058	0.048		0.034
	[0.053]	[0.045]	[0.049]	[0.052]	[0.053]		[0.048]
Female	-0.023	-0.066	0.147	-0.027	0.231	0.628***	
	[0.313]	[0.253]	[0.281]	[0.312]	[0.281]	[0.194]	
CE	-0.173***	-0.173***	-0.146***	-0.173***			-0.167***
	[0.055]	[0.049]	[0.049]	[0.055]			[0.047]
RiskAverse	-1.393***	-1.518***	-1.467***	-1.394***			-1.503***
	[0.411]	[0.347]	[0.387]	[0.405]			[0.381]
Self-Confidence	0.680***	0.460***	0.532***	0.678***	0.592***		0.693***
	[0.122]	[0.087]	[0.109]	[0.122]	[0.114]		[0.119]
lnTotProf	0.016	0.026	0.013	0.018	0.031	0.005	
	[0.057]	[0.048]	[0.056]	[0.056]	[0.055]	[0.045]	
Expected-Kindness	-0.002	-0.001	-0.000	-0.002	-0.001		-0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]		[0.002]
HR_DIF	-0.050***		-0.033**	-0.050***	-0.044***		-0.050***
	[0.016]		[0.014]	[0.016]	[0.015]		[0.016]
Constant	1.549	2.100*	1.670	1.493	-2.234***	-0.178	2.342**
	[1.349]	[1.160]	[1.204]	[1.268]	[0.841]	[0.413]	[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 21: LOGISTIC MODEL OF *INFOSHOWN*. NOTE: ROBUST STANDARD ERRORS IN PARENTHESES. *, ** AND *** INDICATE SIGNIFICANCE OF A FACTOR ON 10%, 5% AND 1% LEVEL, RESPECTIVELY.

6.2.4 EXPLANATORY POWER OF THE FULL MODEL[29]

As described in the section 0, 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

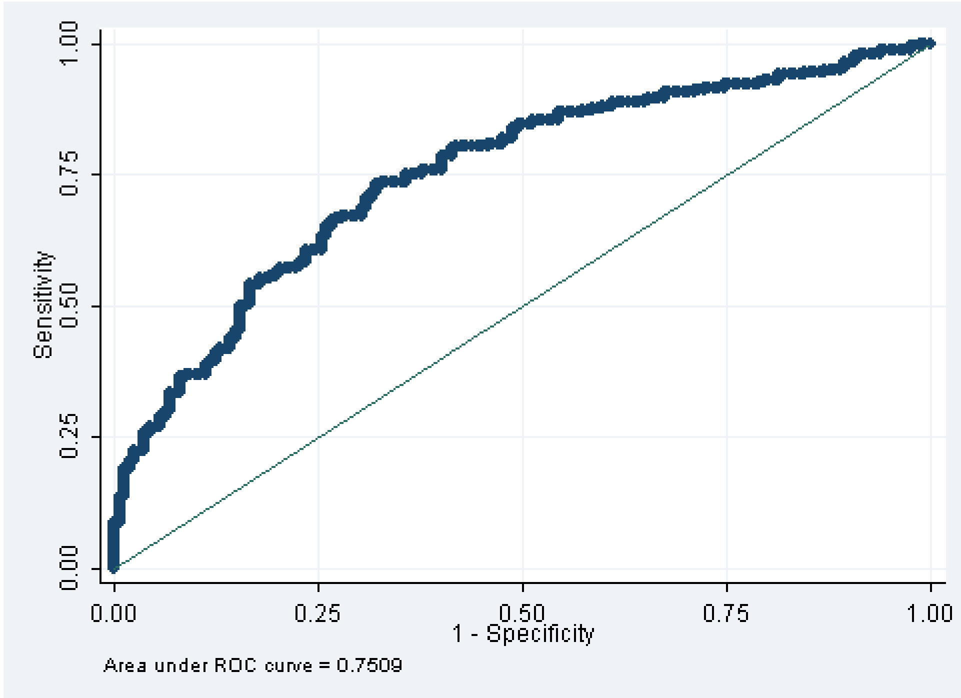
TABLE 22: CLASSIFICATION TABLE OF OBSERVED VS. PREDICTED OUTCOMES. TRUE *D* DEFINED AS INFOSHOWN = 0; CORRECT CLASSIFICATION OF CASE: + IF PREDICTED PROBABILITY > 0.5. CORRECTLY CLASSIFIED CASES: 69.21%

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 8.1.4: 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 4. 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.

[29] 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 4: THE ROC CURVE FOR FULL MODEL OF INFOSHOWN.

6.2.5 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 21 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*

6.2.5.1 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.

6.2.5.2 Attitude to risk

RiskAversion and *CE* are, of course, correlated[30], 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.

6.2.5.3 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).

6.2.5.4 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 performed task and the base level of heart rate. The relationship to *InfoShown* implies that the higher

[30] $\rho = -0.713$

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[31]. 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.

6.2.5.5 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.

6.2.6 *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 23.

[31] 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 23: PERCENTAGE CHANGES IN PREDICTED PROBABILITIES

6.2.6.1 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.

6.2.6.2 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.

6.2.7 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.

