

WORKING PAPER

An Experimental Test of the Dual Self Model

Hrvoje Stojić, Michael R. Anreiter and José A. Carrasco Martinez*

May 9, 2013

Abstract

We empirically test the predictions of a simplified version of the dual self model as developed by Loewenstein and O'Donoghue (2004) in an experimental setup. In this model, individual behavior is seen as the result of interaction between two "selves" - a deliberative, rational self focused on long term goals and an affective self that is only interested in immediate gratification after evaluating alternatives through simple heuristics. In order to test the model, we exogenously reduce the role of the former using willpower depletion and evaluate whether this leads to the predicted change in behavior. We elicit discount rates and attitudes towards risk from a sample of 54 individuals and find (1) in the case of risk preferences, the treatment results in greater risk aversion as predicted by the model, and (2) in the case of time preferences, we find no effect.

Keywords: Self-control, Dual self theories, Time preferences, Risk preferences

*This working paper is a result of a project done as a partial fulfillment of the master of research degree in economics at the University Pompeu Fabra and is largely built on the master thesis that came out of it. All three authors contributed equally to the paper. We are grateful for the help received from the faculty regarding conducting the experiment. Special thanks are due to Rosemarie Nagel for helpful discussions and comments on earlier drafts. It goes without saying, all errors are our own. Correspondence concerning this article should be addressed to Hrvoje Stojic, Universitat Pompeu Fabra, Department of Economics and Business, Ramon Trias Fargas, 25-27, 08005 Barcelona, Spain. E-mail: hrvoje.stojic@upf.edu.

1 Introduction

Most of us have found ourselves in a supermarket after a long day of work, loading up the shopping cart with massive amounts of food and other items. Later on, when we unload the items at home, we wonder what we must have been thinking in the supermarket. Similarly, many people regularly experience themselves lying on the couch with an overfull stomach, regretting having indulged in an all-you-can-eat buffet a couple of hours before. In these and many other situations of everyday life, people behave as being of "two minds": On the one hand, they feel tempted by immediate gratification, while on the other hand they want to pursue long-term goals.

There is a rising view in contemporary psychology that individuals' behavior is determined by two type of processes [see, for example, Evans, 2008, Kruglanski and Orehek, 2007]. Many models have been proposed, but the common denominator seems to be that one type is of automatic nature and affective based, while the other is controlled and deliberative, which mainly envelopes the concept of rationality extensively used in economics. Strongest support comes from relatedness of deliberative processes, which are characterized as slow, effortful and of limited capacity, with evidence on working memory [e.g., Baddeley, 2003]. Also, in social neuroscience fMRI studies find that usage of different processes is related to the activation of different brain areas - deliberative processes with the prefrontal cortex, and affective processes to the midbrain [e.g., Lieberman et al., 2002]. In spite of gaining popularity for explaining all sorts of behavioral findings, this approach has no lack of critiques. One of the first ones

was by Newell [1973], who criticized dichotomic approach in modeling in general, that it grossly oversimplifies real nature of the phenomena and does not produce any gain in knowledge. More recent critiques accuse it of being good only as a post-hoc explanation and for its lack of theoretical consistency [Kruglanski and Gigerenzer, 2011]. Keren and Schul [2009] present extremely convincing argument against dual system approach, that it fails essential requirements for constituting systems. Each system’s characteristics should be of discrete nature, characteristics of one system should be highly correlated among each other and not correlated with characteristics of the other system, and finally that systems should be independent, one system cannot be an input to another. In this paper we refrain from taking a stance on this debate and seek to evaluate usefulness of such approach in the context of time and risk preferences as used in economics. Particularly insightful formalizations of dual process idea have appeared recently in economic literature, one by Loewenstein and O’Donoghue [2004] and second by Fudenberg and Levine [2006]¹. Since their mathematical structure offers valuable and clear insights into the interaction of these processes and offer several testable predictions, we decided to restrict our attention on these models. We focus on Loewenstein and O’Donoghue [2004] model as it seems to be fitting the literature from psychology to a greater extent.

Surprisingly enough, although it has been several years since these formal models of the dual system have appeared, most of their predictions have not yet been tested empirically. In Loewenstein and O’Donoghue [2004] model, the decision maker is seen as making a compromise between the urges of an affective and a deliberative system. These two systems have different and often conflicting goals. The preferences of the decision maker then depend on the weight that she attaches to the affective system. This weight, in turn, is seen as being dependent, among other things, on willpower – the higher the willpower of the agent, the lower the weight she attaches to the urges of the affective system.

¹Similar models along the same lines have been proposed by Benhabib and Bisin. [2002] and Bernheim and Rangel [2004]

We believe that effects of this kind of model should be most evident in risk and time preferences, as the anomalous findings in this literature have been thought to be stemming from a struggle between two opposing types of processes in one body [e.g., Frederick et al., 2002]. Since in this context the model predicts that usage of different systems leads to opposite effects, we use risk and time preferences as an area with a clearcut falsification strategy. Key ingredient in this approach is ability to experimentally affect the willpower. For this reason we are particularly interested in factors that diminish willpower, a phenomenon known in psychology as self-control or willpower depletion [e.g., Baumeister et al., 2008]. As we illustrate in more details below, translated to the domain of time preferences, the model predicts that willpower depletion should decrease the amount of willpower available for the subsequent decision task and therefore diminish the involvement of the deliberative system. This in turn leads to more impulsive decisions driven by the short-sighted affective system, which we should be able to measure in the form of a higher discount rates. Analogously, in the domain of risk preferences, the model predicts that in a wide range of settings, an increase in the weight attached to the affective system will result in a higher degree of (measured) risk aversion. Loewenstein and O’Donoghue [2004] argue that the affective system cares more about outcomes and less about probabilities, and moreover, that it exhibits a certain degree of loss aversion. Therefore, our hypothesis is that willpower depletion, and thus, attaching more weight to the affective processes should lead to higher risk aversion. The decision maker is likely to shy away from potential losses and put up with low paying, but safer options.

The rest of the paper is organized as follows. We present theoretical framework and related findings in the next section. Section 3 briefly describes our experimental design. The experimental results are presented in section 4 and section 5 concludes.

