The Evolution of Confidence

Caught between Euphoria and Despair

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Abstract

This paper provides – by means of an experiment- a consistent explanation for the timing and occurrence of radical changes in confidence: if a sequence of past gains (losses) is interrupted by a loss (gain), then agent's beliefs change instantly, radically and significantly different from the predictions of Bayesian theory. In addition, the paper reveals that the shorter the time spans to a reference period (e.g. bonus) the more people on average overestimate their likelihood of success. The paper brings about three innovations: (1) it provides empirical evidence on a multiple stage game with sequences of gains and losses, (2) it measures confidence and action explicitly and separately (3) it makes an explicit and measurable distinction between the two minds of agents (see Seligman, 1990). Policy recommendations are to moderate and regulate market forces.

KEY WORDS: regime shifts, confidence, prior gains and losses, CBDT, reference point

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Introduction

The current economic system relies heavily on the confidence of agents. In particular, "radical" changes in confidence have a profound effect on economies shaping the magnitude of - and recovery from recessions (see f.i. Chauvet and Guo, 2003). Understanding the factors that enable the prediction of the timing of these events would provide important tools for policy makers to maximize welfare. However, to the best knowledge of the author, no researches have focussed on the specific issue of the cause of "radical" changes in confidence, which would enable prediction of this phenomenon. Rather, economic literature assumes an information shock in a Bayesian framework to explain the phenomenon. Inherent to the meaning of an information *shock* is that it cannot be predicted.

Still, parallel to literature on macroeconomic confidence, a vast literature has been devoted to investigating behavioural (and thus predictable) factors in the face of losses and gains and the effect of past events on the risk attitude of agents. Potentially, this literature can provide some clues. In their seminal paper, Kahneman and Tversky (1979) claim that agents become more risk averse if the prospect is a gain while they become more risk taking if the prospect is a loss. This effect is thus based on forward-looking confidence. This could suggest that ("radical") changes of hearts could be explained by the perceived prospect of the agent.

Thaler and Johnson (1990), on the other hand, use the framework of prospect theory and find evidence to suggest that a prior gain or loss has a significant effect on subsequent behaviour- the house money effect. They argue that prior gains give investors a 'cushion of money' that makes them less sensitive to the prospect of a loss in the future which makes them more risk taking. Similarly; if there were prior losses, investors become more sensitised by the prospect of future losses of the same magnitude. This makes them more risk averse. The results are subject to the existence of a reference point for the agent. This evidence could suggest that ("radical") changes of confidence are backward-looking.

Taken together, it would mean that prior gains (losses) make agents more(less) risk taking while the prospect of a gain (loss) makes them less (more) risk taking. The net effect is not clear a priori. The insights of both papers also do not explain how these effects would lead to "radical" changes in confidence. The main reason is that the set up of both papers is too restricted to zoom in on "radical" changes. Kahneman and Tversky's (1979) paper only measure stated preferences of respondents and neglects action. That is, they assume a priori congruence between (stated) beliefs and action rather than test it. Thaler and Johnson's (1990) paper is restricted in two ways: first beliefs are not measured – only action is measured, second the conclusion is drawn from a two-stage game (i.e. only two periods). Finally, both papers do not make a distinction between the beliefs of agents about the movement of the markets and the beliefs of agents about their own likelihood of success. This distinction is important as will be described in section 2.

This paper provides three innovations in this respect: (1) it provides empirical evidence on a multiple stage sequence of gains and losses, (2) it measures beliefs/confidence and action separately (3) it makes an explicit and measurable distinction between the two minds of agents (see Seligman, 1990); beliefs about the 'market' and beliefs about their own likelihood of success. The main contribution of this paper is that it provides a consistent explanation for the timing and occurrence of "radical" changes in confidence. The main thesis is that an interruption to a –long- sequence of gains (losses) would invoke despair (euphoria) or "radical" changes of confidence[1]. More specifically the main research question is: Do economic agents have radical changes in confidence and behaviour that is significantly different from Bayesian predictions when faced by a sequence of gains interrupted by a loss or vice versa? To answer the question, which is causal in nature, an experiment is conducted.

The experiment is loosely based on Camerer (1987) and consists of an investment game where subjects receive a noisy signal. Subjects state their confidence prior to observing the signal and they choose the amount to invest after observing the signal. Subjects are randomly assigned to treatment groups with a predetermined trajectory of gains and losses and a control group where gains and losses are random.

The data from the experiment is compared to a simulated Bayesian agent benchmark. The main results are that (a) there is significant and structural difference both in the beliefs and in the actions of the subjects compared to Bayesian agents, (b) interruptions of sequences of gains (losses) cause subjects to become overly pessimistic (optimistic) first in their confidence and then in their actions and (c) interruptions of a sequence of gains with losses has a larger effect in magnitude on confidence than the other way around. The author anticipates that this

[1] Radical changes in confidence can best be defined as an instant and structural change in the direction of confidence and which is high in magnitude. Bayesian theory, which has been put forward in the literature as a non-restrictive theory that could potentially explain anomalies as rational behaviour of agents, is used as the benchmark against which to compare and identify (radical) changes in confidence.

paper contributes to developing better insights in the evolution of confidence and helps designing better policies.

The paper is organized as follows, in the following section the theoretical foundations are elaborated and hypotheses are formed. In section three the methodology is discussed. Section four provides the results of the empirical analysis. Finally, in section five a discussion of the results is followed by a conclusion.

Section 2: Theory and Hypotheses

To work towards the hypotheses, literature is explored beyond prospect theory of Kahneman and Tversky (1979) and the house money effect of Thaler and Johnson (1990). In particular, there is some part of the literature that investigates the fallacies of agents in predicting[2] sequences of events such as gains and losses. Furthermore, another part of the literature investigates the psychological factors, which sheds some light in the black box. Both parts of literature are explored in subsection 2.2. In order to provide consistent explanations for the thesis, a solid theoretical framework that unifies fragmented evidence as well as characteristics of the thesis is necessary. In subsection 2.2 the main theoretical frameworks are explored in order to find a framework that provides a natural conceptualization of the thesis.

2.1.1 Individual Decision Making: Fallacies and Judgement Biases

The literature on prediction fallacies provides valuable insights through three fallacies describing the prediction behaviour of agents when faced with a sequence of events. Rabin (2002) explores the 'law of small numbers' and develops a simple model to explain the phenomenon. According to the 'law of small numbers', agents infer from a small sample something about the whole population. This means that after a very short sequence of say the flipping of a coin, agents makes inferences about the rest of the sequence. A related bias is the gamblers fallacy; agents infer that if a population exists of an equal amount of binary signs (a fair coin), then after one sign –say heads- is shown in a sequence a different sign –say tails- is more likely to be shown following the first sign. These two fallacies are thus focussed on the short term predictions of agents.

On the long term, a different fallacy drives the predictions - the hot hand fallacy (f.e. Gilovich et al., 1985; Tversky and Gilovich, 1989a; 1989b; Camerer, 1989). This fallacy explains that people perceive a sequence of events as rare while in fact it could be random. Because people observe this 'initially unexpected sequence', they over-predict the continuation of the streak. For instance, if they observe that an average football player scores several goals in subsequent games, then they infer that he will continue to do so in the future even though his true ability

[2] Note that this literature focuses on 'prediction'. The main difference between prediction and confidence is that an agent can make predictions on events where he is only an observer while confidence implies that the agent is always a player in the forming of the events. It thus follows that confidence always entails predictions while predictions does not always entail confidence. This notion restricts inference from the 'prediction'-literature on confidence of agents.

is average. The 'hot hand' stands thus for positive serial correlation. Crucial notion is that both the hot hand and the 'law of small numbers' hinge on the initial beliefs of agents.
Beyond this commonality, researchers suggest that agents exhibit the gamblers fallacy until the streak gets too long in their perception. Agents infer that the streak is too long to be due to chance and thus start exhibiting the hot hand fallacy. Some empirical evidence implicitly supports this view; short term under reaction by investors to announcements of firms and mid- and long term overreaction (for a survey see Barberis et al., 1998). From this point of view, valuable insights could be obtained if the hot hand fallacy could be provoked with a sequence of gains(losses) and then unexpectedly interrupted. The essential questions that arise are: (a) what would be the effect on confidence and (b) what would be the effect on choice/action?

Massey and Wu (2005) provide some initial evidence. In their paper, they develop a system-neglect hypothesis; agents a more focussed on the direct signals they observe and they neglect the underlying system that produces them. Subjects are asked to predict regime shifts (i.e. when a sequence of red ball draws shifts to a sequence of blue ball draws). Massey and Wu (2005) find that given a stable environment (i.e. low transition probability) with noisy signals subjects tend to overreact while subjects tend to under-react in an unstable environment with precise signals. Their analysis, however, is limited to prediction tasks.

In summary, the evidence provided by Kahneman and Tversky (1979) and Thaler and Johnson (1990) suggests respectively that gains and losses are weighted differently and that prior gains or losses influence current behaviour. The evidence on prediction fallacies reveals that agents make systematic prediction errors such that overreaction or under reaction to sequences of similar events can occur. The contents of the black box, however, remain undisclosed. The questions arise; how exactly can past behaviour that led to losses or gains influence present beliefs? and what role do prediction fallacies play? The psychological factors are explored in the following subsection to work towards the hypotheses.

2.1.2 Individual Decision Making: Psychological factors

Compte and Postlewaite (2003) argue that present beliefs are guided by a *distorted* recollection of a set of past events that resemble the present event faced by an agent. The agent's belief about the likelihood of success for a particular action is formed by past events. The subsequent decision to action is subject to the agent's recollection of past events. The agent's recollection is distorted, because his recollection of gains (success) is significantly

different from his recollection of losses (failure). Past gains are easier remembered than past losses (Seligman, 1990). More importantly, gains are attributed by agents to endogenous factors (e.g. own effort) while losses are attributed to exogenous factors (e.g. bad luck) (Seligman, 1990). Given these empirical findings one could hypothesize that the present beliefs of an agent would fundamentally change if a sequence of gains in the past is interrupted by a loss in the present or vice versa.
This could indeed be the case, because the status quo is no longer valid and the new 'alien' situation requires the agent to review his beliefs and his behaviour. If the agent experienced a sequence of past gains, the agent is under the impression that he controls his own success (endogeneity) and subsequently he is overoptimistic about the future i.e. over-predicts the likelihood of success in the future. If the sequence of gains is interrupted by a present loss, then the agent would attribute the loss to exogenous factors which means that the sense of uncertainty –about the external environment- becomes prevalent. This sudden sense of uncertainty could lead to a drastic negative change in the perceived likelihood of success in the future. The agent becomes pessimistic or even desperate in his expectations of the future and behaves accordingly.

Similarly if the agent experienced a sequence of past losses the agent behaves in an accommodating way. The perceived likelihood of success in the future is low and he attributes his losses to exogenous factors. Once the losses are interrupted by a gain the agent reshapes his beliefs about the future and attributes the sudden gain to endogenous factors. As a result the agent forms overoptimistic expectations about the future and the agent behaves accordingly.

Although this explanation brings new insights, it still does not explain how agents can believe one thing and act in another way. As Rabin (2002) and others suggested, agents anticipate a change in the future far more often than what rationality would prescribe. Existing literature suggests that the answer potentially lies in the fact that agents are of two minds; each agent has similar expectations about the movement of the *market* (driven by biases such as law of small numbers, gamblers fallacy, hot hand fallacy), yet at the same time each agent is overoptimistic about his *own* likelihood of success *relative to others* (e.g. Weinstein, 1980; Taylor and Brown, 1988; Guthrie et al., 2001). Hence, there exist a conflict between beliefs about the market and subsequent behaviour. This conflict is reconciled through beliefs of the agent about his relative ability to succeed, which are formed parallel to his beliefs about the market.

In summary, radical changes in confidence are hypothesized to occur once a long sequence of gains (losses) is interrupted**.** These radical changes are driven by psychological factors and prediction fallacies. In this paper, radical changes in confidence are defined as an instant and structural change in the direction of confidence and of which the change is high in magnitude compared to the Bayesian predictions. For instance a radical change is when high confidence is suddenly and structurally changed into low confidence and the magnitude of the decay of the confidence is high relative to the Bayesian predictions. To identify radical changes in confidence, the Bayesian benchmark is thus used in two steps; first if the direction changed suddenly in the data this is compared of whether this is also the case in the Bayesian benchmark, second if the direction changes at similar points in time for the data and the benchmark then the magnitude of the change is compared to the magnitude of the change in the Bayesian benchmark. If however, the change in direction occurs in the data and does not occur in similar periods according to the Bayesian predictions than the magnitude of the change is obviously and logically high in the data, since there is little to no real change detectable in the Bayesian benchmark. More formally, the hypotheses are;

> **H1A:** There is radical change in the confidence of agents after a sequence of gains is interrupted by a loss.
>
> **H1B:** There is a radical change in the confidence of agents after a sequence of losses is interrupted by a gain.

Since the cognitive treatment of success and failure is not symmetric for agents (see Seligman, 1990; Compte and Postlewaite, 2003) and the behavioural treatment of gains and losses is also asymmetric given evidence from prospect theory, it could be argued that the magnitude of the effect when gains are interrupted by a loss would be higher than when losses are interrupted by a gain. This argumentation stems from the understanding that gains are attributed to the own effort and ability of the agent while losses are attributed to exogenous factors such as bad luck. The impact of gains that are interrupted with losses can be argued to be more profound on the confidence of an agent in his ability to succeed than vice versa.

> **H2**: The magnitude of the effect of an interruption of a sequence of gains on confidence is larger compared to the case in which a sequence of losses is interrupted by a gain.

Hypothesis 1 and 2 only relate to the *beliefs* of agents. The risk taking behaviour relates to the *behaviour* of investors. Evidence from prospect theory suggests that agents show asymmetry in behaviour when faced with gains or (Kahneman and Tversky, 1979), Within this framework, Thaler and Johnson (1990) argue that if there is a clear reference point –which is the case in the experiment- and if there are more two periods, agents become less risk taking in case of prior losses and more risk taking in case of past gains. This means that with a sequence of losses that interrupts a sequence of gains, agents invest significantly less than a Bayesian benchmark would. In other words, the proportion invested (percentage of current wealth that is invested) would decrease more than what the Bayesian benchmark would suggest. Similarly, with a sequence of gains that interrupts a sequence of losses agents invest significantly more than a Bayesian benchmark would prescribe. In other words, the proportion invested would increase more than what the Bayesian benchmark would suggest. In both cases there is thus an overreaction to change in regime.

> **H3A:** An interruption of a sequence of losses causes an instant increase in the proportion invested that is more than proportional

> **H3B:** An interruption of a sequence of gains causes an instant decrease in the proportion invested that is more than proportional

This hypothesized effect of overreaction can be limited to only the setting of the game or spill over to other settings, such as different games. For example, an investor who overreacts in the stock market could also overreact in his private consumption. That is, risk taking is affected well beyond the peak moment of radical changes in confidence and well beyond the setting in which they occur.