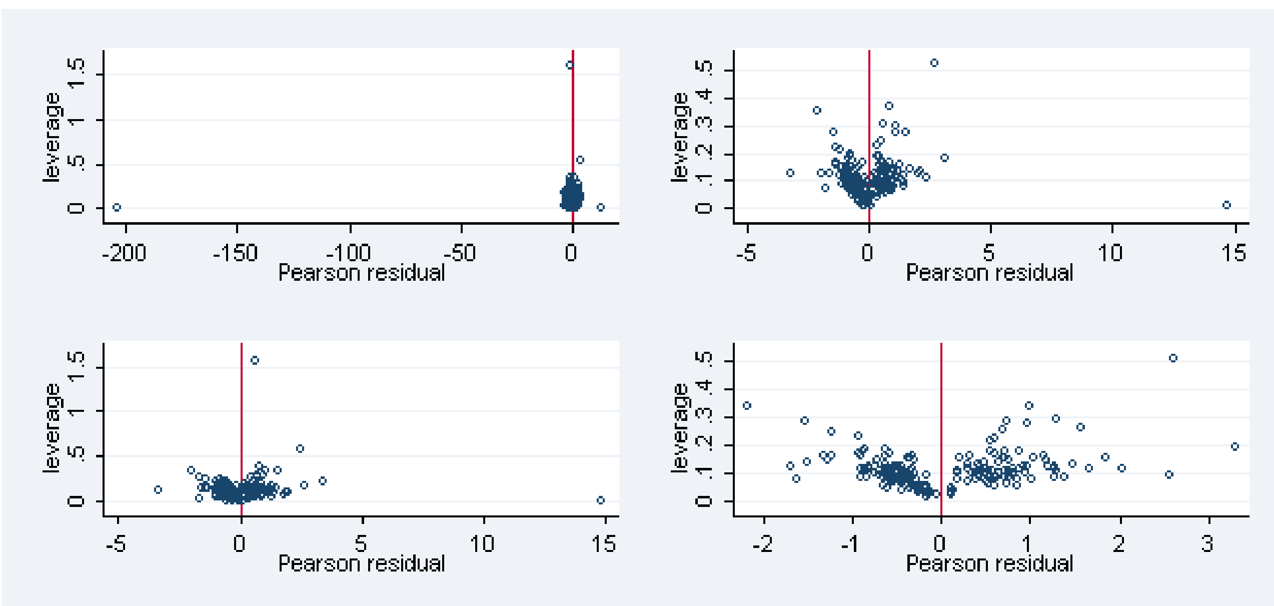
As analyzed at the beginning of this section, the model as such has a satisfactory explanatory power; it was tested for stability of coefficients and the possible heteroskedasticity problem was prevented by using robust standard errors and the leverage points were analyzed in Graph 3: Pearson residuals vs. leverage., where we concluded that no significant leverage points exist. Even if we consider that we are dealing with micro-data, then pseudo-R^2 of 0.14 also does seem rather small.

6.3 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.

6.3.1 LEVERAGE POINT DETECTION

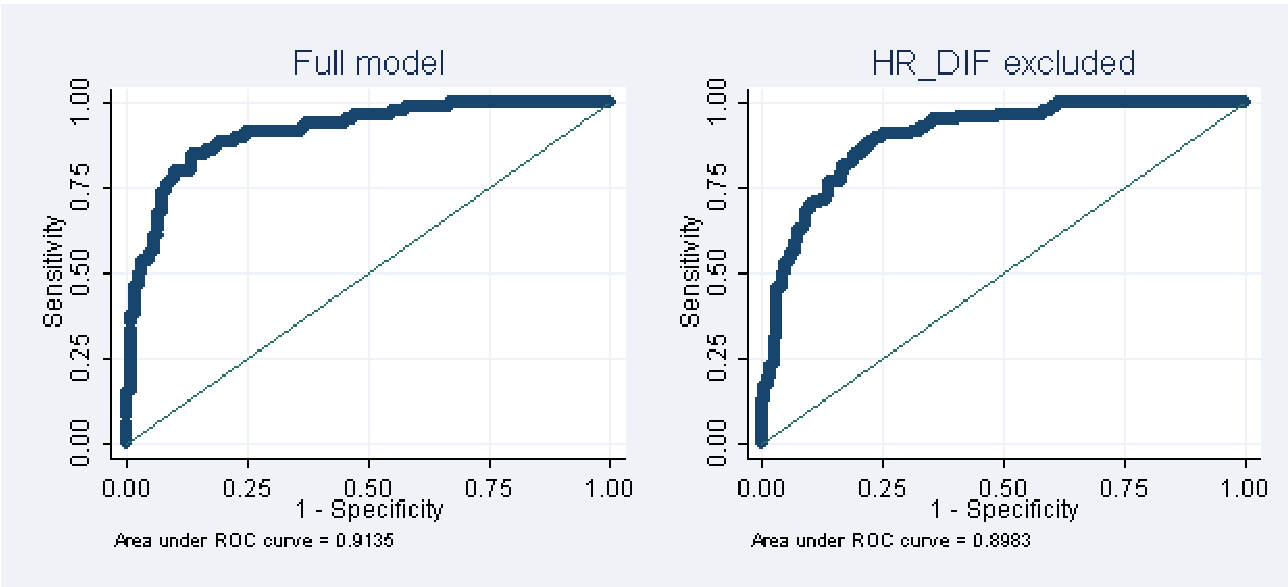
Before choosing the right model, I excluded the influential observations. By using the predicted Pearson residuals and leverage, I found 4 very influential points, which were the same for both models (with or without *HR_DIF*) and in Graph 5 you can clearly see the effect of their removal. In the end 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 5: LEVERAGE POINT IDENTIFICATION AND REMOVAL (MIND THE DIFFERENT SCALES OF BOTH X AND Y AXES)

6.3.2 MODEL SELECTION

Choice of a proper specification is then not very clear: as you can see in Table 24, 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 6, the area under the curve is slightly but insignificantly larger in case of the full model.



GRAPH 6: 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 [32] 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.

[32] BIC stands for Bayesian information criterion, which is often known as Schwartz criterion 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 24: 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 25: 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 25 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.

6.3.3 STABILITY OF COEFFICIENTS – EXCLUSION OF GROUPS OF VARIABLES

Table 24 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[33] 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.

[33] The value of LR χ^2 (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.

6.3.4 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.

6.3.4.1 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.

6.3.4.2 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).

6.3.4.3 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.

6.3.4.4 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 cannot 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.

6.3.4.5 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.

6.3.4.6 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.

6.3.5 Coefficients – Percentage Changes

6.3.5.1 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 26 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 6.2.6 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 26: PERCENTAGE CHANGES IN PREDICTED PROBABILITY OF INFOUSED WRT TO CHANGE IN PARTICULAR VARIABLE.

6.3.5.2 “Min to max” change

Table 26 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 cannot really take this result seriously.

6.3.5.3 *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 27)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 27: CHANGE IN PREDICTED PROBABILITIES OF INFOUSED WITH RESPECT TO CHANGE IN PARTICULAR VARIABLES. *SCORE* IS FIXED.