2 The Dual System Framework

Loewenstein and O’Donoghue [2004] characterize decision problems by a set of alternatives, \mathcal{X} , given

the current state of willpower, W . Decision makers are modelled as trading off the (often contradicting) goals of a "deliberative system" and an "affective system". The deliberative system (which we will index by D) ranks the alternatives according to a preference relation, \succeq^D , that can be represented by U^D while the affective system (indexed by A) has a different ranking, \succeq^A that can be represented by U^A with bliss points that are defined by $x^D \equiv \arg \max_{x \in \mathcal{X}} U^D(x)$ and $x^A \equiv \arg \max_{x \in \mathcal{X}} U^A(x)$, respectively. To make things interesting, the rankings of alternatives differ and we assume $x^D \neq x^A$. Moreover, we assume that we can give the utility functions of the two systems a cardinal interpretation. The decision maker then aggregates these two preferences in a way similar to a social welfare functional. We assume that this aggregation process can be summarized by the following utility function

$$U(x) = U^D(x) + h(W) \cdot U^A(x) \quad (1)$$

where $h(W) \geq 0$ represents the weight that the decision maker attaches to the affective system and we assume that it is a decreasing function of the current state of willpower, W . In what follows we will suppress the argument of the function h , with the understanding that a higher h corresponds to a lower state of willpower W and vice versa.

Willpower, W , in turn is sensitive to outside factors, such as cognitive load and stress, as well as decisions per se. For a dynamic setting, Loewenstein and O'Donoghue [2004], postulate that willpower replenishes at a certain rate after being depleted. This assumption allows for interesting choice settings and scenarios where an economic agent facing the same set of alternatives twice, could very well make two different choices corresponding to two different states of willpower. Coming back to our introductory example of the hungry economic agent shopping in a supermarket, we can expect her making more impulsive purchases, buying more greasy and bigger bundles of food when doing the shopping tired after work than doing the shopping well rested, on a Saturday morning.

In this paper, we will specifically analyze choices over dated outcomes and over gambles. We consider them in turn.

2.1 Time Preferences

In the domain of *time preferences*, the set \mathcal{X} is in general given by $X \times T$ where X is the space of outcomes (here $X \subset \mathcal{R}_+^2$) and $T \subset \mathcal{R}_+^2$ is the timing of the rewards, a typical element of \mathcal{X} being $((x_1, t_1), (x_2, t_2))$. We follow Loewenstein and O'Donoghue [2004] and make the simplifying assumption that the deliberative system is perfectly far sighted and does not discount the future at all, while the affective system only cares about the earlier reward. Moreover, we assume the deliberative system to have time preferences adhering to the standard axioms, i.e. apart from rational preferences, we also assume separability *across* time and separability *between* time and outcomes² - $U^D(((x_1, t_1), (x_2, t_2))) = u(x_1) + u(x_2)$ and $U^A(((x_1, t_1), (x_2, t_2))) = u(x_1)$, which the decision maker aggregates in the following (additive) way:

$$U(((x_1, t_1), (x_2, t_2))) = U^D + h \cdot U^A \quad (2)$$

$$= (1 + h)u(x_1) + u(x_2) \quad (3)$$

If we assume $h > 0$ (the affective system always enters the considerations) and allowing for possibility that the deliberative system exhibits positive discounting, we find that

$$U(((x_1, t_1), (x_2, t_2))) = u(x_1) + \frac{1}{1+h}u(x_2) \quad (4)$$

$$= u(x_1) + \frac{\delta^D}{1+h}u(x_2) \quad (5)$$

$$= u(x_1) + \delta u(x_2) \quad (6)$$

which is observationally equivalent to observing a discount rate, $\rho \equiv \frac{1}{\delta} - 1$ that is higher, the lower the state of willpower, W .

2.2 Risk Preferences

In the domain of *risk preferences*, \mathcal{X} is a set of lotteries. We assume the deliberative system to be a

²Separability across time essentially precludes intertemporal complementarities (a necessary and sufficient condition being the so-called "double-cancellation" or Thomson condition), while separability between time and outcomes means that the way time enters the consideration is irrespective of the outcomes [e.g., Ok and Masatlioglu, 2007, Fishburn and Rubinstein, 1982]

standard expected utility maximizer, while the affective system follows some simple heuristic. The heuristics we are going to elaborate on are the *maximin* heuristic and *equal probability measure* heuristic.

Maximin For the Maximin approach, the deliberative system evaluates lotteries according to their expected utility, $U^D(\mathcal{L}) = \mathbb{E}(u(\mathcal{L}))$, while the affective system uses the maximin criterion, $U^A(\mathcal{L}) = \min_{x \in \text{Supp}(\mathcal{L})} \{u(x)\}$, where $\text{Supp}(\mathcal{L}) = \{x_i | p(x_i) > 0\}$ denotes the support of lottery \mathcal{L} . The latter can be seen as infinite risk aversion³. The decision maker then aggregates these to:

$$U(\mathcal{L}) = \mathbb{E}(u(\mathcal{L})) + h \cdot \min_{x \in \text{Supp}(\mathcal{L})} \{u(x)\} \quad (7)$$

Suppose that the agent faces a choice over two lotteries. Lottery A is characterized as being a relatively riskless lottery with two similar prizes while lottery B is characterized as being more risky, with one very high and one very low outcome. Therefore, lottery A becomes more and more attractive compared to lottery B the higher h is. And thus, an increase in h is *observationally equivalent to an increase in r , the coefficient of relative risk aversion*. Participants will require a relatively high probability mass on the high reward to be willing to switch to the risky lottery.

Equal Probability Measure Analogously to an affective system evaluating alternatives using the maximin-criterion, Loewenstein and O'Donoghue [2004] discuss the idea of an affective system being completely agnostic about the probabilities of the lottery. That is, instead of weighting outcome i with probability p_i , the affective system weights the outcome with $1/N$, where N is the number of possible outcomes. Assuming the deliberative system to be a standard expected utility maximizer, $U(\mathcal{L}) = \mathbb{E}u(\mathcal{L}) + h \cdot \mathbb{E}u(\mathcal{L}_{1/N})$, we find that

$$\begin{aligned} U(\mathcal{L}) &= \sum_{i=1}^N p_i u(x_i) + \sum_{i=1}^N \frac{1}{N} u(x_i) \quad (8) \\ &= \sum_{i=1}^N \frac{h + N p_i}{N(1+h)} u(x_i) = \sum_{i=1}^N q_i u(x_i) \quad (9) \end{aligned}$$

so that the decision maker is effectively using the particular probability weighting function, $q_i(h) = \frac{h + N p_i}{N(1+h)}$, which can be seen to result in less dispersion among the subjective probabilities, compared to the objective ones - i.e. probabilities are concentrated around $\frac{1}{N}$. In the case of our experiment with $N = 2$ this means that *for a risk averse person* (in the vonNeumann/Morgenstern sense), we will systematically *overestimate* her coefficient of relative risk aversion. Conversely, we will *underestimate* the coefficient for *risk-loving people*. However, as we can expect many more risk averse than risk loving people [Holt and Laury, 2002], the net effect is likely to be an overestimation of the coefficient of relative risk aversion.