> **H4a**: Risk taking behaviour in a different setting will increase after ending a sequence of losses with gains

> **H4b**: Risk taking behaviour in a different setting will decrease after ending a sequence of gains with losses

The ambition of this paper is to provide a consistent explanation of radical changes in confidence. To achieve this, the empirical setup, hypothesis testing and findings need to be well grounded in a theoretical framework. In the following subsection, three main theoretical frameworks are explored for this purpose.

2.2Theoretical Frameworks

In the literature two paradigms underlying decision theories are prominent: probabilistic and statistical reasoning of which Bayesian modelling in subjective expected utility (SEU) is the main reference and (editing) rules based deductive systems of which prospect theory is the main reference. Recently a third paradigm is added: reasoning by analogies of which Case Based Decision Theory (CBDT) is the main reference. In the subsequent subsections, each main reference is investigated to find the most natural conceptualization of this paper's thesis.

2.2.1 SEU

Bayesian modelling in SEU assumes that agents form beliefs about probabilities of states and outcomes – subjective probabilities- which determine their action. To form and update these beliefs agents use Bayes' rule. Within the setting of the experiment, the necessary input for Bayesians –a probability distribution describing the uncertainty – is given. Despite the mathematical beauty of this approach, Bayesian modelling in SEU is not appropriate for the purpose of this paper for reasons given below. These same reasons also make Bayesian modelling in SEU a natural benchmark against which to identify 'irrational' behaviour.

First, SEU is a normative theory (see for instance Allais, 1953; Savage, 1954) that shows how agents ought to form beliefs and act while the purpose of this paper is to investigate how subjects actually form beliefs and act.

The second reason is that SEU implies that agents have to imagine all possible states and outcomes to determine their optimal strategy. In this experiment, it is unlikely for the subjects to make a sequence of 18 decisions under uncertainty; the large amount of investment strategies (unit of investment is 1 MU) and predictions create a complex analysis that is not feasible given the time frame of the experiment. In addition, each prediction and each investment would lead to a reassessment of the analysis. Although the framework has rigor it thus seems not a plausible description of the actual cognitive process of the subjects given the thesis at hand.

The third reason is that in SEU the decision of an agent is only conditioned on the final outcome; only the absolute level of outcomes is relevant for the decision problem under SEU. Previous periods can thus only influence current decisions through a wealth level effect. The implication is that whether an agent has lost or won a period does not matter in itself; the only factor is the absolute level of wealth accumulated which is assessed against the reference point (bonus threshold in the experiment).

The final reason is that SEU cannot account for nor allow the well documented fallacies and judgement biases found in empirical research (a good starting point here is Camerer, 1987). Nevertheless, as mentioned the same reasons that make it not fit as a framework for the current thesis also make SEU a natural benchmark against which to identify anomalies in the experiment.

2.2.2 Prospect theory

Prospect theory provides a potentially useful framework. In contrast to SEU, prospect theory codes outcomes not in absolute levels of wealth but in terms of gains and losses. Prospect theory assumes that agents use editing rules to simplify prospects (i.e. decision problems under uncertainty). In prospect theory, the value function describes the value agents ascribe to event outcomes while the decision weight function transforms probabilities into decision weights. In addition, agents value gains and losses asymmetrically such that there is loss aversion. An implication is that the framing of decision problems can change the choice of agents. Kahneman and Tversky (1979) argue that prior gains and losses can have an effect on current decision problems if there exists a reference point (bonus threshold) different from the status quo. So far, the framework of prospect theory provides a good conceptualization of the thesis: agents value gains and losses (i.e. change in wealth) and prior gains and losses play a role in current decision problems given the bonus threshold.

There is however a problem; prospect theory only considers changes in wealth and not levels of wealth. This would mean that making an investment for instance in period 18 does not hinge on the level of accumulated wealth (say around the bonus threshold) but only the anticipated change in wealth (increase of wealth or decrease of wealth). This is not consistent with the thesis, since radical changes in confidence are hypothesized to be both driven by the change in wealth and levels of wealth.

To elaborate, consider the case when gains are interrupted by losses; the agent wants to make the bonus threshold and starts off on a streak of gains. His confidence gets a boost as he assumes he is winning because of his own ability. In addition, the rapid accumulation of wealth makes him even more confident that he will make the benchmark. Then he experiences a streak of losses. The change affects his confidence negatively, yet he remains a non-zero confidence as long as his accumulated wealth is large enough to be close around the bonus threshold. This is a level wealth effect.

2.2.3 Case Based Decision Theory

The final potential framework is Case-based Decision theory (CBDT), first proposed by Gilboa and Schmeidler in a series of papers (1995, 1996, 1997a, 1997b, 1999a, 1999b, 2000, 2001. CBDT provides a basic framework for why 'irrational' phenomenon could be common practice in markets. CBDT is founded on Hume's argumentation that "From causes which appear *similar* we expect similar effects (Hume 1748, Section IV). CBDT suggests that agents draw from a <u>set</u> of past cases (i.e. experiences) to evaluate present decision problem. A case is defined as a combination of a problem, an act and a result. This property allows prior gains and losses to have influence on current decision problems. At the same time, it does not attach any specific value function to a gain or a loss. Rather it specifies a utility functions where gains and losses can be valued either symmetrically or asymmetrically. The utility function increases with the desirability of outcomes. The set of cases is restricted by the memory of the agent. To evaluate the current decision problem, the agent ranks the available set of choices according to the similarity-weighted sum of utilities which were derived in the (memorable) past. Agents themselves determine the similarity between past cases and current decision problems given their own (subjective) reference of the past. This property allows for a wide and non-restrictive interpretation of 'similar' that respects individual cognitive processes.

It is argued that an agent uses his experience from similar past cases in order to evaluate the current decision problem: the agent has backward looking beliefs. In other words, agents have a homogenous way of processing information –with potential anomalies-which leads to similar beliefs about the future provided that the same past cases are assessed as 'similar' to the current decision problem. This property allows it to encompass explanations for fallacies and judgment biases documented in the literature. It also allows explanation of macroeconomic phenomenon. In addition, given the generality of the framework and the explicit valuation of gains and losses, CBDT allows the current decision problem to be affected by both the change in wealth as well as the level of wealth given the bonus threshold.

The bonus threshold, in CBDT dubbed the aspiration level, is critical for the choices of the agent. Gilboa and Schmeidler (2001) argue that; "the decision maker would cling to an act that achieves this value without attempting other acts and without experimentation. It is only when the decision maker's current choice is evaluated below the aspiration level that the decision maker is "unsatisfied" and is prodded to experiment with other options." (Gilboa and Schmeidler, 2001: 49). This shows the wealth level effect. At the same time they point out that the aspiration levels are likely to change subject to past experiences. This signifies the change in wealth effect. CBDT has thus a non-restrictive character which allows it to be employed as a general framework.

In the remainder of this paper, CBDT is used as the underlying theory for explaining beliefs and behavior of agents and their aggregate dynamics. CBDT can also easily be tested with the experimental design of this paper. Therefore, CBDT extends to the empirical analysis of this paper as an underlying framework.

Section 3: Methodology

This study treats agents as unit-of-analysis and focuses on the economic choices and believes of agents in a dynamic environment. Believes and behavior are measured by means of an experiment in order to determine the existence of a causal relationship between incurring gains and losses and waves of optimism and pessimism.

3.1 Data and Methods

The experiment design is built on the experiment design of Camerer (1987). This experiment takes the principles of that design and applies them for its main focus: (1) ‘effects – if any- of a gain (loss) on beliefs (i.e. confidence)’, (2) ‘the evolution of beliefs given a predetermined trajectory of gains and losses, (3) the magnitude of the effect of beliefs on action. The principles behind the experiment of Camerer (1987) are: (1) subjects have an investment task with noisy signals as information reference points, (2) subjects have all the necessary information to be able to behave as Bayesians (the Bayesian benchmark thus can be constructed). The Bayesian benchmark is simulated in the following subsections.

Camerer’s (1987) design is extended and simplified in this experiment design, subjects have next to the investment task also a prediction task. In addition, building on the vast literature after Camerer (1987) and others, the experiment design makes use of surveys to control for relevant variables.

More precisely -as depicted in table 1- the experiment consists of four parts: first the benchmark survey, second is an investment game with multiple rounds, third is a one shot fair gamble and finally an identical survey as the first one to monitor any changes in mood. Figure 1 elaborates on the timing of the tasks in each round. In the next subsections the different parts are described.

3.1.1 Surveys

In this experiment, subjects are asked to play an investment game and to participate in a fair gamble. Several control variables need to be considered to secure the internal validity of the experiment. Risk-taking behavior is an often stated control factor, yet no widely accepted questionnaire to measure this factor has been developed (see for instance Nicholson et al. 2002). However, Dohmen et al. (2005) find in their study that one particular question has very high correlation with conventional risk attitude outcomes measured in controlled experiments.

This question is:

> *How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?*
>
> *Please tick a box on the scale, where the value 0 means: 'risk averse' and the value 10 means:'fully prepared to take risks'. You can use the values in between to make your estimate.*

Dohmen et al. (2005) also state that even though this survey measure shows high correlation with experimental outcomes, the measure is also imperfect. For the purpose of this study, risk measure is a control variable. Therefore, the inclusion of this survey measure could allow accounting for some variance although caution is required in the interpretation.

Emotional states are found to be significant factors in investment decisions by several papers (see f.e. Grossberg and Gutowski,1987; Damasio, 1994; Elster, 1998; Lo, 1999; Loewenstein, 2000; Peters and Slovic, 2000; Lo and Repin, 2002). Lo et al. (2005) perform a clinical study among a sample of 80 day traders. They find a significant relationship between emotions and trading performance. In addition, when in a positive mood, agents tend to be more risk averse (see also Isen and Geva, 1987; Isen et al. 1988). To correct for this, subjects are asked to fill in a survey that establishes their initial mood. This survey - UWIST Mood Adjective Checklist- is adopted from Matthews et al. (1990) and is recognized to serve as a good first order approximation.

In Matthews et al. (1990) four factors are considered: energetic arousal (EA), tensional arousal (TA), hedonic tone (HT) and a general factor general arousal (GA). Guardia and Adan (1997) find, however, a very low definition of GA suggesting that it is a poor factor. Therefore, in this experiment only the first three factors are considered. The survey allows for subjects to participate in the experiments on different times of the day. Guardia and Adan (1997) find that the UMACL survey gives reliable results for different times of the day. More specifically, Guardia and Adan (1997) analyse the reliability of the test at 09.00hr, 13.00hr, 17.00hr and 21.00hr. The UMACL survey asks subjects to rate their agreement with a certain adjective describing mood on a four point Likert scale denoting ‘definitely’ (score 4 points), ‘slightly’(score 3), ‘slightly not’(score 2) and ‘definitely not’(score 1). Each of the three factors is measured through eight adjectives and has a range of 8 to 32.

Lo et al. (2005) also find that there exists no significant relationship between personality traits and trading performance. This means no account has to be made for different personality traits.
Special attention is given to the pathological gambler. A pathological gambler is a person who cannot resist impulses to gamble and who has suffered in his personal life as a result of this mental disease (Cunningham et al., 1998). Mild cases are referred to as problem gambling. Subjects who suffer from this disease, even mild cases, could contaminate the results of the experiment. To control for this, a questionnaire developed by Johnson and Hamer (1998) is used to screen for the illness. This questionnaire consists of two items and is reported to have a high degree of reliability. The two items are derived from the DSM IV criteria for pathological gambling. These items are: DSM-IV (6) Have you ever had to lie to people important to you about how much you gambled? and DSM-IV (3) Have you ever felt the need to bet more and more money?. Subjects who confirm both questions are excluded from the empirical analysis.

3.1.2 Investment Game with Multiple Periods

Subjects are asked to play a game called ‘Investment Game’. The game consists of a series of investment decisions that the subject has to make over 18 periods. The game is programmed using zTree software (Fischbauer, 2007). The investment decision is to allocate an investment among an opportunity and a bank savings account with 0% interest rates. Borrowing is not allowed. The allocation can be chosen freely. Subjects are informed that returns are IID; in each round there is an objective probability for a firm to have a positive return equal to 50%. All subjects receive 100 monetary units (MU) - 50 MU = €1 - at the beginning of the game, this is their initial capital. In each period, the firm submits a signal that is noisy but that could provide information about its state. This noisy signal illustrates the noise people face in real life decision making as an investor in the stock market or as a consumer aiming for the next job promotion. The subjects then choose to make an investment. The signal consists of two letter ‘R’ and/or ‘B’. These letters represents ‘red’ and ‘black’ balls in a basket.

There are two baskets each with a different proportion of red balls and black balls. Basket 1 represents a positive state of the opportunity such that it would yield a positive return. In basket 1 there are 3 red balls and 3 black balls. Basket 2 represents a negative state of the opportunity such that it would yield a negative return. In basket 2 there are 4 red balls and 2 black balls. Draws are made with replacement to form the signal. Subjects observe the signal, but they do not observe from which basket this signal is drawn. Depending on the composition of the signal and using Bayes rule subjects could make inference about which basket is most likely to be the source of the signal. Based on this inference they can make a decision to maximize the expected return. Figure 2 shows for each group in each round whether there is a gain or a loss and what the signal is.

Points can be accumulated through investment: a positive return yields '+10% of invested amount' points, a negative return yield '-10% of invested amount' points and the savings account yields zero return. Ultimately, winning is defined as collecting 150MU's at the end of the final period in order to receive an additional bonus of €5,-. If a subject collects this pre-determined minimum amount of points than the subject receives a monetary reward (a bonus) otherwise (s)he receives nothing. This serves as an incentive mechanism and to separate beliefs about the opportunities and beliefs about their perceived likelihood of success. One main interest is the confidence level (i.e. their perceived likelihood of success) of the subject, therefore before each round starts the subject is asked to state his confidence to 'win'. This is the first prediction task. The second prediction task requires the subject to predict whether there will be a positive return in the next period, if s/he were to invest.

The experiment has two treatments and a control group. Each treatment consists of a different trajectory of gains and losses which is pre-determined by the researcher. This fact is not communicated to the subjects. The control group faces a trajectory with a random distribution of gains and losses. All treatments have the same average expected return of 0%.

Figure 2 shows the sequences for each group and the signals in each period the subjects receive. Treatment 1 is a pre-determined trajectory of a long sequence of gains eventually interrupted by losses. Similarly, treatment 2 is a pre-determined trajectory of a long sequence of losses eventually interrupted by gains. The necessary amount of periods to be set for the sequences of gains (losses) is not clear and therefore arbitrarily set. The 'turning point' period is set where the subject has gotten sufficiently close (far) from the benchmark points.