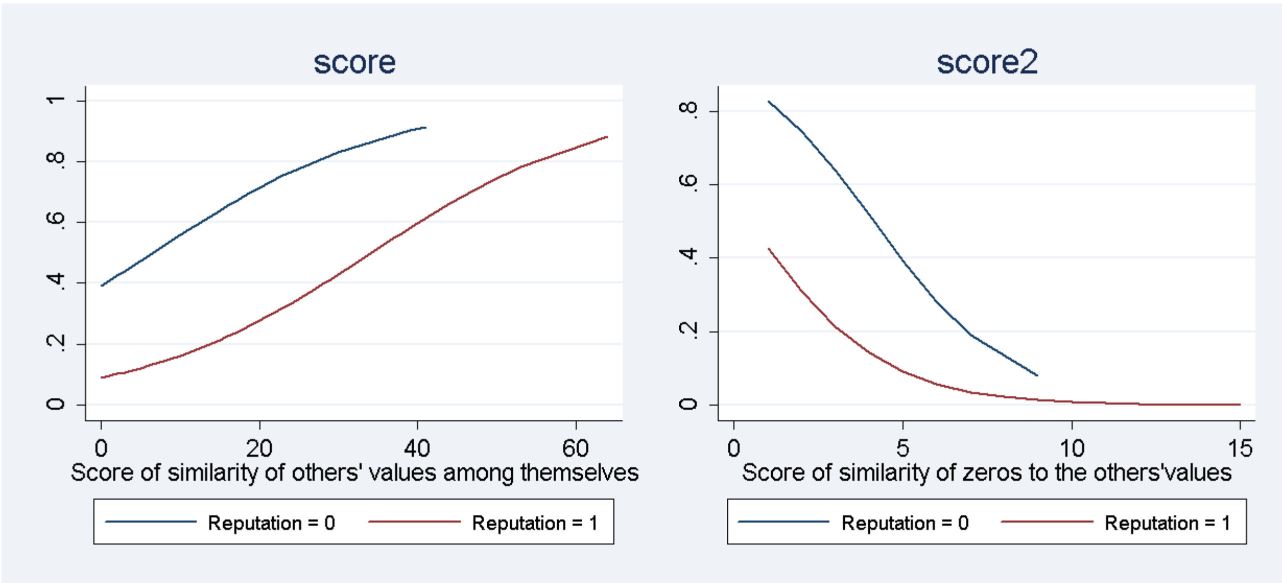
On the other hand, if we set the *score* to be the highest value, 64, the difference in the predicted probability becomes to be (-) 93.8%, which is again intuitively correct. If there are only similar estimates on the public screen, then if one's own estimate changes from totally unlike to totally alike, 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.

6.3.5.4 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.

6.3.5.5 Reputation

The effect of presence of the reputation of others can be well seen in Graph 7 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 7: VARIATION OF CHANGE IN THE PREDICTED PROBABILITY (THE Y-AXIS) WITH RESPECT TO CHANGES IN *SCORE* AND *SCORE2*.

6.3.5.6 Relative importance: difference of ½ SD

If we go back to Table 26, 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.

6.3.6 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 than 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 cannot 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 (2008) 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. 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 28, 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, it was however disconnected by the "honest" subjects who revealed the true information. This result actually supports the continuous critique as in Lee In (1993) and fragility of cascades in general.

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

7.2 HYPOTHESES EVALUATION

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 6.3.4, 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 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 6.3.5.3 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 3

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 4 and 5

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 4 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 5 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 6.2.5 but the direction is the opposite: the propensity to look at the public information is negatively influenced by the risk-aversion. In section 5.6.3 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 4. Similarly, we have to reject Hypothesis 5 because risk preferences do not significantly influence the propensity to switch from the original estimate.

Hypotheses 6 and 7

The sixth hypothesis concerned the role of the reputation effect (or endorsement effect as originally called). In section 3.4.2 I discussed that the expected effect on the probability of switching should be significantly positive. In section 6.3.4.5 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 8

The last 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.[34] 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 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 8 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.

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

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

To summarize, 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 a 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. 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 they occasionally made mistakes.