To illustrate this, suppose that a participant declares herself to be indifferent between lottery A (€900,0.9; €800) and lottery B (€1925,0.9; €25) and has a reported income of €900. We then calculate an implied coefficient of relative risk aversion (CRRA) of around 3.8. However, if she puts weight on her affective system, which follows the above heuristic, of $h = 1.75$, then she acts *as if* she was indifferent between lotteries lottery A' (€900,0.8; €800) and lottery B' (€1925,0.8; €25), which would have lead us to calculate, $r \approx 2.5$. Therefore, a subject with a *true* CRRA of 2.5 and an h of 1.75 will be indifferent between lotteries A and B but will prefer lottery A' over lottery B', which in any revealed preference experiment will lead the experimenter to calculate a CRRA of 3.8.

To sum up, we expect that when more weight is attached to the affective system (i.e. h is increasing), the agent is more likely to choose the safer option, pushing the decision maker towards a higher *measured* degree of risk aversion⁴.

⁴More risk averse" is defined in the usual way: "The preference relation \succeq_1 is more risk averse than \succeq_2 if for any lottery p and degenerate lottery c , $p \succeq_1 c$ implies that $p \succeq_2 c$ " [Rubinstein, 2010]

³Indeed, with CRRA utility, the expected utility function converges to a Leontief utility function as $r \rightarrow \infty$

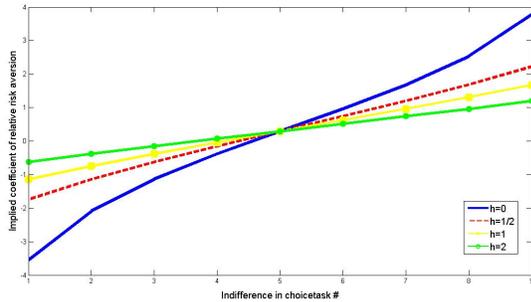


Figure 1: Implied rates of risk aversion for different levels of h for the lottery described in the text.

2.3 Related Findings

In the last couple of years, some empirical studies directly or indirectly tested dual self models with respect to time and risk preferences. Most of these studies examine the effect of cognitive load (i.e. exogenous increase of h) on decision making. Cognitive load is usually operationalized by having participants doing two tasks at the same time: For instance, one task is a working memory task (e.g. memorizing a sequence of digits), while the other is a decision task.

With respect to time preferences, support for the model's predictions can be found in results of the study of Hinson et al. [2003]. The authors examined how cognitive load (which is likely to influence the state of willpower in a negative way) affects the discounting of money. The results were that higher cognitive load lead to greater discounting of delayed monetary rewards. On the other hand, there is also evidence that cognitive load does not lead to more impulsive behavior. Franco-Watkins et al. [2010] report that taxing working memory by cognitive load is neither necessary nor sufficient to produce impulsive decision making; instead, it just seems to result in an increase in the number of inconsistent choices. Furthermore, the field of neuroscience has seen several papers that support the dual system model in inter-temporal setting, for example McClure et al. [2007] building on prior work [McClure et al., 2004], where they show that emotional brain structures are more active when immediate reward is available, while deliberative brain structures are active in general and are not sensitive to immediate rewards. In later research they extend these

findings to primary rewards (e.g. juice) instead of money, and use shorter delays (minutes) rather than longer delays (weeks).

Concerning risk preferences, several studies have examined the role of the amount of available cognitive resources. In a laboratory experiment Benjamin et al. [2006] show that reducing cognitive resources tends to increase small-stakes risk aversion. In her doctoral dissertation Hart [2005] examines the role of cognitive resources in risk preferences and finds that adults (but not children) rely more on automatic, emotion based responses when under cognitive load. Whitney et al. [2008] study framing effects and cognitive load, they confirm the existence of framing effects and find that under cognitive load participants tend to choose less risky gambles. Interestingly, this happened regardless of the frame – in both gains and losses. In addition, they have found that decisions were made more rapidly in positive frames and under cognitive load.

One interesting finding that supports the predictions of dual system models as well, comes from Masicampo and Baumeister [2008], who find a way to influence willpower capacity, W , in a positive way – by supplying participants with glucose in a random way. With more glucose (the energy source of the nervous system) in their system, participants seemed to rely less on affective-based judgments and heuristics. Moreover, they find that glucose positively affects the replenishment rate of W when it is depleted.

2.4 Willpower Depletion

As we stated, the crucial part of our test is ability to reduce the willpower in participants. We use a procedure called willpower depletion, which depletes the limited willpower resources of subjects by having them regulate their automatic responses. This approach was first developed by John R. Stroop in 1935. For example, the word "yellow" is shown in the color green to a subject, who has to name the color of the word. The automatic response is to read the word, i.e. answer "yellow" and therefore, the subject has to exert an effort to suppress this automatic response and correctly answer "green". Loewenstein and O'Donoghue [2004] argue that depletion, along

with factors such as cognitive load⁵ and stress, undermines the deliberative system (i.e. cost of mobilizing willpower h increases). There are no studies that confirm the supposed effects of willpower depletion on time and risk preferences. The concept of willpower depletion stems from an extensive literature in psychology [see, for a review, Baumeister et al., 2008]. Past research mostly investigated willpower depletion in relation to subsequent self-control and impulsive actions. One more economically relevant example is the research of Vohs and Faber [2007], who find that participants whose resources were depleted felt stronger urges to buy, were willing to spend more, and actually did spend more money in unanticipated buying situations. For operationalizing willpower depletion various methods are used – from self-regulation tasks [e.g. by controlling the emotional expression, in Vohs and Heatherton, 2000] to actually making choices [e.g. choosing between courses for the next academic year versus just rating some products, in Vohs et al., 2008]. In our experiment, we use the approach used by Baumeister et al. [1998], since it suits the best our experimental design and method of collecting the data.

Collecting the predictions of the model, as well as the existing empirical evidence, we are going to test the following hypotheses in the present paper. First, we expect that subjects in the treatment group, whose willpower was previously depleted to have significantly higher discount rates in inter-temporal choices. Second, for risk preferences, the dual self model predicts subjects with depleted willpower to exhibit a higher degree of risk aversion.

3 Experimental Design

In order to test our hypothesis, we follow an experimental approach where we use a two-group post-test-only randomized experiment. The subjects in

⁵It is important to note that willpower depletion and cognitive load are not the same concept, although to some extent they do overlap. Cognitive load is mostly related to working memory (represents resource we have to actively operate with information, e.g. in arithmetic calculation), while willpower depletion tasks tap partly into the working memory, but also to some other brain structures involved in deliberative processing [e.g. Richeson et al., 2003].

our experiment were randomly assigned to one of the two experimental conditions – willpower depletion (treatment group) and no depletion condition (control group). The independent variable is willpower depletion, while the dependent variables are the discount rate and the attitude towards risk (measured as the coefficient of relative risk aversion).