Payoff

Subjects earn points that are conversed to monetary rewards at the end of the experiment (conversion rate is 50 MU's = € 1,-). Subjects can earn points with the investment task. Only the accumulated points at the end of the experiment are used to pay out subjects. The subjects can also earn points with the prediction task. A quadratic scoring rule is used as suggested by the literature (see for instance Blanco et al, 2008; Costa-Gomes and Weizsäcker, 2008):

$$\pi = €0.1 - €0.1(a-b)^2 \quad (1)$$

Where *a* stands for actual Bayesian probability of winning the next round (prior belief=50%) and *b* stands for the stated beliefs of the subject.

3.1.3 Beliefs and Behaviour in the game

Choices are driven by beliefs (Costa-Gomez et al. 2010). Yet this relationship is not necessarily one-on-one, meaning that choices are potentially imperfect measures of beliefs. In this experiment, beliefs and behavior can be treated separately. This is done by making a distinction in the tasks as investment tasks and prediction tasks. The investment task is straight forward. The prediction task elicits explicitly the beliefs of the subjects. Before each round, subjects are asked to state their beliefs by the following two questions:

> "In your opinion, how likely is it that you will make a positive return in the next round if you were to invest? Indicate this on the sliding scale underneath. The likelihood is increasing from left to right."

> "In your opinion, how likely is it that you will win the game (i.e. reaching the 150 points) at the end of the last round? Indicate this on the sliding scale underneath. The likelihood is increasing from left to right."

3.1.4 Investment game analysis for Bayesians.

Let θ denote the noisy signal, let '+' denote a gain and let '–' denote a loss. The prior probability is equal to ½ . If agents are Bayesian, then the beliefs in table 2 would guide the agents in each round after the noisy signal has been observed.

3.1.5 Prediction task for Bayesians

The subjects are asked to predict their likelihood of success at the start of each round and before they observe the signal. For Bayesians, the answer to the prediction task is equal to the prior probability, which is in this case ½ .

3.1.6 Investment task for Bayesians

Bayesian will only invest if the expected return is higher than the outside option (savings account) which is equal to zero. The expected return us described by:

$$E(R) = 0.1 \times P(+\,|\,\theta) - 0.1 \times P(-\,|\,\theta) \quad (2)$$

Where 0.1 signifies the 10% return. Bayesians are assumed to be risk neutral and they either invest all or save all such that the decision rule is: $invest \Leftrightarrow E(R) \geq 0$. Given the *i.i.d.* assumptions, a strategy profile can be constructed as depicted by table 3. Risk neutral Bayesians always invest, except when they observe RR.

3.1.7 Bayesian Investment Benchmark

The investment strategies, the returns and the confidence are related; the higher the accumulated wealth, the more confident a Bayesian is about winning the game. In this game, there are a large amount of different optimal strategies. Assuming myopic agents and risk neutral agents, Bayesians would invest 100% if BB is observed, 50% (expected return is assumed approximately 0%) if BR or RB is observed and 0% if RR is observed[3]. The assumption of myopic agents is consistent with empirical evidence that suggests that people tend to behave myopically in similar settings to the current setting (see f.i. the system-neglect hypothesis of Massey and Wu, 2005). Assuming myopic agents therefore allows for a better comparison and testing of the data. Note that this is not an optimal strategy, but it approximates a myopic optimizer.

3.1.8 Confidence benchmark

A Bayesian benchmark for confidence can be constructed by exploiting the prior probabilities of 0.5 and using the binomial probability formula:

$$\mathrm{P}(X = k) = \binom{T}{k} \mathrm{p}^{\mathrm{k}} q^{(T-k)} = \frac{T!}{k!(T-k)!} \times 0.5^{T}$$

Where k is the number of gains and T is the remaining time periods. With this formula, the minimum stock per time period can be determined as well as the confidence level given the stock at the beginning of the period. This confidence is the cumulative probability $\mathrm{P}(X \leq k)$. Using this methodology and backward induction from period 18, table 4 can be constructed. The results in table 4 can be held against the stock values of each and every subject in the experiment and in each period. Once the Bayesian confidence levels for winning the game are determined for each subject at each period, the average for each group can be derived. This average is then used to benchmark the data. This benchmark can be used to test the results of the experiment against rationality. In particular, the 'behavioral' effect of interruption can be quantified.

[3] Alternatively, the assumption is of myopic and risk averse agents who are indifferent if the expected return is 0.58% (when the signal is RB or BR).

3.1.9 Fair Gamble

After the investment game with 18 periods, subjects are told that they now van choose to play a completely different game called 'Double or Nothing'. As the title suggest they can bet any amount they of a separate endowment of € 2,- in a fair gamble that would either double the bet or take it. They can also choose not to participate in the gamble. Prospect theory would predict that the subjects who ended on a winning (losing) streak in the previous game would be more inclined to reject (accept) the gamble. Alternatively, the house money effect suggests the opposite. In particular, subjects who make the benchmark and win the monetary reward in the previous game would be more risk seeking. The novelty is the pattern of the history of gains and losses. This game allows testing of the hypothesis of radical changes in confidence –if any- on behavior in the long run.

3.1.10 Case Based Decision Theory

Conveniently, the experiment design also allows for testing of the CBDT. There are a limited amount of possible signals and subjects have to make investment decision in each round for a different firm. CBDT could thus be tested on two dimension; (I) the decision (invest/ do not invest) for similar cases (i.e. identical signals from different firms) and (II) the variance in the amount invested for similar cases.

3.2 Sampling Design

Since the unit of analysis is economic agents a random sample out of students at the economic faculty and the business faculty of the Erasmus University in Rotterdam is drawn. These students are trained in economic thinking and investment decisions and they are familiar with finance principles. In order to ensure randomness in the selection of subjects, each subject is randomly assigned to one of the treatments by software. This means that even though the sample is not completely randomly selected it can be defined as randomly conducted. To be precise, there is some kind of selection because the sample only contains 'trained' students to approximate investor behaviour. The sampling design is therefore a *convenience sample*.

3.3 Measurement and Variables

Measurement occurs at two levels. First, the amount a subject invests each time is measured and second the subject's stated beliefs about winning the game and about a positive return in the next period are measured.

3.3.1 Dependent Variables: Probability of winning:

Each hypothesis has its own dependent variable. For H1 and H2 the dependent variables are the confidence of winning the game 'PWIN' and the confidence of a positive return in the next round 'PNEXT'. To reduce heteroskedasticity and to be able to make more general inferences both variables are transformed using the log function. Since respondents also reported 0 probabilities for both variables the transformation is a s follows:

(3) $\mathrm{LNPWIN}_{it} = \mathrm{Log}(\mathrm{PWIN}_{it} + 1)$

(4) $\mathrm{LNPNEXT}_{it} = \mathrm{Log}(\mathrm{PNEXT}_{it} + 1)$

This transformation slightly affects the mean but has no effect on the variance since the variance of a constant is zero.

Amount invested in investment game

For H3 the dependent variable is 'INV' and it measures the action of respondents. With each investment choice they can chose the amount they want to invest. This variable is first transformed into a share of accumulated wealth:

(5) $\mathrm{S}INV_{it} = (\mathrm{INV}_{it} + \mathrm{STOCK}) \times 100\%$

This is both convenient and logic; it is convenient because it allows mean comparisons with the benchmark case, it is logic because respondents care about their relative amount invested rather than the absolute level. The second transformation is a log transformation to reduce heteroskedasticity and allow elasticity measures:

(6) $\mathrm{LNS}INV_{it} = \mathrm{Log}(\mathrm{S}INV_{it} + 1)$

Amount invested in gamble

The final hypothesis H4 has a dependent variable 'IGAMBLE' which is the amount invested in the fair gamble. This variable is both transformed into a share of total endowment:

(7) $SIGAMBLE_{it} = (IGAMBLE_{it}/2) \times 100\%$

And into a dummy variable indicating if someone has invested a positive amount or not: (8)

$DUMGAMBLE_{it} = 0 \quad \text{if} \quad \mathrm{INGAMBLE} = 0$

3.3.2 Independent variables

Confidence variables of H1 and H2 are independent variables in H3 and H4. The independent variables in H1 and H2 are lagged dependent variables.

3.3.3 Control Variables

Signals:

'BB_t'is a dummy variable with value 1 if BB was observed in period *t*. 'RR_t'is a dummy variable with value 1 if RR was observed in period *t*. 'BR_t'is a dummy variable with value 1 if BR was observed in period *t*. 'RB_t'is a dummy variable with value 1 if RB was observed in period *t*.

Gender

Barber and Odean (2001) suggest that gender plays a significant role in investment behavior. Gender is a dummy variable denoted 'G_i'

Mood or Emotional State

Emotional State is a measured across three factors: energetic arousal (EA), tensional arousal (TA) and hedonic tone (HT). Each of these variables takes a numerical value between 8 and 32.

Risk

'$Risk_i$' is a variable measured on an 11-point scale.

3.4 Statistical Methodology and Model Selection

To test the hypotheses two different regression models are used to:

3.4.1 Model Selection H1

H1 states that a radical change in confidence would occur just after the interruption of the sequence of gains or losses depending on the treatment. A radical change in confidence would by its definition (see footnote 1 or section 2.1.2) imply a structural break in the empirical data. A structural break means that a regression consists in reality of two separate regressions with significantly different parameter estimates instead of one regression. The break point is hypothesized to occur right after the interruption of the experienced sequence of gains or losses; period 11 and 12. Establishing that there is a structural break, shows that there are indeed significant changes in confidence. Whether these changes are radical depends on the comparison to the benchmark case. In this first hypothesis only an indication of whether these changes are radical can be given. That is, if there exists a structural break in the data around the interruption period while it does not exist around the interruption period for the

benchmark case would suggest that these changes cannot be attributed to rational Bayesian behavior and therefore they are radical.
To be meticulous, first the Bayesian benchmark is constructed using the real investment levels of subjects. The rationale for this is that subjects might have less than optimal investment strategies, but the evolution of their confidence could still be comparable to Bayesians. This means that for each subject at each period and given the wealth of the subject at that period, the confidence (BAYESWIN) of Bayesian agents is calculated using table 4. Table 4 provides for each wealth level and each possible sequence the cumulative probability that an agent would make the bonus threshold (reference point). BAYESWIN is thus constructed using the actual subject's wealth levels in each round and then BAYESWIN is derived using table 4 – this variable presents what subjects ought to predict given their actual wealth levels. This approach guarantees some collinearity between the benchmark case and the subjects since confidence is inherently dependent on the wealth level in Bayesian theory. However, it could also taint the results, since the collinearity could decrease the power of the benchmark to falsify the hypothesis. A full simulation could thus potentially falsify the hypothesis even if the aforementioned conditioned simulation does not.

Therefore a second and full Bayesian benchmark case is simulated; here both investment and confidence (PWIN) and predictions of positive returns in the next round (PNEXT) are simulated in all periods. So in contrast to the first benchmark case, in this case both what agents ought to predict and how they ought to invest are simulated. The simulated PWIN and PNEXT and all other simulated variables are thus not conditioned on what actually happened in the experiment. Because there are many strategy profiles for Bayesians, the risk neutral myopic optimizer's optimal strategy profile is taken as the base for the simulation. Section 3.1.7 elaborates on this issue.

To test H1 two steps need to be conducted. First the regression is performed; next a structural break test is conducted. Since no structural break tests are available in EVIEWS or SPSS for panel data, the regressions must be performed using OLS. This means that an $AR(1)$ model is estimated. This is the simplest model and it is consistent with the previously explored theory that suggests positive serial correlation in confidence – the hot hand fallacy. However, it is well documented that OLS provides biased and inconsistent estimates for panel data (Bond, 2002). To get around this hurdle, the average is taken of each period in each group's separate panel data. The result is an OLS that provides BLUE estimates about the means. The models for each dependent variable are:

(9) $PWIN_{\text{it}} = \beta_0 + \beta_1 PWIN_{\text{it-1}} + \varepsilon_t$

(10) $PNEXT_{\text{it}} = \beta_0 + \beta_1 PNEXT_{\text{it-1}} + \varepsilon_t$

Regression equation (9) is of main interest since it signifies the confidence of subjects in winning the game. In addition, equation (10) is for the Benchmark case constant since PNEXT is always equal to 50% in the benchmark case. In conclusion, two main insights can be gained; whether the evolution of confidence of subjects in their own likelihood of success differs significantly from the benchmark case to suggest radical changes in confidence and (2) whether the beliefs about a positive return in the next round (PNEXT) differ significantly from the constant value of 50% in the benchmark case such that the parameter estimate beta 1 is not equal to 1 and beta 0 is not equal to zero. To test for structural breaks, the Chow breakpoint test (Chow, 1960) is employed:

(11) $V = \frac{(\text{SSE}_{\text{R}} - SSE_U)/J}{\hat{\sigma}^2} \sim \chi^2_{(J)}$ where J is the number of joint hypothesis

H_0: no structural break

Since the sample in this case only contains 18 observations, the chi-square statistic is used to test the hypothesis instead of the F-statistic. For the benchmark case and the control group there are no clear indication of where a structural break might be. In this case the Quandt-Andrew test (Andrews, 1993) is used to determine the breakpoint period. This test performs the Chow breakpoint test for all pairs of observations. The result can be compared with the results for the two treatments.

3.4.2 Model Selection H2

H2 aims to measure the magnitude of the effect –if any- of an interruption. It states that the magnitude of the effect of an interruption of a sequence of gains on confidence is larger compared to the case in which a sequence of losses is interrupted by gains.

To quantify the behaviourist effect, H2 is tested. This means that the sum of the parameter estimates of lags of the lagged dependent variable are compared for the two treatments. It is hypothesized that in absolute terms (only the magnitude, disregarding the direction) the effect is larger when a sequence of gains is interrupted by a sequence of losses than vice versa.

Let the subscript *gl* denote gains interrupted by losses and *lg* the reverse. Let T denote the period and let delta denote the coefficient in the in the regression model for respectively treatment 2 (gains then losses) and treatment 1 (losses then gains). H2 then becomes:

H2: $\left|\sum_{k=1}^{k}\delta_{gl,k}^{T11-18}\right| > \left|\sum_{k=1}^{k}\delta_{\lg,k}^{T11-18}\right|$

To test this, a second regression is performed. The data consists of a panel of 40 subjects divided in three groups and 18 periods. In addition, if significant evidence is found for structural breaks than those 18 periods will be divided accordingly. Estimation occurs for each group separately and makes use of all panel data points. Several methods for estimating dynamic models in panel data are suggested in the literature. OLS, Within, Between, feasible GLS methods, MINQUE, Henderson's method III, true GLS and ML estimation (see f.i. Maddala and Mount, 1973) are commonly found. Maddala and Mont (1973) argue that there is no ranking of these methods and that all yield similar results provided that there is no misspecification. Taylor (1980) finds significant support for the feasible GLS method compared to the Within method in the case of finite sample results. Baltage (1981) corroborates this outcome.