8 APPENDIX

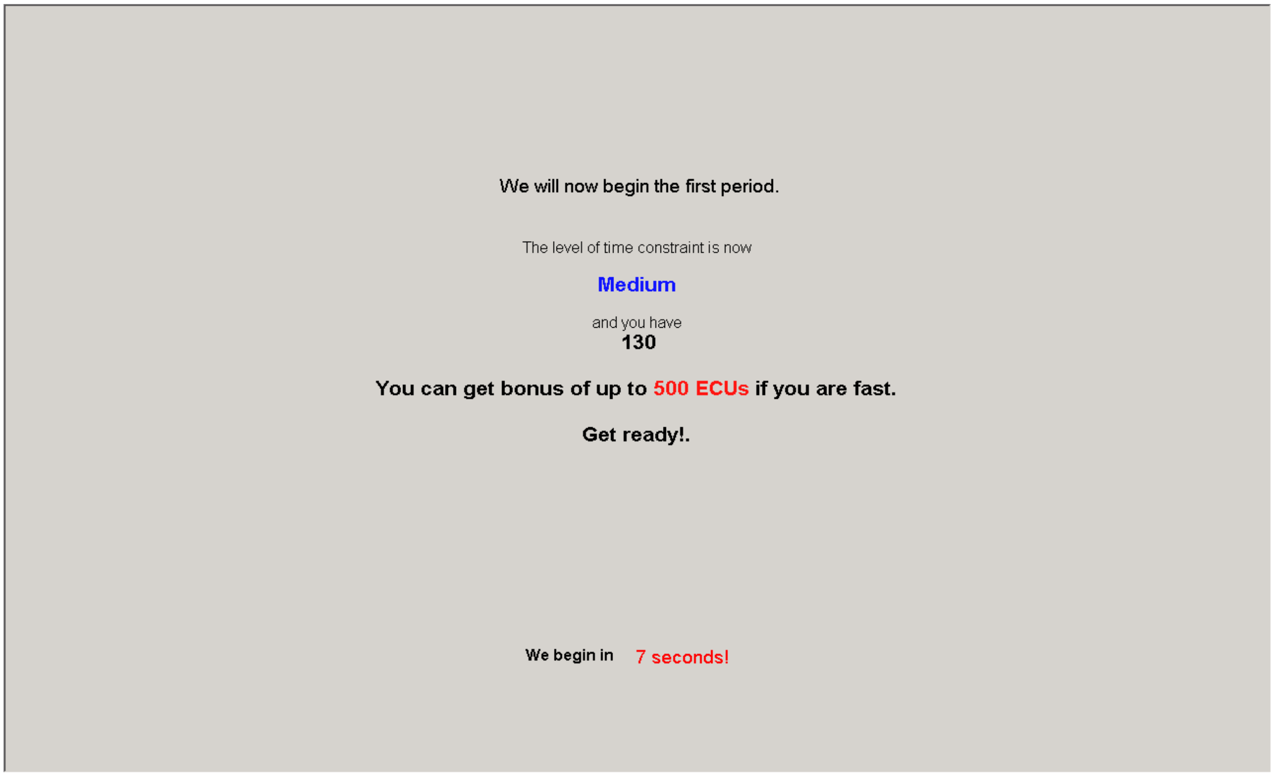


FIGURE 3: INTRODUCTION SCREEN

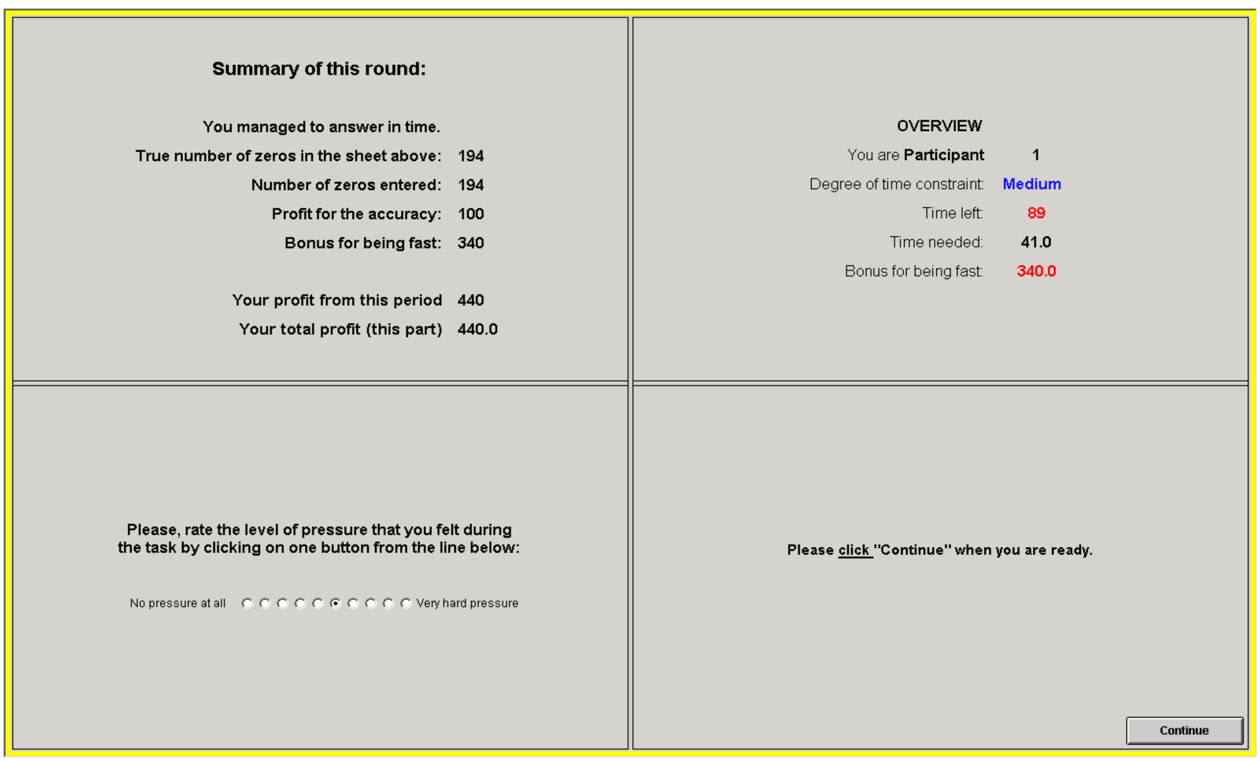


FIGURE 4: SUMMARY SCREEN