Depletion Treatment. In this paper we use a method for depleting willpower used in Baumeister et al. [1998], which is a version of a Stroop task that involves willpower in a way that a person must override her normal or automatic responses and conform to standards [Stroop, 1992]. Each subject was given a page of text (a page from an advanced statistics book) and told to cross off all instances of the letter "e". People can learn to do this easily and quickly; and they become accustomed to scanning for every e and then crossing it out. For the subjects assigned to the depletion condition (treatment group), the task was made substantially more difficult, requiring them to cross off letter "e" only if further conditional rules applied – if it was not adjacent to another vowel or one extra letter away from another vowel (thus, one would cross the first, but not the second "e" in "describe"). On the other hand, participants in the no depletion condition (control group) had to cross off every single "e" with no further rules. Subjects in depletion group would presumably scan for each "e" but would have to override the response of crossing it out whenever any of those criteria were met. Their responses thus had to be regulated according to multiple rules, unlike the others who could simply respond every time they found an "e". The assumption is that consulting the complex decision rules and overriding the simple response would deplete the willpower capacity, unlike the simpler version of the task. In addition, to raise the subjects' effort, they were informed that for each mistake in the task €1.5 will be deducted from their reward, if they will be chosen for the reward.

The original Stroop task would probably have a stronger depletion effect, but is less suitable for paper & pencil experiments conducted in classrooms, which is used in our case. Exact copies of depletion and no depletion condition used in our experiment

are available on request.

Eliciting Discount Rates and Risk Aversion

With respect to eliciting discount rates and risk aversion, we follow the design of Andersen et al. [2008], who elicited those jointly in the case of the Danish population by using the “Multiple Price List” (MPL) format.

In our experiment, in order to elicit time preferences, we use preferences we use the procedure designed by Coller and Williams [1999] and expanded by Harrison et al. [2002]. Subject were asked to respond to six discount rate tasks. Each discount rate task was represented by a payoff table with 15 symmetric intervals which consider a certain time horizon. Each of the 15 rows of the table consist of two options, A and B, and subjects had to choose one. For example, option A offers €800 *today* and Option B offers €800+ x *in six months*, where x ranges from a return of 5% to 75%. As we increase x we will expect more individuals to take the future income option. Assuming risk neutral subjects, the point at which each individual switch from choosing the Option A to the Option B provides an interval on their discount rate. In three of the tasks (Set I – without front end delay), the earlier payment option (A) was an immediate outcome, while in the other three tasks (Set II – with front end delay) the earlier payment was to occur in one month. This feature has been chosen in order to obtain a measure of the “present bias” within and between the treatment/control groups. In each set of the tasks, tasks were equivalent in terms of discount rates, but they differed in terms of time horizon. We considered three different time horizons: one month, six months and 12 months. This multiple-horizon treatment, considered by Harrison et al. [2002], was replicated in both Set I and Set II. The switching point in each of the six tasks enable us to infer the time preferences of the subjects. It is important to stress that since our experiment uses hypothetical payoffs, question of transaction costs related to cashing the future reward is not relevant.

Following the same design, in eliciting risk preferences we use procedure developed by Holt and Laury [2002]. Each subject was asked to respond to four risk preference rate tasks. Tasks were represented

by a table with 10 binary choices between two lotteries (say, A and B). Payoffs are the same throughout the table, but probabilities change in a way that the difference in the expected values (EV) of lotteries A and B is large and positive in the first row and goes to large negative value in the last row. In short, option A is a safer option in the sense that payoffs of the lottery are more similar. The logic behind this test for risk aversion is that only risk loving subjects would take lottery B in the first row, and only risk-averse subjects would take lottery A in the 9th row. A risk-neutral subject should switch from choosing A to B when the EV of each is about the same, so a risk-neutral subject would choose A for the first four rows and B thereafter.

Participants The subjects in the experiment were 54 graduate students (30 male, 24 female), all of which are participants of several master programs in economics at the Barcelona Graduate School of Economics (Universitat Pompeu Fabra). Average age is 25 years and 50% of participants already have a master degree.

Procedures The sessions were conducted in the classrooms directly after the subject’s lectures. Professors and students were notified in advance and asked for participation. In a personalized notification e-mail, the topic of the experiment was presented as “...research in economic decision-making...” and they were not told anything specific about the experiment. In the same e-mail they were notified about the possibility to win substantial reward for the participation. Data were collected in six group sessions, using paper-and-pencil method. Each session lasted for about 40 minutes. The experimenter gave a brief oral instruction to the subjects, the information about the possibility to get rewards for the participation and said that all the necessary instructions are provided for in the questionnaire. In addition, if subjects had any further questions they were instructed to raise their hand and the experimenter would come and answer their question in private. Participants did not know that there are two different groups with slightly different questionnaires.

The questionnaire itself consisted of instructions

and five parts. The first part consisted of a question measuring tiredness and two small personality questionnaires measuring attitudes toward risk and impulsivity – the Impulsive Sensation Seeking scale from Zuckerman-Kuhlman Personality Questionnaire [ImpSS, Zuckerman et al., 1993] and the Brief Sensation Seeking Scale [BSSS-4, Stephenson et al., 2003]⁶. These questionnaires were put mainly to mask the tiredness question, which serves as a manipulation check. Second part of the questionnaire was the most important for the study since it involved manipulation of independent variable – the depletion task. This part was the only difference between the treatment and control group. We followed the willpower depletion used in Baumeister et al. [1998], as described in a depletion treatment above. In part three and four of the questionnaire we elicited time preferences jointly with risk preferences, following closely the design of Andersen et al. [2008]. In brief, each subject was asked to respond to four risk aversion tasks and six discount rate tasks. Each such task involved a series of binary choices, 15 in discount rate task and 10 in risk aversion task. Before the real tasks, subjects were provided with several examples. Thus, each subject typically provided 130 binary choices that can be used to infer time and risk preferences. In fifth part subjects had only a small socio-demographic questionnaire, and more importantly, questions related to their expenditures, level of tiredness and concentration needed for the depletion task in part two.

Decision tasks were not incentivised, and therefore were of hypothetical nature. In order to stimulate participation in the experiment, four participants (ID number of their questionnaire) out of 60 were chosen randomly and rewarded with €30. At the end of the questionnaire subjects were given the information where the results of the draw will be published and where they would be able to collect the reward.