Judson and Owen (1999) perform a Monte Carlo study on GMM and find that if the sample contains T<20 a GMM is appropriate. If T>30 they recommend the use of a fixed effect t estimator. Attanasio et al. (2000) underline this conclusion by arguing that the bias created by a fixed effect estimator is more than offset by its greater precision compared with GMM or IV. However, Bond (2002) points out that the fixed effects estimator yields inconsistent results due to correlation between the transformed lagged dependent variable and the transformed error term. Bond (2002) also argues that the Within estimator is biased downwards even for large number of cross sections. In the case of this study, the number of periods is less than 20 and if structural breaks are found, than the number of cross sections exceeds the number of periods. The GMM method, therefore, seems as the most suitable way to proceed. For this purpose the Arellano and Bond estimator (1991) is used which exploits the orthogonality between the lagged dependent variable and the error terms. By introducing instrumental variables that are highly correlated with the lagged dependent variable, efficient parameter estimates can be obtained. By using the differencing technique, the instrumental variable can be a lag or series of lags of the lagged dependent variable. These properties are well suited for testing of the hypothesis by using the dynamic GMM model for estimation:

$$LNPWIN_{\mathrm{it}} = \sum_{\mathrm{k=1}}^{\mathrm{k}} \delta_k LNWIN_{\mathrm{it-k}} + u_{it} \qquad (12)$$

$$(13) \qquad LNPNEXT_{it} = \sum_{k=1}^{k} \delta_k LNPNEXT_{it-k} + u_{it}$$

In Appendix E, the GMM method is elaborated and explained. Lags of the dependent variable are used as instrumental variables. The exact weighting option for each estimation is geared towards an optimal fit with the data. The validity of the GMM estimation is evaluated using the Sargan test (Sargan, 1958):

$$(21) \qquad s = \Delta\hat{v}'W\left[\sum_{i-1}^{N} W_i{}' (\Delta\hat{v}_i)(\Delta\hat{v}_i)'W_i\right]^{-1} W'(\Delta\hat{v}) \sim \chi^2_{p-K-1}$$

H_0: The over-identifying restrictions are valid.

3.4.3 Model Selection H3

The previous two hypotheses were only concerned with beliefs of subject. These beliefs where first compared against the Bayesian benchmark case and then, in the second hypothesis compared across treatment groups. The third hypothesis relates to action. It states that action – investments - will change in the same direction of the interruption, meaning that they would increase if the interruption is a sequence of gains (Treatment 1) and they would decrease if the interruption is a sequence of losses (Treatment 2). In addition, the hypothesis states that the change would be more than proportional to the experienced gains or losses. That is, there is an overreaction compared to the Bayesian benchmark case. To capture the relative change and to facilitate comparison with the Bayesian benchmark case, investments are measured as a proportion of current wealth – a percentage. As established in section 2 and 3, beliefs cause actions. In the experiment design, the beliefs are stated before an action is chosen, see figure 1. This means that a regression equation can be constructed with the two beliefs (PWIN and PNEXT) as independent variables and with inclusion of the control variables.

To test the hypothesis four steps are conducted; first the Chow breakpoint test is performed on an OLS regression on the means of each group. This is different from H1, because the test of structural break is here performed on investments and not on confidence. This procedure is necessary to establish whether the data can be organized as two regressions for each treatment group with the interruption period being the break point. If significant evidence is found, then H3 can be tested, which ultimately compares the proportion invested before the interruption and after the interruption. Second a t-test is performed to see whether the mean of the period T1- 11 is equal to the mean of T12-18. This test provides the level effect; parameter estimates might be different, but that says nothing about the level of investments. Third, a t-test is performed to test whether the mean proportion invested by each treatment is equal to the mean of the Bayesian benchmark (see table 6). This test compares the behaviour of the subjects with the simulated behaviour of the Bayesian benchmark. If this is significantly different, there is enough evidence to suggest that the reaction is more or less proportional. However, H3 hypothesizes that there will be an overreaction, therefore a one sided test is performed to see whether the proportion invested by the subjects is significantly higher (Treatment 1) or lower (Treatment 2) than the benchmark case. The final step is to run a regression and compare the parameter estimates of LNPWIN and LNPNEXT over the two periods T1-11 and T12-18. This final step measures the effect of beliefs on action. The comparison here involves comparison between parameter estimates before and after the interruption provided that there is a structural break there. H3 hypothesizes that the elasticity of beliefs is higher after the interruption such that a relatively small percentage change in beliefs induces a relatively large percentage change in the proportion invested. To do this precisely, the correlations between variables and the potential resulting collinearity are taken into account. The hypothesis can thus be quantified as follows:

H3A.1 $\mu_{TR1}^{T11-18} > \mu_{TR1}^{T1-10}$ **H3B.1** $\mu_{TR2}^{T12-18} < \mu_{TR2}^{T1-11}$

H3A.2 $\mu_{TR1}^{SINV} > \mu_{BAYES}^{SINV}$ **H3B.2** $\mu_{TR2}^{SINV} < \mu_{BAYES}^{SINV}$

H3A.3 $\left|\beta_1^{T11-18}\right| > \left|\beta_1^{T1-10}\right|$ **H3B.3** $\left|\beta_1^{T11-18}\right| > \left|\beta_1^{T1-10}\right|$

To test H3, the parameter estimate of the confidence variables in a regression with investment as the dependent variable needs to be evaluated. To analyse the panel data, both a fixed effects model can be used as well as a random effects model. The number of subjects is small enough to enable fixed effect estimation (Least Square Dummy Variables (LSDV)) without loss of too many degrees of freedom. However, the control variables, GENDER, MOOD and RISK are time-invariant. The fixed effects model does not allow inclusion of time-invariant variables and measures the effect indirectly through the error component. The random effect, on the other hand, does allow for inclusion of the control variables. In addition, the loss of degrees of freedom is avoided in the random effects model since it assumes μ_{it} to be random. More specifically, it assumes:

$$\mu_{it} \sim IID\left(0, \sigma_\mu^2\right),\ v_{it} \sim IID\left(0, v_\mu^2\right), COV(\mu_{it}, v_{it}) = 0,\ COV(X_{it}, v_{it}) = 0,\ COV(X_{it}, \mu_{it}) = 0$$

Although the fixed effects model is appropriate when a specific selection of subjects is made for data collection, the random effects model suits the design of this experiment better since it is best practice when a random selection of subjects is drawn from a large population. Some ambiguity might be of concern with regards to the definition of a large population. In this case Haavelmo's (1944) view applies; a population "consists not of an infinity of individuals, in general, but of an infinity of decisions". This definition captures both the cross section and the time effects and is consistent with the random effects specification.

The model selected is a one-way random effects model, since there might be heterogeneity between subject while the periods are fixed by the researcher. The exact weighting specification depends on the treatment group and the resulting data points. The aim is to minimize the standard errors and to choose a specification that is logic when looking at the data. The general model is:

$$LNSINV_{it} = \beta_0 + \beta_1 LNPWIN + \beta CONTROLVARIABLES_{it} + u_{it} \qquad (22)$$

And

$$LNSINV_{it} = \beta_0 + \beta_1 LNPNEXT + \beta CONTROLVARIABLES_{it} + u_{it} \qquad (23)$$

$$u_{it} = \mu_{it} + v_{it} \qquad (24)$$

where μ_{it} stands for the unobservable individual specific effect and v_{it} denotes the remainder disturbance. (Baltagi, 2005). The Swamy-Arora random effects method (Swamy and Arora, 1972) is used in estimation (see for a discussion Baltagi, 2005). To test the validity of the model, the Hausman specification test (Hausman, 1978) is performed.

3.4.4 Model Selection H4

H4 states that the effect of radical changes in confidence would have influence on the behaviour of subjects beyond the setting of the investment game. That is, dependence between membership of treatment groups and the choice to gamble or not is hypothesized. To test the final hypothesis, a cross tabulation is performed. This is a chi-square test on dependence between groups and participation or investment in the fair gamble. The test does not require a model selection.

4. Results[4]

The experiment is conducted among 50 subject. Three subjects did not answer the control questions correctly and were asked to leave. Seven subjects confirmed both questions on the pathological gambling. Their data points are excluded from the analysis. From the final 40 subjects there are 14 in the control group and 13 in each treatment group. Some descriptive statistics can be found in table 13 in the appendix. In the following subsections, the results for each hypothesis are reported and interpreted.

4.1 Results for H1

H1: There is a structural break at T=12

Casual evidence of the structural break can be observed in the graphs of the average data points. Graphs 1 and 2 show respectively the confidence levels and the investments of the control group. A clear divergence is observable in confidence level. Yet the confidence levels do not show any sign of a structural break. The investments have upward sloping trend. The graphs of treatment group 1 reveal a clear break between period 11 and 12 for confidence statistics as well as investments. The same holds for treatment group 2. The difference here is that the structural break is in opposite direction.

Table 5 reports the regression results. The results in table 5 indicate that the control group shows no evidence of a structural break. Furthermore, the results indicate that there is indeed significant evidence of a structural break in both treatments at the round in which the interruption occurs, except for PNEXT in treatment 1. However, the fact that PNEXT has a structural break at all is evidence against the Bayesian benchmark, since PNEXT is constant and equal to 50% in the Bayesian benchmark case. The result that in both treatments PNEXT shows a structural break provides evidence against Bayesian behaviour. However, confidence in winning the game shows more subtleties.

The Bayesian confidence (BAYESWIN) –which is calculated using the actual wealth levels of subjects- for winning the game benchmark shows significant evidence of a structural break in both treatments. For treatment 1 there the structural breaks precedes the interruption period (occurs at T=8). For treatment 2 the structural break for the Bayesians occur after the interruption period in T=15.

[4] Regression tests are performed on serial correlation, heteroskedasticity, misspecification and normality of errors. Results are only reported if significant evidence of the aforementioned is found.

It could be argued that this result in favour of the behaviourist explanation is driven by collinearity between Bayesian confidence levels and the subjects' investment strategies. This is indeed the case; the confidence levels for the Bayesians are determined using the stock as accumulated by the subjects, so a correlation between the confidence levels as measured in the experiment and the Bayesian simulation is plausible. To test this argument, a full simulation is of the Bayesian approach where both the confidence variables (PWIN and PNEXT) and the investments and wealth levels are simulated. As described in section 3.1.7 the investment strategy is on average: 100% if BB, 50% if BR or RB and 0% if RR. Using this information and table 4 and the fact that the endowment is 100 MU's a simulation is made. The results are reported in table 6:

Based on the results of table 6, regressions are performed and tests for structural breaks are conducted. The results are reported in table 7. It is clear from table 7 that if subjects are full Bayesians in beliefs and actions, than – ceteris paribus- no structural breaks would exist in the data. This is significant evidence in support of the behaviourist explanation for radical changes of heart provided by this paper.

An interesting side result of the comparison of the evolution of confidence for the treatments vis-à-vis the Bayesian benchmark is that in both treatment groups average confidence starts off significantly lower than in the Bayesian benchmark (see graphs 7,9,12 and 14) – subjects on average under estimate their likelihood of success. For instance, while the Bayesian confidence (both BAYESWIN and the full simulation of PWIN) starts off above 90%, confidence (PWIN) starts off in treatment 1 on average on 45% and in treatment 2 on average slightly higher than 40%. However, after the interruption subjects on average over estimate in both treatments compared to the Bayesian benchmark; for treatment 1 (losses then gains) confidence is much higher in the periods starting the interruption period compared to the Bayesians while for treatment 2 (gains then losses) confidence exceeds the Bayesian benchmark BAYESWIN in the final periods. Note, however, that this is not contrary to the result of radical change in confidence in treatment 2 as this specific effect is a level effect while the radical change is a change effect. This was anticipated by the choice for the CBDT framework.

This symmetry suggests that the sequence has an intrinsic value in itself; subjects tend to overreact to high uncertainty (first periods) and under react to low uncertainty (final periods) when faced with gains or losses in a sequence. This suggests that the intrinsic value of gains and losses creates myopia over sequences that is more than the sum of myopic behaviour in single periods only. This mechanism is at the core of the radical change in confidence; confidence of subjects is conditioned on patterns of gains and losses and not on single gains or losses. The pattern can cause an overestimation and underestimation vis-à-vis (myopic) Bayesians and depending on the degree of uncertainty. In addition, the uncertainty is resolved based on the position in time of the reference point (bonus threshold); the shorter the time to the reference point the more likely it is that subjects will over estimate their likelihood of success.

4.2 Results for H2

Before choosing the weighting matrix and the type of Arallano-Bond estimator, the data is observed. To start, a dot plot is made of the variable LNPWIN in treatment 1. On the horizontal axe, both the subject ID number and periods are displayed. Graph 8 depicts the dot plot of LNPWIN for treatment group 1. The graph shows a high level of variance. Therefore, the white period weighting matrix which assumes that innovations have a time series correlation structure which varies by cross section. This weighting matrix is thus a heteroskedasticity consistent. In addition, the one-step Arellano-Bond estimator is used, because it yields the smallest standard errors.

Graph 9 depicts LNPNEXT for treatment group 1. This graph shows some smaller amount of variance, but still considerable. The same weighting matrix is used for estimation. The only difference is that here the two-step Arellano-Bond estimator is used, because it is better suitable for persistent heteroskedasticity. Graph 10 for treatment group 2 shows LNPWIN. The graph shows considerably less variance compared to graph 8 and 9. For this purpose the Panel Corrected Standard Error (PCSE) methodology (Beck and Katz, 1995) is used. This weighting matrix assumes that innovations have the same time series structure for all cross sections. The same holds for graph 11 that depicts LNPNEXT for treatment group 2. Both regressions are performed using the two-step Arellano-Bond estimator. The results of all GMM estimations are reported in table 8. To test H2, the sum of lagged coefficient values are compared across treatments. Support for H2 is found if the value of the coefficient of treatment 2 is larger than the values in treatment 1, all in absolute terms.

For LNPWIN it follows that the value for treatment 2 $|-0.856|>|0.681|$ of treatment 1. There is significant evidence against the null hypothesis and in support of H2. For LNPNEXT the value of the parameter estimates is $|-1.05|>|0.489|$ of treatment 1. Again, there is significant evidence in support of H2. In conclusion, there is significant evidence to suggest that the magnitude of the effect of an interruption of a sequence of gains on confidence is smaller compared to the case in which a sequence of losses is interrupted by gains.

4.3 Results for H3

The chow breakpoint test in treatment group 1 revealed significant evidence (10% level) of a structural break in T=11 for both regression of LNSINV on LNPWIN and LNSINV on LNPNEXT. The sub hypotheses to be tested thus become. For treatment group 2 the breakpoint occurs at T=12.

The results reported in table 9 suggest significant evidence at 1% in support of H3A.1 and H3B.1; for treatment 1 the mean invested proportion is larger in the second period compared to the first period and for treatment 2 the mean invested proportion is smaller in the second period compared to the first period. Table 9 also suggests significant evidence in support of H3.A.2 and H3A.2; the mean proportion invested for treatment 1 in the second period is at 1% significantly higher (74.77) than the Bayesian benchmark, while for treatment 2 it is at 1% significantly lower (36.49) than the Bayesian benchmark. This provides strong evidence of overreaction by subjects. This Bayesian benchmark of 62.5% for a trajectory of gains and losses the same as treatment 1 and 50 for a trajectory of gains and losses the same as treatment 2.