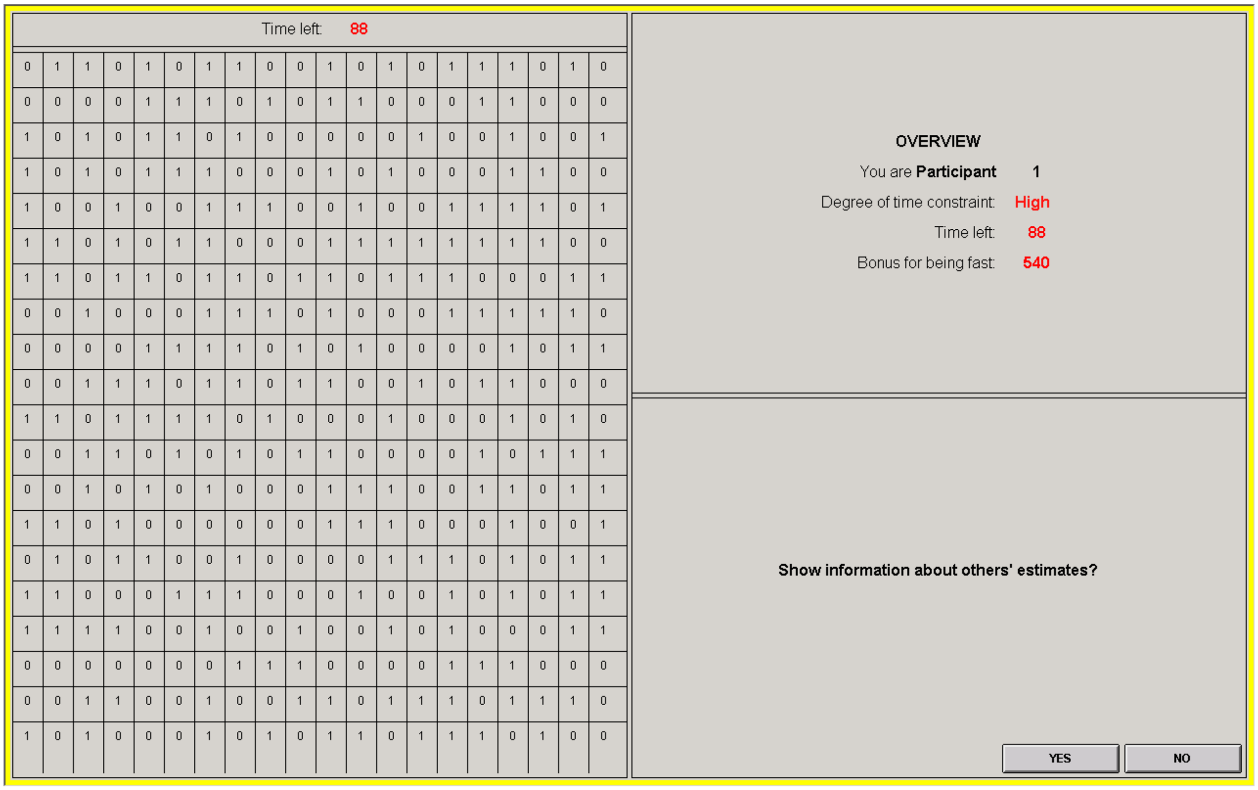


FIGURE 5: DECISION SCREEN

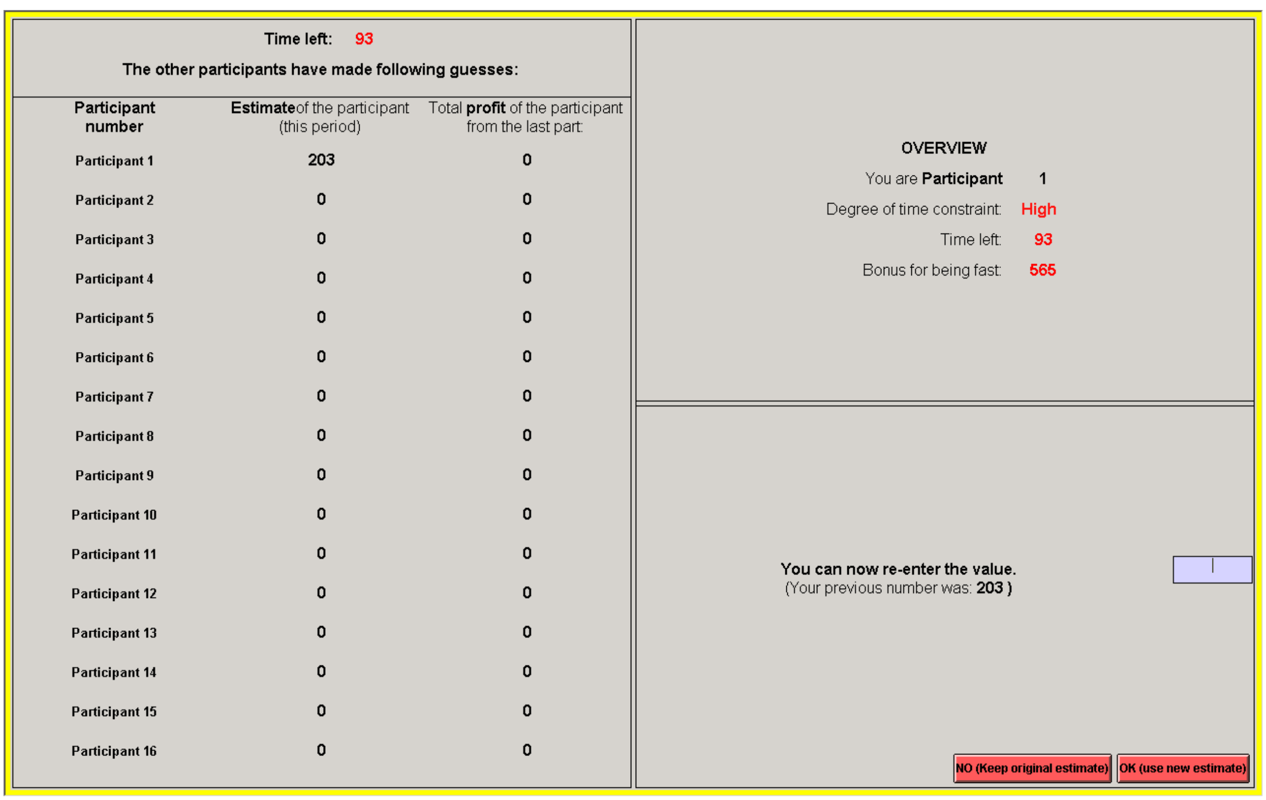


FIGURE 6: SCREEN WITH THE PUBLIC INFORMATION (SITUATION OF THE FIRST ESTIMATE SET)