Weaknesses. We have already highlighted the contributions of this experiment relative to previous studies. We now discuss its weaknesses. Firstly, decision tasks were of hypothetical nature,

⁶We are grateful to the authors for the permissions to use the scales.

which raises the question of reliability of the subjects’ responses. However, the results of Coller and Williams [1999] are encouraging, since they find that the difference between hypothetical and monetary incentivised experiment with respect to discount rate elicitation is small in magnitude – elicited discount rates are higher when there are no financial incentives. Moreover, they used the same method (MPL format) for eliciting discount rates. Secondly, for feasibility reasons the experiment was conducted in classrooms by paper & pencil method, instead on the computers in the laboratory. Classrooms experiments come with less control over the experimental conditions, it is more difficult to guarantee perfect symmetry between sessions in terms of distributions of individuals on the classroom, number of subjects in each session and the time of the session. Thirdly, since we do not provide show-up fees, to increase the participation rate we decided to conduct the experiment with graduate students in economics. Although this increased the participation, it potentially influenced the results. We come back to this point in the results section. Finally, our sample suffers from self-selection bias. On the one hand, people of certain characteristics are offered the opportunity to study a graduate program. On the other hand, only students of certain characteristics would decide to participate in the experiment on a voluntary basis. While we might argue that the former skews the results in a predictable way, for the latter is difficult to argue the direction. Even though a possible self-selection bias poses a serious problem for the external validity, the internal validity should not be affected.

4 Results

Randomization tests. The first step in our data analysis is to conduct a randomization test. That is, we check for significant (partial) correlation between the treatment variable and socio-demographic characteristics. To be more precise, we use the information collected at the beginning of the questionnaire – results in the BSSS-4 and the ImpSS scales, and several variables at the end of the questionnaire – age, gender and the education level. Even though we collected more information at the end of the ques-

tionnaire, we used only the information that should not have been influenced by the treatment. As a randomization test we ran an OLS regression on the treatment indicator variable. We present the results from the regression in the Table 1. We cannot reject the null hypothesis of zero correlation for any of the above mentioned factors, which leads us to conclude that the randomization has worked and we can proceed with the analysis of the (depletion-)manipulation check.

Table 1: Randomization test: OLS regression on treatment indicator variable

	Coeff.	Treatment group		P> t
		S.E.	t	
Age	.013	.031	0.41	0.684
Gender	.053	.148	0.36	0.722
Years of educa- tion	-.001	.049	-0.02	0.983
BSSS-4	.005	.013	0.38	0.708
ImpSS	.009	.023	0.40	0.688

Observations N=54; *** p<0.01, ** p<0.05, * p<0.1

Manipulation Check. Direct verification whether depletion treatment has the intended effect is possible only with using a neuroimaging method. Many studies checked with fMRI (functional magnetic resonance imaging) what brain structures Stroop and similar tasks involve, with the result that various regions in the prefrontal cortex (regions related to the deliberative system in our model) are more active during such tasks [e.g., Milham et al., 2003]. Such tools for verifying depletion treatment were unfortunately not at our disposal. However, an indirect verification is always possible: Following Baumeister et al. [1998] we included several questions into the questionnaire that served as a proxy for the depletion treatment verification. In the socio-demographic part, at the end of the experiment, we asked subjects how much they had to concentrate in the depletion task. The main assumption was that subjects in depletion condition have to exert more effort and willpower, and therefore will have to concentrate correspondingly harder. Subjects assigned to the

depletion condition (mean=16.85) reported having had to concentrate on the task of crossing off the e’s significantly more than subjects assigned to the no depletion condition (mean=13.4) (Wilcoxon rank-sum test: $p = 0.0161$). A further check on effectiveness of the depletion treatment was supplied by having subjects rate their level of tiredness at the beginning of the experiment and at the end of the experiment. The difference in tiredness seems to increase more for the subjects in the depletion condition (mean=1.27) than for the subjects in no depletion condition (mean=0.52), but not significantly so (Wilcoxon rank-sum test, $p = 0.2003$). The result for tiredness seems to be conflicting with the result for concentration, but since both questions are proxies, this does not necessarily mean that the depletion treatment did not have an effect. However, this does pose a concern and we will have to take into account the possibility that the treatment was not as strong as intended.

In the remainder of this section, we will first check for consistency in the choice patterns. Then, we turn the issue of eliciting discount rates and rates of risk aversion from the subjects’ choices. Afterward, we estimate treatment effects both non-parametrically and parametrically, and discuss the results. Lastly, we discuss alternative explanations and limitations of our results.

Consistency Checks. In the context of risk tasks, being consistent means to choose the safer option (A) till the point you are indifferent between (A) and the alternative, the more risky option (B)⁷. More importantly, consistent agents would not switch back later to the safer option. Equivalently, in the context of time preference tasks, consistent agents will choose the earlier reward (A) till the point they become indifferent to the later, larger reward (B)⁸. In general, lack of consistency is a usual concern when using MPL format to elicit preferences, because having more than one switching point makes inferring subjects’ preferences less reliable (for example, Holt and Laury [2002] report

⁷Assuming monotonicity of the preferences in prices.

⁸Assuming monotonicity in timing (negative) and prices (positive).

that 13% of subjects make inconsistent choices). We find no inconsistent subjects in our sample, which we speculate is an advantage of using the graduate students as subjects.

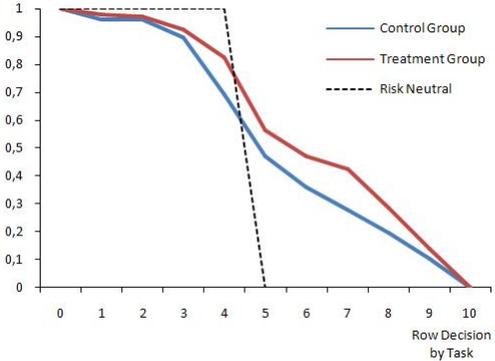
To get a raw overview of the treatment effect over time and risk preferences, we plot the proportion of safer or earlier responses against each row decision in time and risk tasks. Since we have consistent subjects, the total number of safer (in case of risk tasks) or earlier (in case of time tasks) choices (A) could be used as an indicator of risk aversion and impatience. Figure 2a displays the proportion of A choices for each of the ten decisions subjects took in each of the four risk tasks. The dashed line shows the predictions under an assumption of risk neutrality. More precisely, following the expected value difference of each pair of lotteries (A-B is positive in the first four decisions), a risk neutral agent will choose the safe Option A in the first four decisions, and Option B in remaining decisions. Both control and treatment series in Figure 2a lie right to the risk-neutral prediction, showing a tendency toward risk-averse behavior. Furthermore, this figure also shows that subjects in the treatment group choose safer option in greater proportion, which indicates that there might exist a treatment effect over risk aversion.