The results reported in table 10 suggest evidence to support H3A.3 and H3B.3; all parameter estimates of LNPWIN and LNPNEXT are higher in magnitude in the second regression period.

For treatment group 1 (H3A.3):

LNPWIN parameter estimate: |-0.038| in T11-18 > |0.032|in T1-10

This means that a 1% increase in the confidence that the subject will win the game causes an effect of 3.8% in LNSINV in T11-18 while a 1% in T1-10 causes only an effect of 3.2% on LNSINV. The fact that the direction of the effect is negative in the second regression shows that subjects believe less that they will win the game and this belief results in a higher proportion of investments. This supports the loss aversion axiom in prospect theory.

LNPNEXT parameter estimate: |0.030| in T11-18 > |0.020| in T1-10

Similar to LNPWIN; a 1% increase in confidence that the next round will have a positive return causes an effect of 3% on the proportion invested in the second period while it causes only an effect of 2% in the first period.

For treatment 2 H3B.3:

LNPWIN parameter estimate: |0.277| in T11-18 > |0.045|in T1-10

A 1 % increase in the confidence of the subject to win the game causes an effect of 27.7% on the proportion invested in the second period while it causes only 4.5% in the first period. The high increase could suggest evidence in support of the house money effect; subjects have earned a lot during the sequence of gains and this return is easily invested once the sequence is interrupted by a sequence of losses. This is in accordance with the theory in section 2.

LNPNEXT parameter estimate: |0.325| in T11-18 > |0.222| in T1-10

A 1% increase in the confidence of the subject that the next round will bring a positive return causes an effect of 32.5% on the proportion invested in the second period, while it causes a lower but substantial effect of 22.2% in the first period. This evidence could be interpreted as overconfidence; subjects experience a sequence of gains and believe that it is because of their ‘superior’ ability to predict and invest. Once the interruption occurs, they maintain their belief in their ability, but the effect is exacerbated by the experienced losses.

There are however some caveats; the R^2 is low all around and does not exceed 0.50, furthermore, two regressions in treatment 2 are rejected by the Hausman test. The explanation is twofold; the R^2 is low for a part because ability is an unobserved variable that could explain some part of the variance. The other reason why R^2 is low applies also to the rejection by the Hausman test; the sample size is too small in some instances to show enough variance for the random effects model. To test the robustness of the results for H3 a fixed effects model is estimates for all equations. Time-invariant variables are dropped since they are not supported in the fixed effect framework. The results are reported in table 11. Again, significant evidence is found to support H3: all coefficient estimates for LNPWIN and LNPNEXT for both treatments are larger in magnitude in the second period regression.

For treatment 1:

LNPWIN: |-0.049| in T11-18 > |0.034| in T1-10

LNPNEXT: |0.022| in T11-18 > |0.052| in T1-10

The results here are very much similar to the results of the random effects model.

For treatment 2:

LNPWIN: |0.328| in T12-18 > |0.000| in T1-11

LNPNEXT: |0.370| in T12-18 > |-0.328| in T1-11

In H3B.1 it is established that the mean proportion invested in the second period is lower than in the first period. The negative direction of the parameter estimates in the first period suggest that in contrast to the random effects model, subject are careful with the proportion they invest in the first period, while they significantly increase the proportion invested subject to their beliefs in the second period. One explanation could be that they become risk averse when they have positive returns while they become risk seeking when they experience losses. This explanation is consistent with prospect theory. The fact that the parameter estimate of the confidence of subjects that they will win the game is zero (insignificant) could be because it shows low variance since subjects believe with consistently high probability that they will win.

4.4 Results for H4

> **H4a**: Risk taking behaviour in a different setting will increase after ending a sequence of losses with gains
>
> **H4b**: Risk taking behaviour in a different setting will decrease after ending a sequence of gains with losses

To test the two hypotheses a cross tabulation chi-square test is performed. This test checks for dependence between the groups on one hand and the investment amount in the fair gamble. Before the test is conducted, the investment variable for the gamble is transformed into dummy variable with value 1 if any positive amount is invested. The new variable is named DUMILOT. The results are reported in table 12.There is no significant evidence that there is any dependence between treatment group. A possible explanation is that the sample of 40 subjects is too small to give significant results. Alternatively there might not be any dependence regardless of sample size.

4.5 CBDT

The signals have significance in the regressions performed under H3. This supports CBDT. At the same time, some care must be considered; the significance of the signals was lower or vanished with increased uncertainty (i.e. signals RB or BR). This suggests that similar cases are evaluated in a similar fashion by agents, as long as uncertainty is limited.

5 Discussion, limitations and implications.

The main question of this thesis is: Do economic agents have radical changes in confidence and behaviour that is significantly different from Bayesian predictions when faced by a sequence of gains interrupted by a loss or vice versa? To answer this question an experiment is conducted using 40 admissible subjects to test four hypotheses. The results show that in contrast to Bayesian agents, subjects showed a radical change of confidence after the interruption of a sequence. This change effect was tested using hypothesis 1. Testing of hypothesis 1 also reveals that subjects on average underestimate the *level* of their likelihood of success when uncertainty is high while on average they overestimate it when uncertainty is low. Corollary to this result is that the shorter the time to the bonus threshold, the more likely it is that people on average will overestimate the likelihood of success. This could have implications for bonus structures in firms; the shorter the time spans between bonus periods, the more likely it is that employees will on average overestimate the level of their likelihood of success and potentially takes unjustifiable risks.

Furthermore, the results of H2 suggest that the magnitude of the effect of confidence intensifies after an interruption of gains vis-avis an interruption of losses. This means that agents react more intensively to an interruption of a sequence of gains than an interruption of a sequence of losses. This seems to fit the economic reality where recessions tend to happen fast (f.e. contagion of crisis is rapid), while the recovery is relatively slow. This statement is of course nuanced, in the sense that prior to a bust not every agent experiences a sequence of gains and during a bust not every agent experiences a sequence of losses. Some agents in the economy might gain during a recession and some might lose during economic prosperity. The experiment, however, allowed disentangling the effects. Beliefs are thus subject to the pattern of gains and losses that an agent experiences.

What about action? H3 reveals that the ‘overreaction’ in beliefs spills over to action; subjects invest a significantly higher percentage of their wealth after an interruption of a sequence of losses compared to the Bayesian agents. Similarly, subjects invest a significantly lower percentage of their wealth after an interruption of a sequence of gains compared to Bayesian agents. In addition, the magnitude of the effect of beliefs on action intensifies after the interruption for all treatments. Finally, this effect of radical changes in confidence has not been found significant in a different setting after the initial investment game has stopped;

subjects did not participate significantly more or less in the fair gamble conditioned on what they have experienced.

5.1 Limitations

Some care must be taken in the interpretation of the results. The main limitation is the sample size. Although significant results were found, the variance is limited due to the sample size. A larger sample would allow more confident inferences of the data. In addition, some unobserved variables might have been a factor – such as ability. These factors are not taken into account in the results. Finally, the sample selection is not completely random; subjects were recruited from one particular university (Erasmus University Rotterdam). Self selection might have been in play, since participation in the experiment was voluntary. Taken into account these limitations, the results still seem robust and significant.

6 Conclusion

The answer to the main question: ‘Do economic agents have radical changes in confidence and behaviour that is significantly different from Bayesian predictions when faced by a sequence of gains interrupted by a loss or vice versa?’ is unequivocally “yes”. Building on existing literature on economic decision making and on the effect of prior gains and losses, this paper provides evidence to suggest that the sequence matters for the beliefs *and* the actions of agents. The paper brings forward two innovations: (1) the effect of beliefs and the effect of action is separated by means of an experimental design, (2) the effect of sequences of gains and losses on beliefs and actions of agents is disentangled and measured. This second innovation shows that agents have radical changes of in confidence close to despair (euphoria) once a sequence of gains (losses) is interrupted. The main contribution of this paper is that it provides a consistent explanation for the timing and occurrence of radical changes in confidence. The insights are anticipated to be useful to policy makers.

Given the results, the main policy recommendation is to moderate and regulate markets forces; network effects, the timing of bonuses and the fundamentals of capitalism create an environment where large players keep growing (experiencing a sequence of gains) such that overconfident behaviour inevitably will surface. Shorter time spans between bonus periods or other reference points can act as a catalyst to this process. The overconfidence is in vain such that it creates its own sequence of losses for the future by the taking of unacceptable risk. The sequence of losses need not to be long, it simply needs to be long enough to crush the overconfidence of players that has been built over a longer period. The time span between bonus periods (quarterly or yearly or otherwise) is an important catalyst in this respect. On its turn, this twist of events will create the perfect environment for long lasting recessions as the road to “despair” makes it marks on players. Inevitably, the sequence of gains will return to build up “euphoria” to a new high just to be crushed once again. Policy makers, therefore, can choose to implement measures of moderation such that welfare is maximized in the long run.

More research with a larger sample, however, is needed to investigate the robustness of the results in the field. Also more research is needed to investigate whether there exist a tipping point of number of agents experiencing one or the other sequence to have a substantial effect on the whole economy. Finally, it would be interesting to investigate exceptions to the results: when would agents not show radical changes of hearts after an interruption of a sequence of gains (losses)?

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Appendix A

WELCOME!
PLEASE WAIT UNTIL THE EXPERIMENTER TELLS YOU TO START!

This is a serious scientific experiment. Talking, looking around or walking around are not allowed. If you have any questions of any kind, please raise your hand and an experimenter will come to you. If you , exclaim out loud, etc., YOU WILL BE ASKED TO LEAVE AND YOU WILL NOT BE PAID. Thank you.

You are about to participate in an experiment in decision making. Universities and research foundations have provided the funds for this experiment.
In this experiment we will ask you to read instructions that explain the decision scenarios you will be faced with. We will also ask you to answer questions that test your understanding of what you read. Finally, you will be asked to make decisions that will allow you to earn money. Your monetary earnings will be determined by your decisions and the decisions of other participants in the experiment. All that you earn is yours to keep, and will be paid to you in private, in cash, after today's session.

The experiment consists of two parts. First you will be asked to fill out a questionnaire. Second you will play an investment game. The questionnaire is concerned with general information about you. In the investment game you face several investment options.

Part 1: Please READ the instructions carefully

This questionnaire is concerned with your current feelings. Please answer **every** question, even if you find it difficult. Answer, as honestly as you can, what is true of **you**. Please do not choose a reply just because it seems like the 'right thing to say'. Your answers will be kept entirely confidential. Also, be sure to answer according to how you feel **AT THE MOMENT**. Don't just put down how you usually feel. You should try and work quite quickly: there is no need to think very hard about the answers. The first answer you think of is usually the best.

Before you start, please provide some general information about yourself.

Age ....

Gender ☐ Male ☐ Female

If student, state your course ....

How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

(Please tick a box on the scale, where the value 0 means: 'risk averse' and the value 10 means:'fully prepared to take risks'. You can use the values in between to make your estimate.)

☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ 6 ☐ 7 ☐ 8 ☐ 9 ☐ 10

Have you ever had to lie to people important to you ☐ Yes ☐ No about how much you gambled?

Have you ever felt the need to bet more and more money? ☐ Yes ☐ No

Here is a list of words which describe people's moods or feelings. Please indicate how well each word describes how you feel **AT THE MOMENT**. For each word, circle the answer from 1 to 4 which best describes your mood.

	Choose the most appropriate answer			
	Definitely	**Slightly**	**Slightly not**	**Definitely not**
1. Happy	☐	☐	☐	☐
2. Dissatisfied	☐	☐	☐	☐
3. Energetic	☐	☐	☐	☐
4. Relaxed	☐	☐	☐	☐
5. Alert	☐	☐	☐	☐
6. Nervous	☐	☐	☐	☐
7. Passive	☐	☐	☐	☐
8. Cheerful	☐	☐	☐	☐
9. Tense	☐	☐	☐	☐
10. Jittery	☐	☐	☐	☐
11. Sluggish	☐	☐	☐	☐
12. Sorry	☐	☐	☐	☐
13. Composed	☐	☐	☐	☐
14. Depressed	☐	☐	☐	☐
15. Restful	☐	☐	☐	☐
16. Vigorous	☐	☐	☐	☐
17. Anxious	☐	☐	☐	☐
18. Satisfied	☐	☐	☐	☐
19. Unenterprising	☐	☐	☐	☐
20. Sad	☐	☐	☐	☐
21. Calm	☐	☐	☐	☐
22. Active	☐	☐	☐	☐
23. Contented	☐	☐	☐	☐
24. Tired	☐	☐	☐	☐
25. Impatient	☐	☐	☐	☐
26. Annoyed	☐	☐	☐	☐
27. Angry	☐	☐	☐	☐
28. Irritated	☐	☐	☐	☐
29. Grouchy	☐	☐	☐	☐

Appendix B

INVESTMENT GAME: Please read the instructions carefully

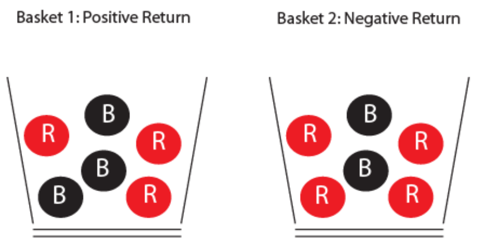
You are about to start participation in the investment game. This game consists of 18 rounds. In each round you can decide to invest in a new opportunity or to put your money in a savings account with 0% return. Each new opportunity emits a signal about its prospects. This signal, however, is noisy. The signal consists of two letters 'B' (black ball) and 'R' (red ball). These balls are randomly drawn with replacement from either of two baskets:

Basket 1: this company will make a positive result

Content: 3 black balls and 3 red balls

Basket 2: this company will make a negative result

Content: 2 black balls and 4 red balls



You cannot observe directly from which basket the signal is drawn. Moreover, on the long run the expected return of the investments is equal to zero. Returns on investment can take only two values: +10% or -10%. Alternatively you can choose to save (some) money in each round on your savings account at 0% return. This is the amount that you choose not to invest.

Your task is thus twofold:

1. Make investment decisions (i.e. invest and/or save) each round to maximize your profit.

2. Predict whether you will win.

You can earn money for each task:

1. Investment decision: at the start you receive 100 points. If you have accumulated at least 150 points at the end of the final round you will receive a 5 euro bonus. If you accumulate less you receive the amount of points you have converted into euro's (conversion rate 50 points = €1).