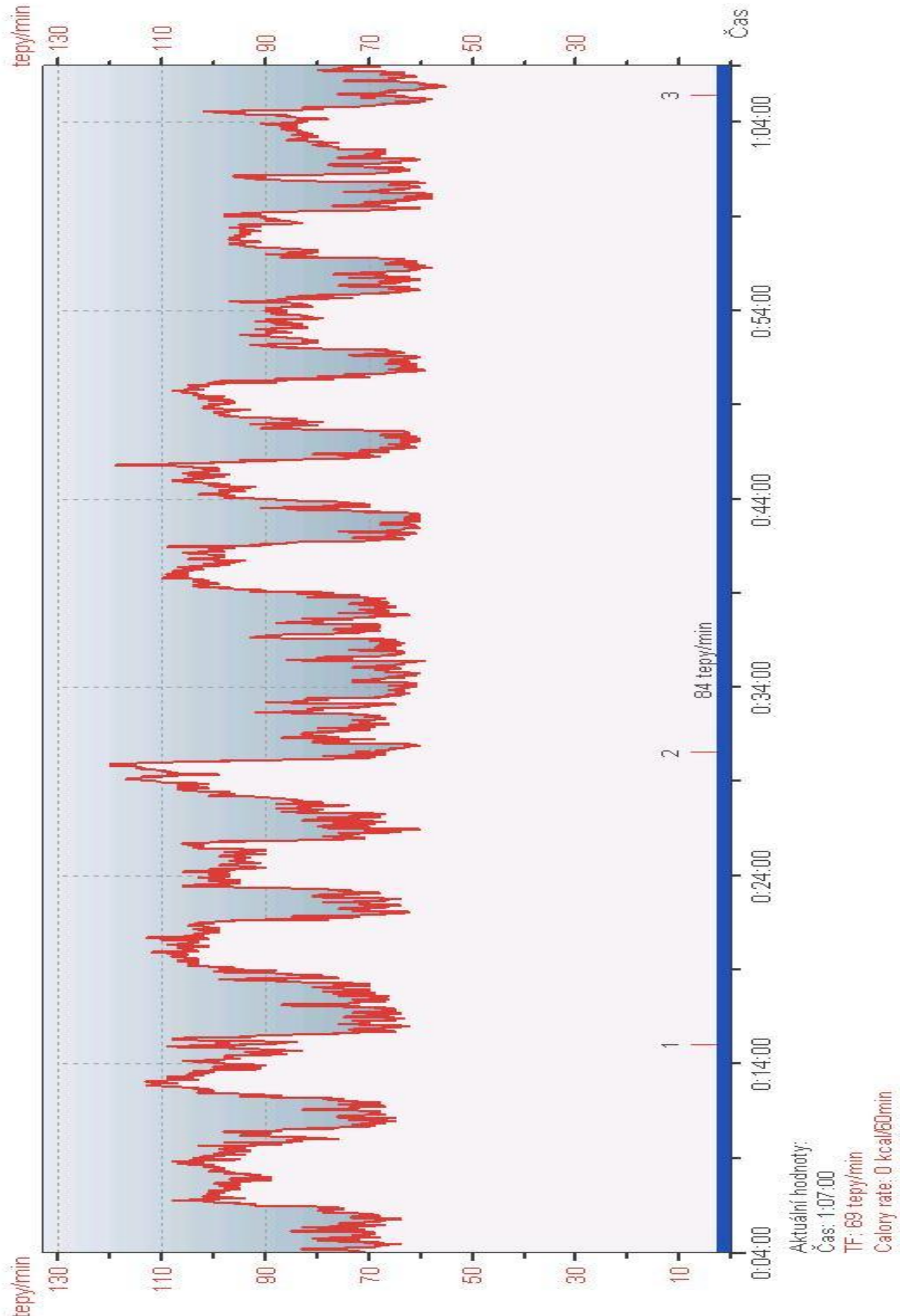


FIGURE 7: CURVE OF HEART RATE FROM THE HR-MONITORS.

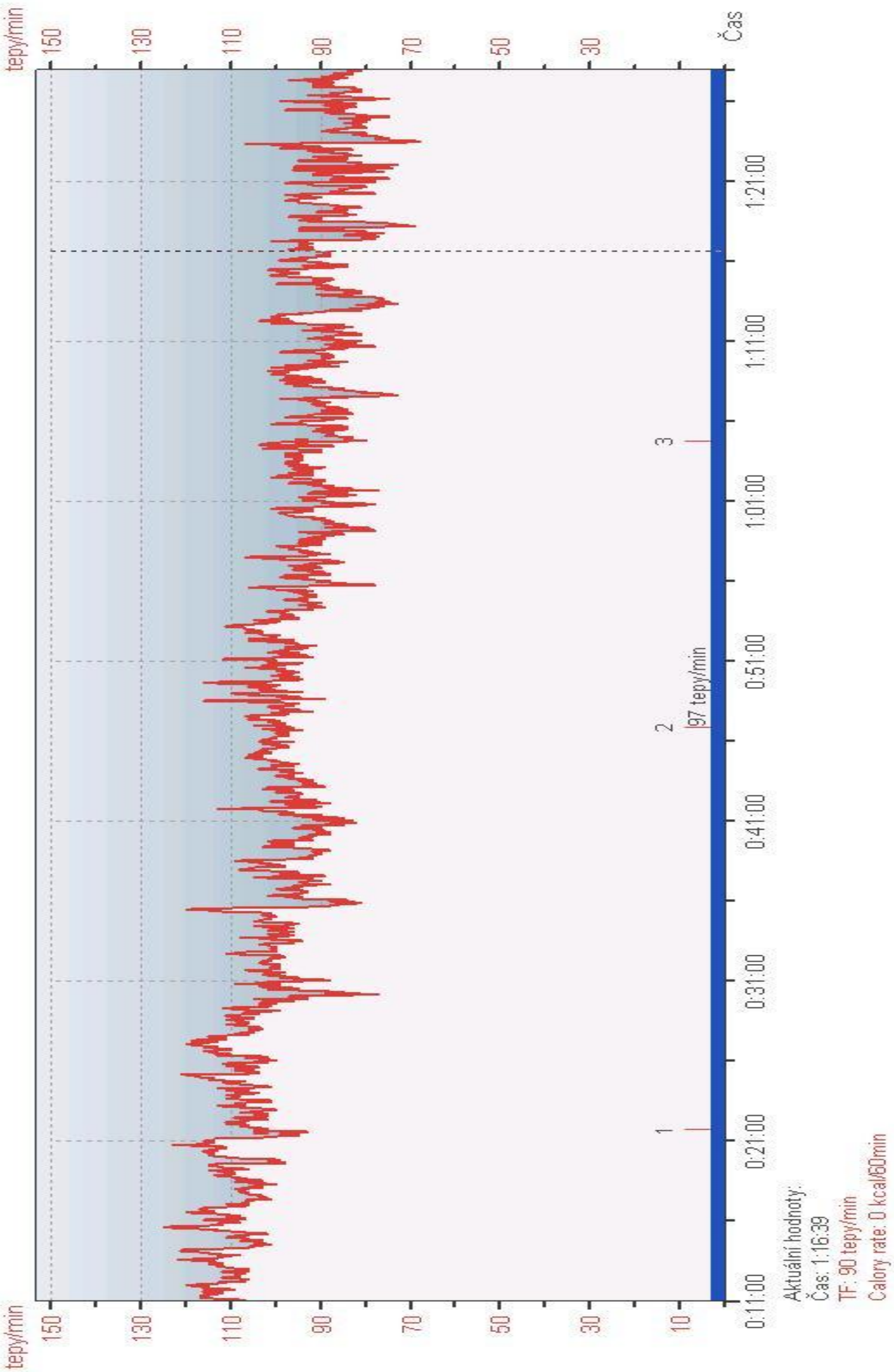


FIGURE 8: CURVE OF HEART RATE FROM THE HR MONITOR.