Similarly, Figure 2b shows the results for the time preference tasks. The higher proportion of A choices the more impatient subjects are. Unlike in risk tasks, here we do not have a natural reference frame, we can compare the difference in impatience between the treatment and control group. This figure is a first indication that depletion treatment did not have an intended effect on the time preference. When time preferences are examined with taking into account the nature of time preference tasks – with and without front-end delay, the result stay roughly the same. It appears that there is very little difference between time preference tasks when subjects consider immediate rewards versus larger delayed reward and when subjects consider two distant rewards, one sooner and one later but larger. This is an evidence against the prediction of Loewenstein and O’Donoghue [2004]. There are several possible explanations for this pattern of behavior and we examine them in more detail later, when

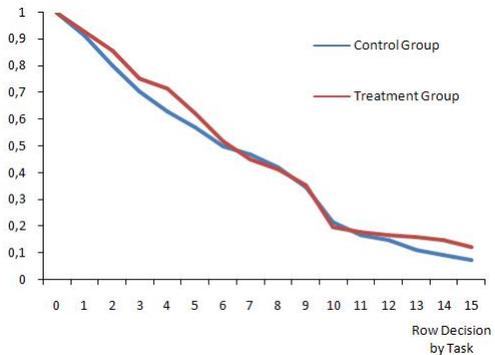
reporting non-parametric and parametric analysis of time preference results.

Figure 2: Graphical display of the treatment effect over time and risk preferences

(a) Proportion of safer choices in each decision in risk tasks



(b) Proportion of earlier rewards in each decision in time tasks



4.1 Parametrization and Identifying Assumptions

In order to arrive at testable predictions, we have to impose more structure on how we model time and risk preferences. First, for risk aversion, we assume that the static (Bernoulli-)utility function is of the CRRA family, i.e.

$$u(x, r) = \begin{cases} \frac{x^{1-r}}{1-r} & \text{if } r \neq 1 \\ \log(x) & \text{if } r = 1 \end{cases} \quad (10)$$

Second, we make an analogous choice about the parametrization of the discount function. On top

of the assumptions made in Section 2 we also assume that stationarity⁹ holds. Then, we can represent the agent's time preferences as in the standard discounted utility model:

$$U(x, t) = \left(\frac{1}{1 + \rho} \right)^t u(x) \quad (11)$$

In what follows we will also make the identifying assumption that subjects consume the outcomes at the very point in time when they are paid out. This explicitly rules out behavior of the following kind. Suppose a decision maker chooses (100, *now*) over (102, *one year*). However, she is not consuming the €100 now, but rather investing it in bonds, say, yielding a return of around 10%. An asset of this kind would censor discount rates at 10%. Effectively, we have chosen parametrizations that allow us to condense attitudes towards time and risk in only two parameters, ρ and r , respectively.

From the discussion in section 2 it should be clear, that we will not be able to measure h , the weight attached to the affective system, directly. Given that the treatment is randomly assigned across the sample, it is justified to assume that *before* the depletion treatment, both groups exhibit the same attitudes towards time and risk. This allows us to estimate the effect of h on time and risk attitudes. We stress that *we are not estimating* the structural model embedded in equations 6 and 7, but rather infer the change of h induced by a change in W indirectly, from estimating the change in ρ and r , respectively.

4.2 Risk Aversion

First, we turn to the issue of estimating the the coefficient of relative risk aversion, r . If we are willing to assume that the standard von-Neumann/Morgenstern assumption on preferences over lotteries hold, then we can represent these preferences by their expected utility, i.e.:

$$U(r) \equiv U(x, y, p; r) = p \cdot u(x, r) + (1 - p) \cdot u(y, r) \quad (12)$$

⁹A time preference on \mathcal{X} is called **stationary** if $(x, t) \succ (y, s) \Leftrightarrow (x, t + \tau) \succ (y, s + \tau), \forall (x, t), (y, s) \in \mathcal{X}$ and $\tau \in \mathbb{R}$ s.t. $s + \tau, t + \tau \geq 0$ [see, for example, Fishburn and Rubinstein, 1982]

For each participant, the survey provides us with data on 4x10 choices between two lotteries each. There are now at least two ways to go about inferring the coefficient of relative risk aversion of each person from his or her choices: Estimating a binary choice model or calibration.

The first approach, followed for example by Andersen et al. [2011], is to set up a non-linear logit model from an additive random utility specification. On top of the utility an agent derives from choosing a lottery, we add a lottery-specific error term such that

$$V_a \equiv V(x_a, y_a, p, r) \equiv U(x_a, y_a, p; r) + \epsilon_a \quad (13)$$

If person i now declares that in table t , row j she prefers lottery P_a^{tj} to lottery P_b^{tj} , then given our assumptions, we conclude that it must be the case that ¹⁰

$$\begin{aligned} P_a^{tj} \succ P_b^{tj} &\Leftrightarrow V_a > V_b \\ &\Leftrightarrow U_a(r_i) - U_b(r_i) > \epsilon_b - \epsilon_a \end{aligned} \quad (14)$$

If we assume ϵ_a to be independent from ϵ_b and that both follow the type I extreme value distribution, then, given $U_a(r_i), U_b(r_i)$, the probability that the event $P_a^{tj} \succ P_b^{tj}$ occurs can be shown to be [Cameron and Trivedi, 2005, p.475]:

$$\frac{\exp(U_a(r_i))}{\exp(U_a(r_i)) + \exp(U_b(r_i))} \quad (15)$$

We can then go about estimating $\{r_i\}_{i=1}^N$ via maximum likelihood. Unfortunately, the relatively small sample size results in a likelihood function that is flat over much of the reasonable domain, which makes the point estimator very sensitive to the initial conditions supplied. Therefore, we opted to calibrate the model in the following way.

For each person i and for each table t , we considered only the row, j^* in which the individual was indifferent between the two lotteries. Given our assumptions on preferences, we can conclude that:

¹⁰Note that we allow the risk aversion to vary across individuals but not across tables

$$P_a^{tj*} \sim P_b^{tj*} \Leftrightarrow U(x_a, y_a, p; r) = U(x_b, y_b, p; r) \\ \Leftrightarrow \mathcal{U}(r_{it}) \equiv U_a(r_{it}) - U_b(r_{it}) = 0 \quad (16)$$

One can show that this equation implicitly defines a *unique* r_{it}^* . We then calibrate each person's coefficient of relative risk aversion, r_i , as the mean of the $\{r_{it}^*\}_{t=1}^4$.