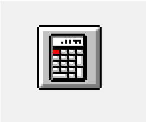
An example: If at the end of the last round you have accumulated 180 points, the you will receive for your investment decisions: €3.60 (=180/50) **PLUS** €5 bonus = €8.60. Alternatively, if you have accumulated 140 MU's at the end of the final round you will receive: 140/50 = € 2.80

2. Prediction: for each round you will be asked to predict whether you will have a positive return in the next round. For each prediction you can earn a maximum €0.10 depending on the quality of your prediction. Your points in each prediction task are calculated using the formula:

Prediction points = 0.10 – 0.10(actual-predicted)^2. This means that you are going to be paid based on what actually happened. The smaller the difference is between what actually happened and your initial prediction, then the higher is your payoff. It is thus in your best interested to make good predictions.

The total amount you receive is the sum of the amounts you receive for your investment decisions and the amount you receive for your predictions. PLEASE NOTE THAT THE EARNINGS OF THE PREDICTIONS ARE SEPARATE FROM THE EARNINGS FROM THE INVESTMENT DECISIONS.

On the screen you will notice a button that looks like this:



This is a calculator. You are free to use it. Click on it to open the calculator.

Finally: To make sure you have understood the instructions you will now have five control questions. If you pass all five questions, you are allowed to start the investment game. THINK CAREFULLY BEFORE ANSWERING AND USE THE INSTRUCTIONS ABOVE AS A REFERENCE.

To make sure you have understood the instructions you will now have five control questions. If you pass all three questions, you are allowed to start the investment game.

Question 1:

If someone accumulates 160 MU's at the end of the last round, how much will ys/he be paid out for his(her) investment decisions?

☐ € 8
☐ € 10
☐ € 13

Question 2

If someone were to invest 100 MU's in an opportunity and that opportunity has a positive return. How much will that person have earned

☐ 110 MU's
☐ 125 MU's
☐ 90 MU's

Question 3

If someone were to invest 100 MU's in an opportunity and that opportunity has a negative return. How much MU's will that person have at the end of that round?

☐ 110 MU's
☐ 90 MU
☐ 95

Question 4

If someone were predict exactly whether s/he will make a positive return in the next round. How much does that person then earn:

☐ € 1
☐ € 0.25
☐ € 0.10

Question 5

If someone invests 50 MU's and saves 50 MU's, and s/he receives a negative return on the investment. How much MU"s does that person have at the end of that round?

☐ 100 MU's
☐ 95 MU's
☐ 90 MU's

Appendix C: Tables

Table 1 : Scheme of experiment design

	Survey	**Investment Game**	**Fair Gamble**
Frequency	- once at the start - once at the end	each round	Once (after investment game)
Task	fill in multiple choice questionnaire	- investment task - prdiction task	Investment task
Purpose	Measure control variables	- Measure confidence - Measure action	Measure changes in risk appetite

Figure 1: Timing of tasks in the experiment

Figure 2: Set up of each period

Period

T1	**T2**	**T3**	**T 4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**	**T11**	**T12**	**T13**	**T14**	**T15**	**T16**	**T17**	**T18**
Control Group																	
-	-	+	-	-	+	+	+	-	+	+	-	+	-	-	+	-	+
RR	BR	RB	RR	BR	BR	BR	RB	BR	RB	BB	RB	RB	BR	BR	BB	BR	RB
Treatment 1:																	
+	-	-	-	-	-	-	-	-	-	+	+	+	+	+	+	+	+
BB	BR	RB	RR	BR	BR	BR	RB	BR	RR	BB	BB	BR	BB	BR	BB	RB	RB
Treatment2																	
-	+	+	+	+	+	+	+	+	+	-	-	-	-	-	-	-	-
RR	BR	RB	BB	BR	BR	BR	RB	BR	BB	BB	RR	BR	RR	BR	RR	RB	RB

Table 2: Posterior Beliefs of Bayesians

	Signal		
Posterior beliefs	θ = BB	θ = BR/RB	θ = RR
P(+ |θ)*	(1/4)/(1/4+1/9) =9/13 ≈ 0.693	(1/4)/(1/4+2/9) =9/17 ≈ 0.529	(1/4)/(1/4+4/9) =9/25 ≈ 0.360
P(- |θ)**	(1/9)/(1/4+1/9) =4/13 ≈ 0.308	(2/9)/ (1/4+2/9) =8/17 ≈ 0.471	(4/9)/(1/4+4/9) =16/25 ≈ 0.640

$$* P(+|\theta) = \frac{P(\theta|+)P(+)}{P(\theta)} = \frac{P(\theta|+)1/2}{1/2P(\theta|+)+1/2P(\theta|-)} = \frac{P(\theta|+)}{P(\theta|+)+P(\theta|-)}$$

$$**P(-|\theta) = \frac{P(\theta|-)P(-)}{P(\theta)} = \frac{P(\theta|-)}{P(\theta|+)+P(\theta|-)}$$

Table 3: Strategy Profile of Bayesians

	Expected Return – value in parentheses		
Action	*θ = BB*	*θ = BR/RB*	*θ = RR*
Invest	YES (3.84%)	YES (0.58%)	NO
Save	NO	NO	YES (2.80%)

Table 4: Bayesian confidence benchmark ***(next to T.. the minimum required wealth level is give.)***

	All Gains	1 Loss	2 Losses	3 Losses	4 Losses	5 Losses	6 Losses	7 Losses	8 Losses	9 Losses	10 Losses	11 Losses	12 Losses	13 Losses	14 Losses	15 Losses	16 Losses	17 Losses
∑Pr	50.00%																	
T18	136.36																	
∑Pr	25.00%	75.00%																
T17	123.97	136.36																
∑Pr	12.50%	50.00%	87.50%															
T16	112.70	123.97	136.36															
∑Pr	6.25%	31.25%	68.75%	93.75%														
T 15	102.45	112.70	123.97	136.36														
∑Pr	3.13%	18.75%	50.00%	81.25%	96.88%													
T 14	93.14	102.45	112.70	123.97	136.36													
∑Pr	1.56%	10.94%	34.38%	65.63%	89.06%	98.44%												
T 13	84.67	93.14	102.45	112.70	123.97	136.36												
∑Pr	0.78%	6.25%	22.66%	50.00%	77.34%	93.75%	99.22%											
T 12	76.97	84.67	93.14	102.45	112.70	123.97	136.36											
∑Pr	0.39%	3.52%	14.45%	36.33%	63.67%	85.55%	96.48%	99.61%										
T 11	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36										
∑Pr	0.20%	1.95%	8.98%	25.39%	50.00%	74.61%	91.02%	98.05%	99.80%									
T 10	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36									
Cum Prob	0.10%	1.07%	5.47%	17.19%	37.70%	62.30%	82.81%	94.53%	98.93%	99.90%								
T 9	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36								
∑Pr	0.05%	0.59%	3.27%	11.33%	27.44%	50.00%	72.56%	88.67%	96.73%	99.41%	99.95%							
T 8	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36							
∑Pr	0.02%	0.32%	1.93%	7.30%	19.38%	38.72%	61.28%	80.62%	92.70%	98.07%	99.68%	99.98%						
T 7	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36						
∑Pr	0.01%	0.17%	1.12%	4.61%	13.34%	29.05%	50.00%	70.95%	86.66%	95.39%	98.88%	99.83%	99.99%					
T 6	43.45	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36					
∑Pr	0.01%	0.09%	0.65%	2.87%	8.98%	21.20%	39.53%	60.47%	78.80%	91.02%	97.13%	99.35%	99.91%	99.99%				
T 5	39.50	43.45	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36				
∑Pr	0.00%	0.05%	0.37%	1.76%	5.92%	15.09%	30.36%	50.00%	69.64%	84.91%	94.08%	98.24%	99.63%	99.95%	100.00%			
T 4	35.91	39.50	43.45	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36			
∑Pr	0.00%	0.03%	0.21%	1.06%	3.84%	10.51%	22.72%	40.18%	59.82%	77.28%	89.49%	96.16%	98.94%	99.79%	99.97%	100.00%		
T 3	32.64	35.91	39.50	43.45	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36		
∑Pr	0.00%	0.01%	0.12%	0.64%	2.45%	7.17%	16.62%	31.45%	50.00%	68.55%	83.38%	92.83%	97.55%	99.36%	99.88%	99.99%	100.00%	
T 2	29.68	32.64	35.91	39.50	43.45	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36	
∑Pr	0.00%	0.01%	0.07%	0.38%	1.54%	4.81%	11.89%	24.03%	40.73%	59.27%	75.97%	88.11%	95.19%	98.46%	99.62%	99.93%	99.99%	100.00%
T 1	26.98	29.68	32.64	35.91	39.50	43.45	47.79	52.57	57.83	63.61	69.98	76.97	84.67	93.14	102.45	112.70	123.97	136.36

Table 5: Hypothesis 1A and 1B

		Dependent Variable							
		Control Group		**Treatment 1**			**Treatment 2**		
		PWIN	*PNEXT*	*PWIN*	*PNEXT*	*BAYESWIN*	*PWIN*	*PNEXT*	*BAYESWIN*
H1	Constant	5.788	40.597***	4.190	12.399	-1.916	7.270	7.944	-18.406***
		(0267)	(0.010)	(0.272)	(0.186)	(0.518)	(0.314)	(0.338)	(0.001)
	y (-1)	0.787***	0.279	0.841***	0.736***	0.923***	0.856***	0.816***	1.165***
		(0.000)	(0.271)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.68	0.08	0.76	0.48	0.96	0.72	0.61	0.97
	Significance of regression	(0.000)***	(0.271)	(0.000)***	(0.002)***	0.000***	(0.000)***	(0.000)***	(0.000)***
	Structural Break	NO (0.501)	NO (0.999)	T=12 (0.032)**	T=10 (0.042)**	T=8 (0.000)***	T=12 (0.003)***	T=12 (0.004)***	T=15 (0.000)***

Table 6: Simulation Bayesian outcomes for the investment game

	Treatment 1				**Treatment 2**			
Period	Signal	Stock	INV	BPWIN	Signal	Stock	INV	BPWIN
1	BB	100	100	98.45581	RR	100	0	98.45581
2	BR	110	55	99.36371	BR	100	50	97.54791
3	RB	104.5	52.25	98.93646	RB	105	50	98.93646
4	RR	99.275	0	94.07654	BB	110.25	110.25	98.24219
5	BR	99.275	49.6375	91.02173	BR	121.275	60.6375	99.35303
6	BR	94.31125	47.15563	86.65771	BR	127.3388	63.66938	99.8291
7	BR	89.59569	44.79784	61.2793	BR	133.7057	66.85284	99.68262
8	RB	85.1159	42.55795	50	RB	140.391	70.19549	99.95117
9	BR	80.86011	40.43005	17.1875	BR	147.4105	73.70526	99.90234
10	RR	76.8171	0	1.95313	BB	154.781	154.781	100
11	BB	76.8171	76.8171	0.39063	BB	170.2592	170.2592	100
12	BB	84.49881	84.49881	0.78125	RR	153.2332	0	100
13	BR	92.94869	46.47435	1.5625	BR	153.2332	76.61662	100
14	BB	97.59613	97.59613	3.125	RR	145.5716	0	96.875
15	BR	107.3557	53.67787	6.25	BR	145.5716	72.78579	93.75
16	BB	112.7235	112.7235	12.5	RR	138.293	0	87.5
17	RB	123.9959	61.99794	25	RB	138.293	69.1465	75
18	RB	130.1957	130.1957	25	RB	131.3783	0	0

Table 7: Results Rational Bayesian Benchmark simulation *(PWIN and PNEXT are here simulated variables using the techniques described in section 3)*

	Dependent Variable	
	Treatment 1	**Treatment 2**
	PWIN	*PWIN*
Constant	-0.492	-261.433***
	(0.902)	(0.000)
PWIN (-1)	0.913***	3.642***
	(0.000)	(0.000)
R^2	0.93	0.93
Significance of regression	0.000***	0.000***
Structural Break	NO 0.243	NO 0.355**

Table 8: GMM estimation for treatment groups

		Dependent Variable			
		Treatment 1		**Treatment 2**	
		LNPWIN	*LNPNEXT*	*LNPWIN*	*PNEXT*
H2	y (-1)	0.681***	0.264***	-0.506***	-0.126
		(0.000)	(0.000)	(0.000)	(0.249)
	y (-2)		0.225**	-0.350***	-1.058***
			(0.016)	(0.005)	(0.000)
Dummies:	Period 12	0.407	0.129	-0.067	-0.016
		(0.110)	(0.340)	(0.199)	(0.753)
	Period 13	0.609**	0.154	-0.398	-0.704**
		(0.0323)	(0.216)	(0.140)	(0.017)
	Period 14	0.430*	0.125	-0.974**	-1.618***
		(0.075)	(0.239)	(0.036)	(0.006)
	Period 15	0.546*	0.338*	-1.381**	-2.258***
		(0.059)	(0.078)	(0.025)	(0.003)
	Period 16	0.479*	0.055	-2.252***	-2.744***
		(0.092)	(0.793)	(0.002)	(0.000)
	Period 17	0.972***	0.096	-2.129***	-2693***
		(0.005)	(0.019)	(0.003)	(0.000)
	Period 18	0.772**	0.369**	-2.111***	-3.092***
		(0.016)	(0.019)	(0.003)	(0.000)
	Sargan Test	(0.170)	(0.340)	(0.894)	(0.348)
	Significance of regression	(0.000)***	(0.002)***	(0.000)***	(0.000)***
	N	91	91	91	91

Table 9: T-tests for SINV

		SINV							
		Control Group		**Treatment 1**			**Treatment 2**		
		All Periods	*BAYES*	*T1-10*	*T11-12*	*BAYES*	*T1-10*	*T11-12*	*BAYES*
H1	Mean	56.98	50	44.82	74.77	62.50	55.20	36.49	50
	StDev	38.596	-	36.698	34.653	-	33.112	37.44	-
	Std. Error	2.431	-	3.219	3.398	-	2.769	3.957	-
	N	252		130	104		143	91	
Test H3.A.1	Levene Test				0.088 (0.767)			2.396 (0.123)	
	t-statistic				6.399*** (0.000)			-3.875*** (0.000)	
Test H3.A.2	t-statistic	2.870*** (0.004)			3.610*** (0.000)			-3.415*** (0.001)	