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 9: LOTTERY TASK

8.1 Analysis: General Description of Econometric Methods Used

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 enough to satisfy the asymptotic normality by the law of large numbers.

8.1.1 Choosing the right model

According to Cameron and Trivedi (2005) we should specify the model according to the underlying dgp[35], 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 $p = \Lambda\left(\mathbf{x}'\beta\right)$ so the logit model should be used or if dgp has $p = \Phi\left(\mathbf{x}'\beta\right)$ 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)).

8.1.2 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

[35] Data generating process

with this reference line, and the further the ROC gets and the more area underneath of it, the better predictive power of the model.

8.1.3 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 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.

8.1.4 Goodness-of-fit tests

8.1.4.1 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.[36]

8.1.4.2 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

[36] "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).

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.

8.1.4.3 Comparison of predicted outcomes with actual outcomes

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 22). The overall classification of correctly predicted cases is sometimes called the "count R^2".

8.1.5 HECKMAN TWO STAGE ESTIMATOR

8.1.5.1 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 contribution. 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 10 for a schematic view of the problem.

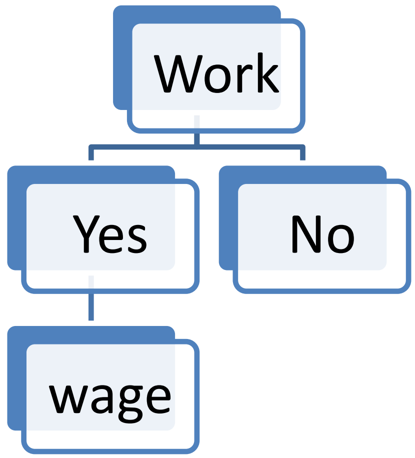


FIGURE 10: DECISION TREE OF HECKMAN'S SETTING

In the Figure 2 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.

8.1.5.2 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):

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

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

$E_i^* = W_i - E_i'$ 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

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

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.

8.1.5.3 Heck(prob)it: Probit model with selection

However, the Heckman's "normal" 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 Praag (1981). This procedure is sometimes called Heckprobit or Heckit and is provided by most of the statistical packages.[37] 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*

[37] Specifically, I use Stata 11, but the choice of a package should not affect any of the computations.

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

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.[38] The package I use, when using the MLE estimation, does not estimate directly the correlation ρ between error terms, but rather "*atanh* " , 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.

8.1.5.4 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.

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

9 References

International Personality Item Pool: A Scientific Collaboratory for the Development of Advanced Measures of Personality Traits and Other Individual Differences [Online]. Available: http://ipip.ori.org/ [Accessed].

ALLSOPP, L. & HEY, J. 2000. Two Experiments to Test a Model of Herd Behaviour. *Experimental Economics,* 3**,** 121-136.

ANDERSON, L. R. & HOLT, C. A. 1997. Information Cascades in the Laboratory. *American Economic Review,* 87**,** 847-62.

ARIELY, D. & ZAKAY, D. 2001. A timely account of the role of duration in decision making. *Acta Psychologica,* 108**,** 187-207.

AVERY, C. N. & ZEMSKY, P. 1998. Multidimensional Uncertainty and Herd Behavior in Financial Markets. *American Economic Review,* 88**,** 724-48.

BADDELEY, M. C., PILLAS, D., CHRISTOPOULOS, Y., SCHULTZ, W. & TOBLER, P. 2007. Herding And Social Pressure In Trading Tasks: A Behavioural Analysis. Faculty of Economics, University of Cambridge.

BANERJEE, A. V. 1992. A SIMPLE-MODEL OF HERD BEHAVIOR. *Quarterly Journal of Economics,* 107**,** 797-817.

BIKHCHANDANI, S., HIRSHLEIFER, D. & WELCH, I. 1992. A THEORY OF FADS, FASHION, CUSTOM, AND CULTURAL-CHANGE AS INFORMATIONAL CASCADES. *Journal of Political Economy,* 100**,** 992-1026.

BIKHCHANDANI, S., HIRSHLEIFER, D. & WELCH, I. 1998. Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades. *Journal of Economic Perspectives,* 12**,** 151-70.

BORGHANS, L., DUCKWORTH, A. L., HECKMAN, J. J. & WEEL, B. T. 2008. The Economics and Psychology of Personality Traits. *Journal of Human Resources,* 43.

CADSBY, C. B., SONG, F. & TAPON, F. 2009. The Impact of Risk Aversion and Stress on the Incentive Effect of Performance Pay. University of Guelph, Department of Economics.

CAMERON, A. C. & TRIVEDI, P. 2005. *Microeconometrics*, Cambridge University Press.

CAMERON, A. C. & TRIVEDI, P. 2010. *Microeconometrics Using Stata, Revised Edition*, StataCorp LP.

CAO, H. H. & HIRSHLEIFER, D. A. 2000. Conversation, Observational Learning, and Informational Cascades. *SSRN eLibrary*.

CORAZZINI, L. & GREINER, B. 2007. Herding, social preferences and (non-)conformity. *Economics Letters,* 97**,** 74-80.

COSTA, J. P. T. & MCCRAE, R. R. 1992. Normal Personality Assessment in Clinical Practice: The NEO Personality Inventory. *Psychological Assessment,* 4**,** 5-13.

DOHMEN, T., FALK, A., HUFFMAN, D. & SUNDE, U. 2008. Are Risk Aversion and Impatience Related to Cognitive Ability? : C.E.P.R. Discussion Papers.

DOHMEN, T., FALK, A., HUFFMAN, D., SUNDE, U., SCHUPP, J. & WAGNER, G. G. 2009. Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences. Maastricht : METEOR, Maastricht Research School of Economics of Technology and Organization.

FALK, A. & FISCHBACHER, U. 2006. A theory of reciprocity. *Games and Economic Behavior,* 54**,** 293-315.

FALK, A. & HECKMAN, J. J. 2009. Lab Experiments are a Major Source of Knowledge in the Social Sciences. Geary Institute, University College Dublin.