Two comments are in order. First, it is essential that the outcomes (x_a, y_a, x_b, y_b) are *not* the prizes of the lotteries but rather the sum of each person's expenditures and the prize in each state of the world. Second, the fact that we used MPL for elicitation (and not say, having the participants state their certainty equivalents) implies that r_{it}^* can only take on 9 different values¹¹, which might potentially influence our results. Essentially, we have potential censoring from below (corresponding to row number 1 - risk loving), as well as from above (row number 9 - very risk averse).

To illustrate the calibration procedure, consider the following example. Subject i states is indifferent between the two lotteries (€1000; €800, .7) and (€1950; €0, .7). Moreover, we know that her monthly expenditure is €900. Following our model outlined above, we conclude that r_{it}^* is the solution to the following equation

$$.7 \cdot u(900 + 1000; r_{it}^*) + .3 \cdot u(900 + 800; r_{it}^*) = \\ .7 \cdot u(900 + 1925; r_{it}^*) + .3 \cdot u(900 + 25; r_{it}^*) \quad (17)$$

which implies a coefficient of relative risk aversion of around 1.8. (The range of admissible values for this table and this income level is (-3.4, 3.9)). If we had ignored the income level, which is equivalent to assuming an income of €0, the implied coefficient would have been around 1.4.

Table 2 presents the results of the calibration of the CRRA. We find that the average CRRA of the entire sample is 0.96, and there seem to exist a difference in the sample means for the treatment (1.21) and the

¹¹Row number 10 in each table constituted the choice between two degenerate lotteries where one paid a strictly higher amount than the other one.

control group (0.71) in a predicted direction. In addition, in the second row of the table we present results when CRRA is calculated with an average expenditure of the whole sample (around €757). Mean for the whole sample is 1.02, while for the treatment and control group is, 1.23 and 0.8, respectively. We calculate CRRA in this additional way to check how sensitive results are on levels of income. Although means do not seem to differ much between these two types of CRRA's, there is a significant difference in the distributions of the CRRA's (p-value of close to 0 in a Kolmogorov-Smirnov test)¹². This would suggest that CRRA's are sensitive to the baseline expenditure level. To further verify this result, we also calculate CRRA's as if we were completely ignorant about the reported level of expenditures (i.e. setting the expenditure level to 0). Then the mean of the CRRA's for the entire sample drops to only 0.5 (these results are not presented). Therefore, due to the concavity of the utility function the lower segments are much steeper than the higher segments, and a lower CRRA is needed to get high differences in the utility values. This result confirmed that the expenditure levels play a large role in determining CRRA and therefore in our further analysis we shall use CRRA's calculated with the individual levels of income.

Table 2: Non-parametric test of the difference in means of CRRA between the treatment and control group

	Whole Sam- ple	Cont. Group	Treat. Group	Rank-sum Test
CRRA	0.96	0.71	1.21	$z = -0.934$; $p = 0.35$
CRRA*	1.02	0.80	1.23	$z = -0.632$; $p = 0.528$

CRRA* = CRRA with average level of expenditures

As indicated above, we find the difference in the sample means for the treatment (1.21) and the con-

¹²A test for the difference *in means* per se is not very informative as we can expect the effects of expenditures to cancel out when we take averages: Individuals with a relatively high level of expenditures (i.e. >€757) will exhibit lower calibrated CRRA's and vice versa.

trol group (0.71). Given the small sample size ($N = 54$), we were cautious to appeal to central limit theorems to justify the normality assumed in parametric tests. Thus, we ran a Wilcoxon-Rank-Sum test on the *distribution* of the CRRA's in the two groups, yielding the statistically non-significant result ($p = 0.35$). Given the apparent difference in risk aversion between treatment and control group, our best explanation for insignificant test statistic is low statistical power. This issue certainly stems from relatively small sample size, but our guess is that it might be only half of the story. At the end, using graduate students as a sample population probably came with a disadvantage. We can argue that these students are on an upper bound regarding cognitive capabilities and therefore have correspondingly higher willpower capacity. This in turn implies that the depletion treatment might have had smaller effect than anticipated. Combination of this effect and a small sample size probably lead to a low statistical power.

To deal with the low statistical power, we include covariates in the regression analysis. We can see in Table 3 that when covariates are not included coefficient on treatment indicator variable is not statistically significant ($p = 0.31$), while when we include some covariates results change, which confirms our suspicions. Covariates include, among other things, socio-demographic characteristics, a number of cigarettes smoked, a dummy representing high expenditure level ($>€1000$), a dummy for stock-market trading experience and an BSSS-4 index for risk attitudes. We find that we can reject the null hypothesis that the depletion treatment has no effect on the CRRA. The effect is positive and significant ($p < 0.1$). This allows us to tentatively conclude that the prediction of the dual system model holds true. When person is depleted, the affective system will exert greater influence on person's choices and lead him to choose among lotteries in a more risk averse manner. Moreover, we see that lower risk aversion is associated¹³ with a higher cigarette consumption, higher monthly expenditure and a higher index in the BSSS-4 scale. These results are in line with the standard findings

¹³Since the covariates were not randomly assigned, we cannot attribute a causal interpretation to the coefficients.

on behaviors related to the risk in the literature.

Table 3: OLS regression results of the treatment and other covariates on the CRRA index

VARIABLES	(1) CRRA	(2) CRRA
Treatment	0.50 (0.41)	0.72* (0.37)
Sex		0.61 (0.4)
Cigarette Consumption		-1.02* (0.54)
High Expenditures		-0.16*** (0.04)
Stock Trading Experience		0.08 (0.42)
Tiredness Before Experiment		0.1 (0.08)
BSSS-4		-0.07** (0.03)
ImpSS		0.03 (0.05)
Constant	0.71** (0.27)	1.46 (0.91)
Observations	54	54
R-squared	0.03	0.35

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.3 Discount Rates

We next turn to the calibration of discount rates. We use the results of the calibration exercise of the previous section to construct the static utility function $u_i(x) \equiv u(x, r_i)$ for each person $i = 1, \dots, N$. In a fashion very much akin to what was discussed above, we calculate implied discount rates for each person and each task. To illustrate the procedure, suppose that person i , declares to be indifferent between option A (€800, now) and option B (€820, one month). Moreover, we calibrated her rate of relative risk aversion to be around 1.8 and we know that she has a monthly expenditure of around €900 (see the example in the previous section). Given our identifying assumptions, we conclude that the discount

rate ρ^* has to be the solution to the following equation:

$$u_i(900 + 800) + \left(\frac{1}{1 + \rho^*}\right)^{\frac{1}{12}} u_i(900) = u_i(900) + \left(\frac{1}{1 + \rho^*}\right)^{\frac{1}{12}} u_i(900 + 820) \quad (18)$$

which is given by

$$\rho^* = \left(\frac{u_i(900 + 800) - u_i(900)}{u_i(900 + 820) - u_i(900)}\right)^{-12} - 1 \quad (19)$$