Table 10: Random effects estimation for LNSINV

		Dependent Variable LNSINV			
		Treatment 1		Treatment 2	
		T1-10	*T11-18*	*T1-11*	*T12-18*
Model 1	Constant	0.168 (0.513)	0.560*** (0.000)	3.003*** (0.000)	1.980 (0.282)
	LNPWIN	0.032*** (0.002)	-0.038*** (0.003)	0.045 (0.391)	0.277** (0.040)
	RR	-0.371*** (0.000)		-0.967*** (0. 000)	-1.620*** (0.000)
	BR				
	RB	-0.029 (0.330)	0.169*** (0.000)	-0.115 (0.444)	-1.116*** (0.000)
	BB		0.245*** (0.000)	0.051 (0.700)	
	EA	-0.001 (0.91)	0.014*** (0.000)		
	TA	0.005 (0.451)			
	HT		-0.010** (0.038)		0.049 (0.471)
	RISK	0.009 (0.651)		0.074 (0.259)	
	G			0.367* (0.053)	-0.713 (0.131)
	AGE				
	R^2	0.45	0.46	0.05	0.28
	Significance of regression	(0.000)***	(0.000)***	(0.015)**	(0.000)***
	Hausman Test	0.643	0.641	0.609	0.0502*
Model 2	Constant	0.165 (0.248)	0.339** (0.036)	2.353*** (0.000)	2.755 (0.236)
	LNPNEXT	0.020 (0.141)	0.030** (0.036)	0.222*** (0.007)	0.325*** (0.007)
	RR	-0.371*** (0.000)		-0.978*** (0.002)	-1.70*** (0.000)
	RB	-0.017 (0.467)	0.121 (0.110)	-0.112 (0.626)	-1.115*** (0.001)
	BB		0.164** (0.049)		
	EA	-0.003 (0.307)	0.006 (0.178)		
	TA	0.003 (0.379)			
	HT		-0.004 (0.501)		0.012 (0.910)
	RISK	0.013 (0.559)		0.074 (0.222)	
	G			0.362 (0.108)	-0.588 (0.378)
	AGE				
	R^2	0.44	0.42	0.13	0.30
	Significance of regression	(0.000)***	(0.000)***	(0.001)***	(0.014)**
	Hausman Test	0.736	0.068*	(0.000)***	(0.812)

Table 11: Fixed effects estimation for LNSINV

		Dependent Variable LNSINV			
		Treatment 1		Treatment 2	
		T1-10	*T11-18*	*T1-11*	*T12-18*
Model 1	Constant	0.564	0.249**	2.515***	0.873
		(0.136)	(0.013)	(0.000)	(0.212)
	LNPWIN	0.034**	-0.049*	-0.075	0.328**
		(0.046)	(0.056)	(0.465)	(0.036)
	RR	-0.463***			-1.475***
		(0.000)			(0.000)
	BR	-0.104		1.028***	
		(0.181)		(0.000)	
	RB	-0.117	0.155***	0.763***	-1.132***
		(0.169)	(0.000)	(0.000)	(0.000)
	BB		0.222***	0.909***	
			(0.000)	(0.000)	
	EA	-0.006	0.018***	-0.045**	0.092***
		(0.382)	(0.000)	(0.018)	(0.007)
	TA	0.007	0.009***	0.045**	0.068
		(0.377)	(0.001)	(0.017)	(0.108)
	HT	-0.006	-0.013***	0.030	-0.068
		(0.619)	(0.002)	(0.134)	(0.231)
	R^2	0.62	0.58	0.20	0.59
	Significance of regression	(0.000)***	(0.000)***	(0.052)*	(0.000)***
	LM test for Redundanct Fixed effects	(0.000)***	(0.029)**	0.091*	0.000***
Model 2	Constant	0.506***	0.348***	0.878	0.770
		(0.000)	(0.000)	(0.102)	(0.163)
	LNPNEXT	0.022*	0.052***	-0.328***	0.370***
		(0.090)	(0.004)	(0.000)	(0.005)
	RR	-0.449***			-1.596***
		(0.000)			(0.000)
	BR	-0.096***		0.990***	
		(0.000)		(0.000)	
	RB	-0.092***		0.840***	-1.298***
		(0.001)		(0.000)	(0.000)
	BB			0.852***	
				(0.000)	
	EA	-0.004*		-0.033**	0.130***
		(0.096)		(0.030)	(0.001)
	TA	0.003		0.047***	0.064**
		(0.204)		(0.002)	(0.037)
	HT	-0.002		0.025	-0.091*
		(0.540)		(0.104)	(0.075)
	R^2	0.61	0.38	0.24	0.61
	Significance of regression	(0.000)***	(0.000)***	(0.007)***	(0.000)***
	LM test for Redundanct Fixed effects	(0.000)***	(0.000)***	(0.028)**	(0.000)***

Table 12: Crosstabulation with DUMILOT and Group

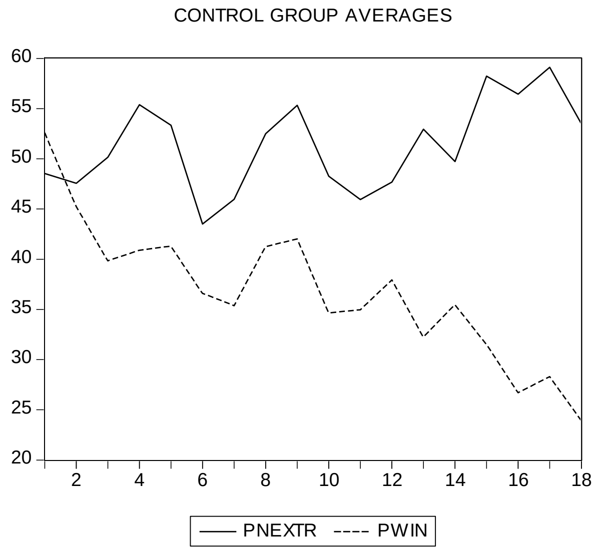
		DUMILOT			
		.00	1.00	Total	Chi Sqr
Group	Control	2	12	14	0.279
	Treatm1	4	9	13	
	Treatm 2	1	12	13	
Total		7	33	40	

Table 13: Descriptives

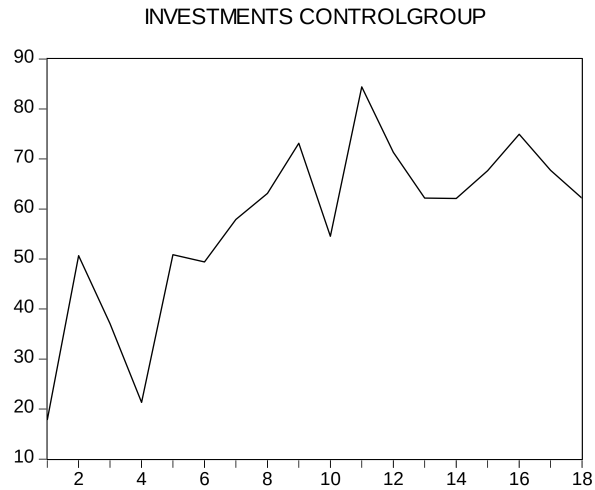
	N	Minimum	Maximum	Mean		Std. Deviation
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
Control Group						
PWIN	252	0	80	32.00	1.361	21.609
PNEXT	252	0	100	52.03	1.610	25.563
INV	252	0	131	59.10	2.612	41.459
RISK	252	1	10	5.21	.159	2.517
EA	252	13	28	21.35	.295	4.677
TA	252	15	25	19.58	.195	3.096
HT	252	16	29	23.02	.252	4.008
INVLOT	252	0	2	1.06	.038	.595
Valid N (listwise)	252					
Treatment 1						
PWIN	234	0	100	29.15	1.873	28.587
PNEXT	234	0	100	45.07	1.647	25.142
INV	234	0	129	53.05	2.334	35.635
RISK	234	2	8	4.99	.129	1.965
EA	234	18	29	23.38	.194	2.960
TA	234	14	25	18.71	.223	3.412
HT	234	23	30	26.15	.123	1.883
INVLOT	234	0	2	1.08	.055	.832
Valid N (listwise)	234					
Treatment 2						
PWIN	234	0	100	49.94	2.058	31.542
PNEXT	234	0	100	46.22	1.817	27.848
INV	234	0	216	59.65	3.213	49.255
RISK	234	0	8	5.39	.134	2.061
EA	234	13	30	21.56	.310	4.755
TA	234	13	23	18.60	.182	2.794
HT	234	16	29	23.83	.231	3.536
INVLOT	234	0	2	1.23	.044	.669
Valid N (listwise)	234					

Appendix D: Graphs

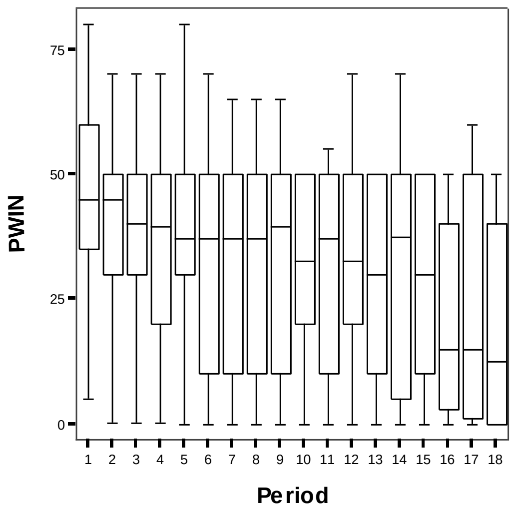
Graph 1: PWIN and PNEXT for Control group



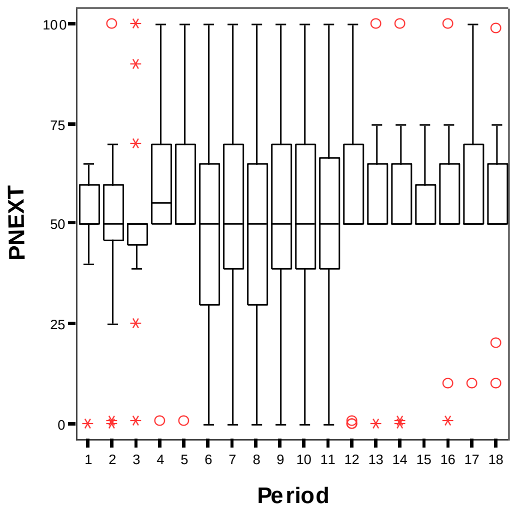
Graph 2: Investment for Control group



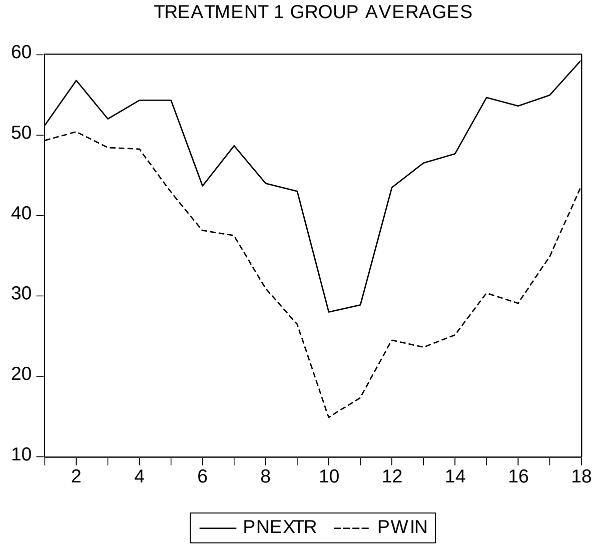
Graph 3: Boxplot for PWIN in Control group



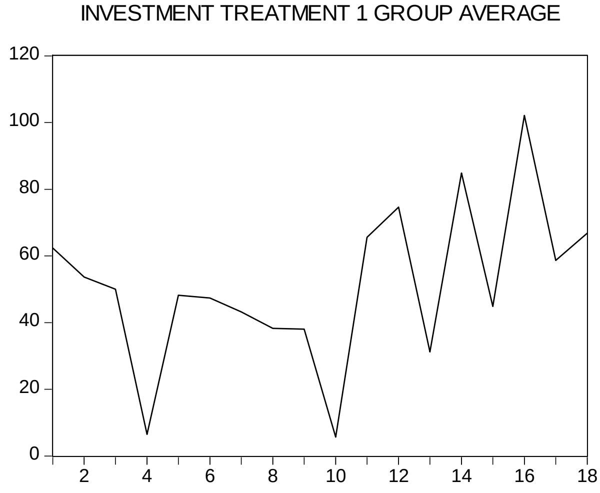
Graph 4: Boxplot for PNEXT in Control group



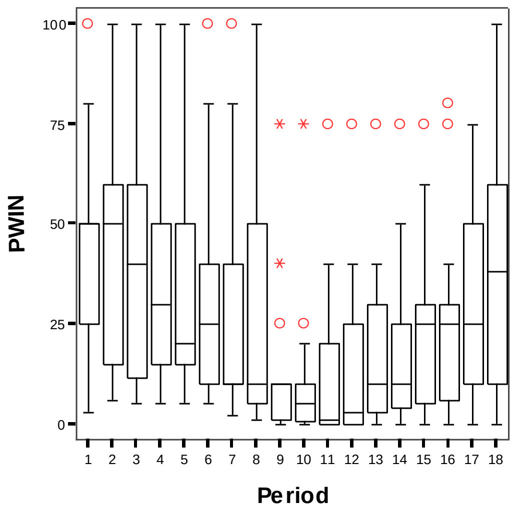
Graph 5: PWIN and PNEXT for Treatment 1



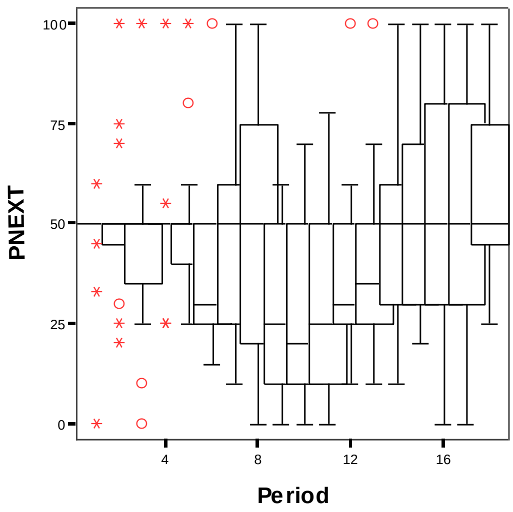
Graph 6: Investment for Treatment 1



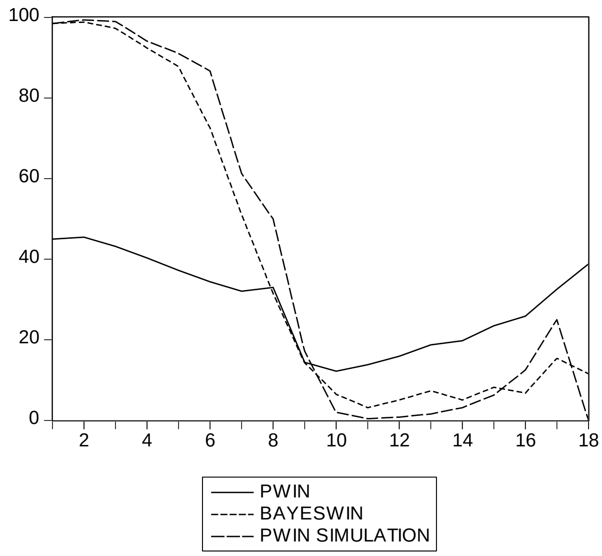
Graph 7: Boxplot for PWIN in Treatment 1