FALK, A., HUFFMAN, D. & MIERENDORFF, K. 2006. Incentive Effects and Political Acceptability of Workfare. Institute for the Study of Labour (IZA).
FISCHBACHER, U. 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics,* 10**,** 171-178.
FORMY-DUVAL, D. L. 1993. Scaling the Adjective Check List for the Five-Factor Model of Personality. *Unpublished master's thesis.* Wake Forest University.
GHASHGHAIE, S., BREYMANN, W., PEINKE, J., TALKNER, P. & DODGE, Y. 1996. Turbulent cascades in foreign exchange markets. *Nature,* 381.
GILBERT, T. & KOGAN, S. 2005. Learning From The Skills Of Others: Experimental Evidence. Carnegie Mellon University, Tepper School of Business.
GREENE, W. H. 2002. *Econometric Analysis, Fifth edition,* Upper Saddle River, New Jersey, Prentice Hall.
HECKMAN, J. J. 1976. The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models. *Annals of Economic and Social Measurement, Volume 5, number 4.* National Bureau of Economic Research, Inc.
HIRSHLEIFER, D. & TEOH, S. H. 2003. Herd Behaviour and Cascading in Capital Markets: a Review and Synthesis. *European Financial Management,* 9**,** 25-66.
HOGAN, R. & HOGAN, J. 2007. *Hogan Personality Inventory Manual, Third Edition,* Tulsa, OK, Hogan Assessment Systems.
HORČIC, J. & FORMÁNEK, J. 2003. *Triatlon: Historie, trénink, výsledky,* Praha, Olympia.
HOSMER, D. W. & LEMESHOW, S. 2000. *Applied Logistic Regression,* New York, John Wiley and Sons.
HUNG, A., A. & PLOTT, C., R. 2001. Information Cascades: Replication and an Extension to Majority Rule and Conformity-Rewarding Institutions. *American Economic Review,* 91**,** 1508-1520.
CHAMLEY, C. P. 2004. *Rational Herds*, Cambridge University Press.
CHARI, V. V. & KEHOE, P. J. 2002. On the robustness of herds. Federal Reserve Bank of Minneapolis.
KOCHER, M. G. & SUTTER, M. 2006. Time is money--Time pressure, incentives, and the quality of decision-making. *Journal of Economic Behavior & Organization,* 61**,** 375-392.
KOWALSKI-TRAKOFLER, K. M., VAUGHT, C. & SCHARF, T. 2003. Judgment and decision making under stress: an overview for emergency managers. *International Journal of Emergency Management* 1**,** 278-289.
KRAEMER, C., NÖTH, M. & WEBER, M. 2000. Information Aggregation with Costly Information and Random Ordering: Experimental Evidence. Sonderforschungsbereich 504, Universität Mannheim.
LEE IN, H. 1993. On the Convergence of Informational Cascades. *Journal of Economic Theory,* 61**,** 395-411.
LO, A. W. & REPIN, D. V. 2001. The Psychophysiology of Real-Time Financial Risk Processing. National Bureau of Economic Research, Inc.
MAULE, J. A. & EDLAND, A. C. 2000. The Effects of time pressure on human judgment and decision making. *In:* RANYARD, R., CROZIER, W. R. & SVENSON, O. (eds.) *Decision making: cognitive models and explanations.* London: Routledge.
MCEWEN, B. M. 2007. Physiology and Neurobiology of Stress and Adaptation: Central Role of the Brain. *Physiological Review***,** 873–904.
MCFADDEN, D. L. 1974. The measurement of urban travel demand. *Journal of Public Economics,* 3**,** 303-328.

OBERHAMMER, C. & STIEHLER, A. 2001. Does Cascade Behavior Reflect Bayesian Updating? –An Experimental Study. Max Planck Institute of Economics, Strategic Interaction Group.

PLOTT, C. R., WIT, J. & YANG, W. C. 2003. Parimutuel betting markets as information aggregation devices: experimental results. *Economic Theory,* 22**,** 311-351.

PRETCHER, R. R. 2001. Unconscious Herding Behavior as the Psychological Basis of Financial Market Trends and Patterns. *Journal of Psychology and Financial Markets,* 2**,** 120-125.

RAAFAT, R. M., CHATER, N. & FRITH, C. 2009. Herding in humans. *Trends in cognitive sciences,* 13**,** 420-428.

RIESKAMP, J. & HOFFRAGE, U. 2008. Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica***,** 258–276.

SALAS, E., DRISKELL, J. E. & HUGHS, S. 1996. The study of stress and human performance. *In:* DRISKELL, J. E. & SALAS, E. (eds.) *Stress and Human Performance.* New Jersey: Lawrence Erlbaum Associates.

SELYE, H. 1936. A Syndrome produced by diverse nocuous agents. *Nature,* 138.

SELYE, H. 1974. *Stress without Distress,* New York, Lippencott.

SGROI, D. 2003. The Right Choice at the Right Time: A Herding Experiment in Endogenous Time. *Experimental Economics,* 6**,** 159-180.

SHARMA, S. & BIKHCHANDANI, S. 2000. Herd Behavior in Financial Markets - A Review. International Monetary Fund.

SCHARFSTEIN, D. & STEIN, J. 1990. Herd Behavior and Investment. *American Economic Review,* 80**,** 465-79.

SMITH, V. L. 2008. Experimental Methods in Economics. *In:* DURLAUF, S. N. & BLUME, L. E. (eds.) *The New Palgrave Dictionary of Economics.* Basingstoke: Palgrave Macmillan.

VAN DE VEN, W. P. M. M. & VAN PRAAG, B. M. S. 1981. The demand for deductibles in private health insurance : A probit model with sample selection. *Journal of Econometrics,* 17**,** 229-252.

WEIZSACKER, G. 2010. Do We Follow Others when We Should? A Simple Test of Rational Expectations. *American Economic Review,* 100**,** 2340-2360.

WELCH, I. 1992. Sequential Sales, Learning and Cascades. *Journal of Finance,* 47**,** 695–732.

WILLIAMS, J. E., SATTERWHITE, R. C. & AND SAIZ, J. L. 2002. *The Importance of Psychological Traits,* London, Kluwer Academic Publisher.

YECHIAM, E., DRUYAN, M. & ERT, E. 2008. Observing others' behavior and risk taking in decisions from experience. *Judgment and Decision Making,* 3**,** 493-500.

ZIEGELMEYER, A., KOESSLER, F., BRACHT, J. & WINTER, E. 2010. Fragility of information cascades: an experimental study using elicited beliefs. *Experimental Economics,* 13**,** 121-145.