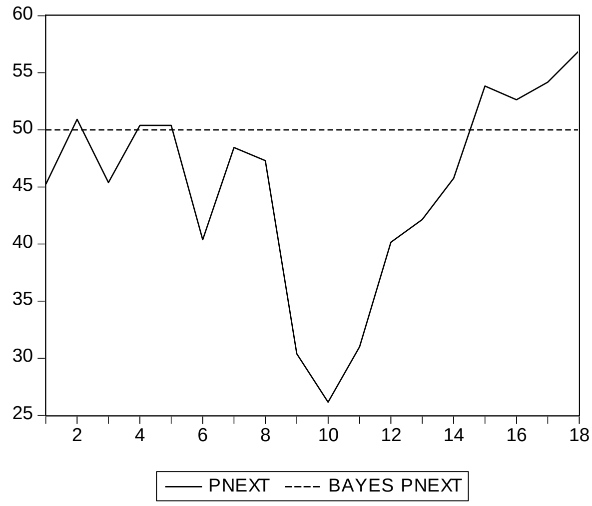
Graph 8: Boxplot for PNEXT in Treatment 1



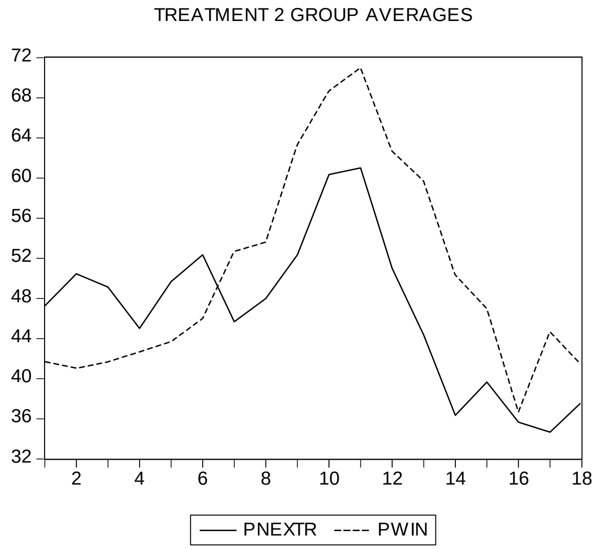
Graph 9: PWIN, BAYESWIN and PWIN Simulation Treatment 1



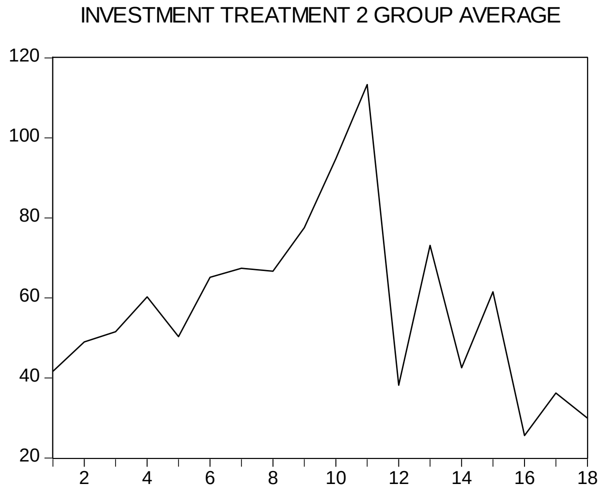
Graph 10: PNEXT and Benchmark Treatment 1



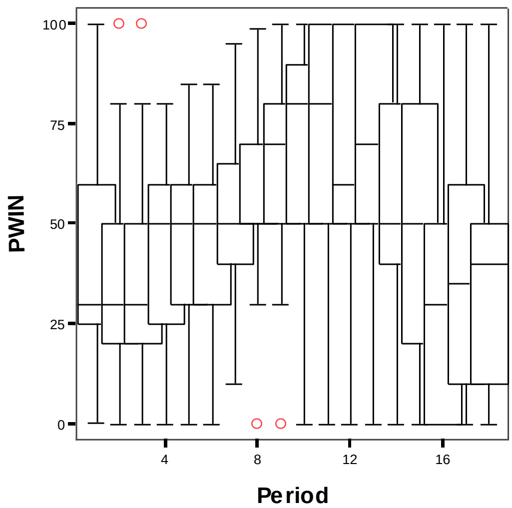
Graph 11: PWIN and PNEXT for Treatment 2



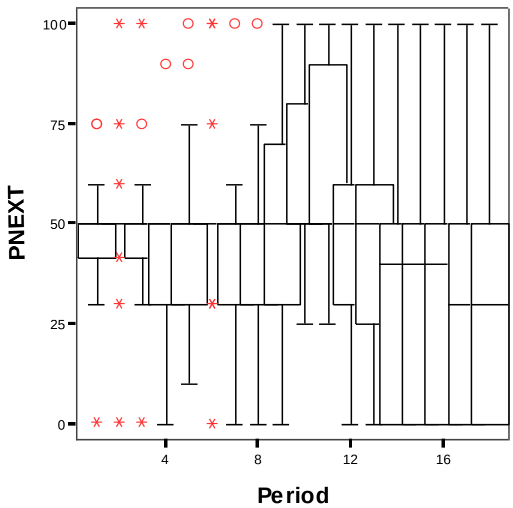
Graph 12: Investment for Treatment 2



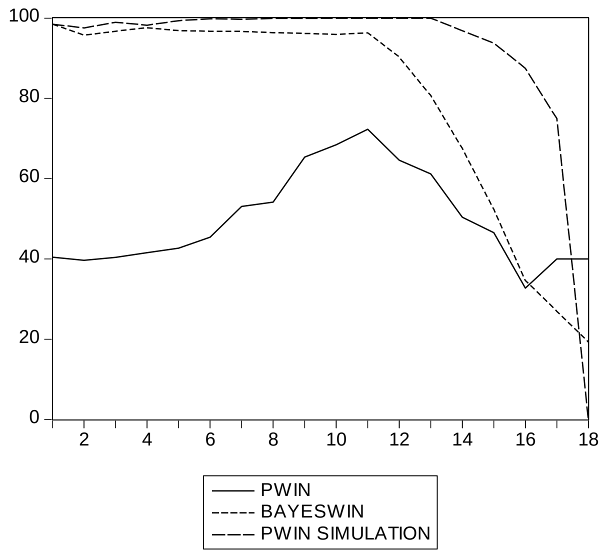
Graph 12: Boxplot for PWIN in Treatment 2



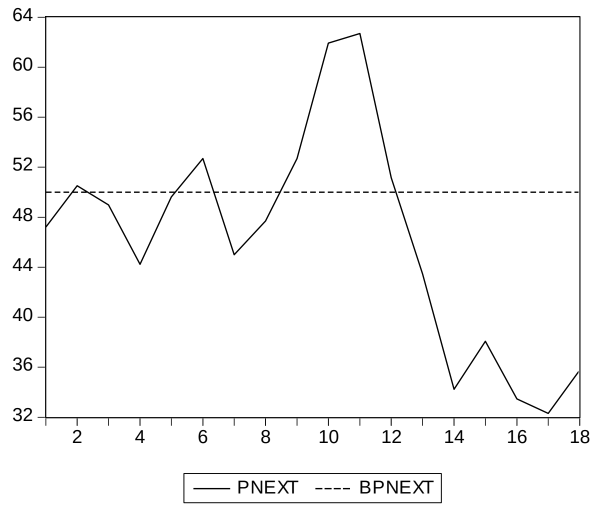
Graph 13: Boxplot for PNEXT in Treatment 2



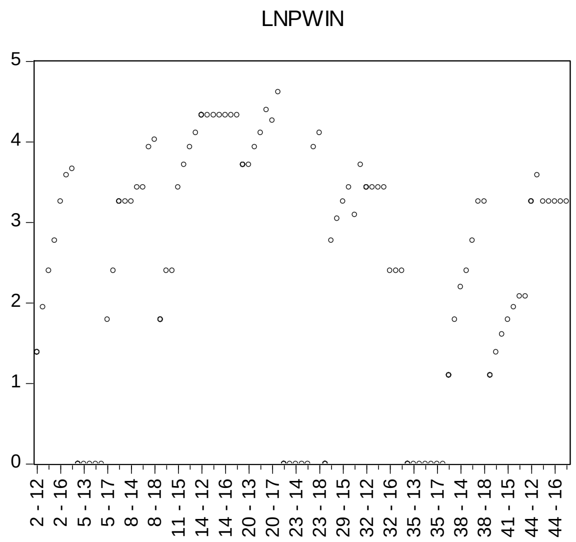
Graph 14: PWIN, BAYESWIN and PWIN Simulation Treatment 2



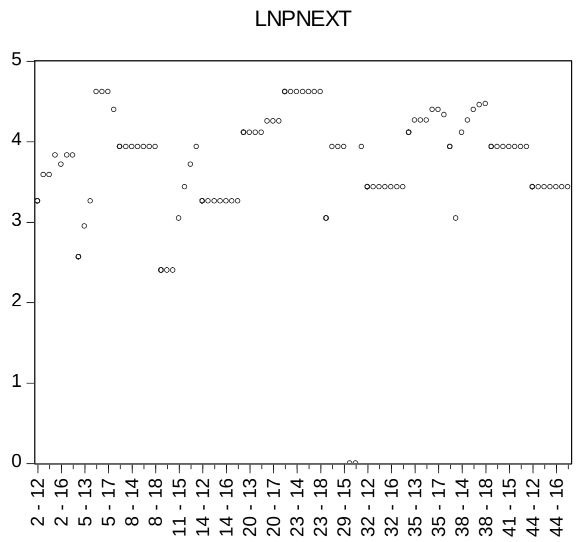
Graph 15: PNEXT and Benchmark Treatment 2



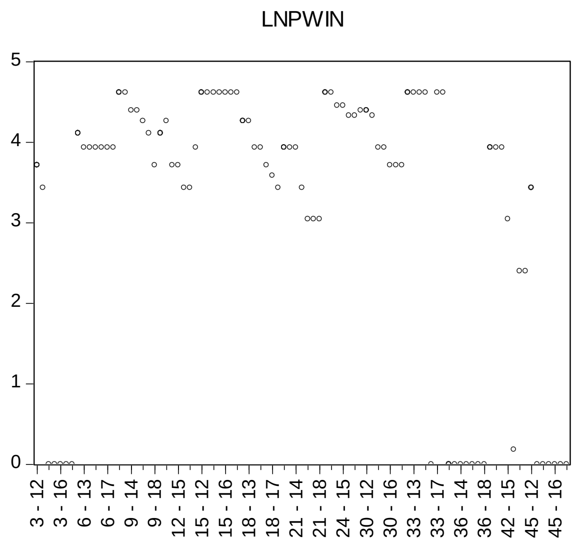
Graph 16: LNPWIN for Treatment 1



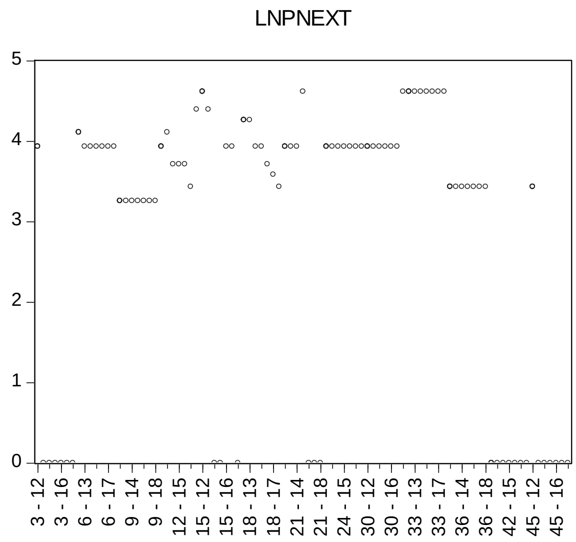
Graph 17: LNPNEXT for Treatment 1



Graph 18: LNPWIN for Treatment 2



Graph 19: LNPNEXT for Treatment 2



Appendix E Generalized Method of Moments

Consider the general case of the model where *y* denotes the dependent variable.;

(14) $y_{it} = \delta y_{it-1} + u_{it} \qquad i = 1,\ldots,N \quad t = 1,\ldots,T$

Where $u_{it} = \mu_i + v_{it}$ and the individual effect error term $\mu_i \sim \text{IID}(0, \sigma_\mu^2)$ and the residual error term $v_i \sim \text{IID}(0, \sigma_v^2)$ are independent from each other and among themselves (Baltagi, 2005). To eliminate the individual effect and obtain a consistent estimate, equation (14) is first differenced. In period 3 and after first differencing, the equation becomes;

(15) $(y_{i3} - y_{i2}) = \gamma(y_{i2} - y_{i1}) + (v_{i3} - v_{i2})$

It is easy to see that y_{i1} is a valid instrument as it is highly correlated with Δy_{i2} but –in the absence of serial correlation- uncorrelated with $(v_{i3} - v_{i2})$. In period 4, both y_{i1} and y_{i2} qualify as valid instruments by the same reasoning. This process goes on until at the final period T the instrument list is ($y_{i1}, y_{i2}, ..., y_{iT-2}$). The moment conditions are:

(16) $E[(\Delta y_{it} - \gamma \Delta y_{it-1}) y_{it-j}] = 0 \qquad j = 2,\ldots,t-1 \quad t = 3,\ldots,T$

However, this procedure does not account for the differenced error term in (14) as this term is MA(1) with unit root. The result is that:

(17) $E[(\Delta v_i \Delta v_i'] \neq \sigma_v^2 = \sigma_v^2 (\text{I}_\text{N} \otimes \text{G})$

Where G:

$$G = \begin{pmatrix} 2 & -1 & 0 & \cdots & 0 & 0 \\ -1 & 2 & -1 & \cdots & 0 & 0 \\ 0 & -1 & 2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 2 & -1 \\ 0 & 0 & 0 & \cdots & -1 & 2 \end{pmatrix}$$

To solve this, a matrix $W = [W_1', \ldots, W_N']'$ of the instrumental variables is defined:

$$W_i = \begin{bmatrix} [y_{i1}] & & & 0 \\ & [y_{i1}, y_{i2}] & & \\ & & \ddots & \\ 0 & & & [y_{i1}, \ldots, y_{iT-2}] \end{bmatrix}$$

Premultiplying this matrix with (14) yields:

(18) $W'\Delta y = W'(\Delta y_{-1})\gamma + W'\Delta v$

It follows that the one-step Arallano-Bond estimator is given by:

(19) $\hat{\delta}_1 = \dfrac{[(\Delta y_{-1})' W (W'(I_N \otimes G) W)^{-1} W'(\Delta y)]}{[(\Delta y_{-1})' W (W'(I_N \otimes G) W)^{-1} W'(\Delta y_{-1})]}$

The two-step Arallano-Bond estimator has the advantage that it does not make any assumptions about the distributions of the variables or initial conditions. It is given by:

(20) $\hat{\delta}_2 = \dfrac{[(\Delta y_{-1})' W V_N^{-1} W'(\Delta y)]}{[(\Delta y_{-1})' W V_N^{-1} W'(\Delta y_{-1})]}$