In this manner we get for each person and each task a calibrated discount rate, $\{\{r_{it}\}_{t=1}^6\}_{i=1}^N$. It is important to note that the results from calibration of the discount rates are sensitive to the utility function employed, since in the standard model agents discount utility and not money/outcomes. However, it is remarkable that many studies that tried to elicit time preferences, (tacitly) assume $u(\cdot)$ to be linear in monetary outcomes [see, for an overview, Takeuchi, 2011]

In order to sketch how the calibrated risk aversion influences choice over time, consider the following simplified choice setting: Suppose a decision maker is indifferent between (€800, now) and (€820, one month). Disregarding wealth considerations for now, we interpret this as:

$$u_i(800) = \frac{1}{1 + \rho} u_i(820) \quad (20)$$

and we calculate

$$\rho = \frac{u_i(820)}{u_i(800)} - 1 \quad (21)$$

If we again assume that $u_i(x) = u(x, r_i)$ is of the constant relative risk aversion (CRRA) family. Therefore, equation 21 reads as

$$\rho = \left(\frac{820}{800}\right)^{1-r} - 1 = \rho(r) \quad (22)$$

which is a decreasing function of the coefficient of relative risk aversion. More generally, it is not difficult to show that the calibrated discount rate, ρ ,

in equation 19 is decreasing in the concavity¹⁴ of the (Bernoulli-)utility function for any combination of wealth and outcomes. Therefore, it is clear that provided the discounted utility model is true and the decision maker is risk averse (risk loving), assuming risk neutrality¹⁵ leads to inflated (deflated) estimated discount rates. By the same token, the calibrated discount rates are also sensitive to the individual specific income level *on top of the* (indirect) influence via the calibrated risk aversion rate¹⁶.

Figure 3 plots the implied discount rates for rates of relative risk aversion and four different wealth levels when the participant states indifference between (€800, now) and (€820, one month). What we observe is that when moving from risk neutrality ($r = 0$) to risk aversion ($r > 0$) the implied discount rate becomes smaller. Moreover, we see that this effect is amplified when moving from higher to lower income groups.

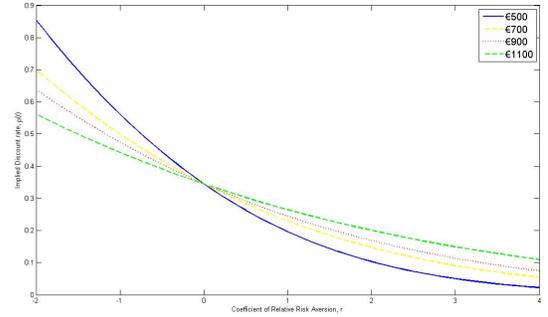


Figure 3: Implied discount rates for different wealth levels and different rates of risk aversion for the choice task (€800, now) vs. (€820, one month)

The mechanics behind this pattern can be easily seen in equation 19: A higher degree of risk aversion in the vonNeumann/Morgenstern framework is equivalent to a higher degree of concavity of the static utility function. But then, the term in parenthesis in (19) (the inverse of the discount factor) becomes bigger as the ratio of differences is

¹⁴Where we say that a function f is more concave than g , if there exists a concave function c s.t. $f = c \circ g$.

¹⁵In our parametrization of CRRA this means setting $r_i = 0$.

¹⁶Unless $r_i = 0$, then income levels have no effects. This can be seen best in equation 19 where the terms involving expenditure levels simply cancel each other when $u_i(x) = x$.

increasing with concavity. Similarly, this effect is magnified if the baseline income is lower since then by concavity, the ratio in equation 19 is increasing.

Table 4 gives the means of the implied discount rates for each of the six time preference elicitation tasks included in the experiment. Recall that three tasks (corresponding to the first three in the table) compare *immediate* with delayed outcomes while the other three compare delayed with further delayed outcomes, each for three different horizons (1, 6 and 12 months). We start by analyzing the results assuming the linear utility function over outcomes (i.e. restricting $r = 0$). These results can be seen in panel one of the table. On average, the mean discount rate across the six tasks is higher in the treatment group than in the control group, however this difference is not statistically significant. Moreover, we see that irrespective of the front-end delay, the one month horizon task is associated with strictly higher discount rates.

When allowing for concavity in the static utility function (i.e. making use of the results of the previous section), we find that, as expected, the discount rates decrease in all the tasks across treatment and control groups. Moreover, since the CRRA in the treatment group is higher, the decrease is higher in magnitude in this group than in the control group.

Proceeding as in the analysis of the risk aversion, we now turn to the a parametric estimation of the depletion treatment effect, which allows us to include covariates which results in higher precision. Table 5 shows the result of an OLS regression of the calibrated discount rates on the same set of covariates as in the case of risk aversion. In this set of regressions, we use a long-format data. Consequently, each observation corresponds to a specific elicited discount rate for each of the six tasks, as well as the characteristics of the task in terms of time-horizon and front-end delay. We found no significant treatment effect in neither the case of a linear static utility function (column 1) nor the case of allowing for concavity/convexity (column 2).

Table 5: OLS regression results of the treatment and other covariates on the discount rate

VARIABLES	(1)	(2)
	Discount Rate	Discount Rate*
Treatment	-0.03 (0.08)	-0.11 (0.11)
FED	0.03 (0.03)	0.02 (0.02)
Treat. x FED	0.05 (0.04)	0.04 (0.03)
TH 1 Month	0.1** (0.05)	0.1* (0.05)
TH 6 Months	0.03 (0.03)	0.01 (0.02)
Treat. x TH 6 Months	-0.02 (0.06)	0.05 (0.07)
Treat. x TH 12 Months	0.06 (0.07)	0.1 (0.08)
Cigarettes Consumption	-0.01** (0.00)	0.02** (0.01)
BSSS-4	0.01 (0.005)	0.02*** (0.001)
Constant	0.34* (0.17)	0.09 (0.16)
Observations	324	324
R-squared	0.120	0.145

Robust standard errors in parentheses, clustered by subject (N=54); *** p<0.01, ** p<0.05, * p<0.1; Discount Rate* = Concave Utility with Individual Level of Expenditures; TH = time horizon; FED = Front-End Delay; Other covariates considered in these regressions are: Sex, High Expenditure, Level of tiredness before the experiment and ImpSSS. The coefficient associated with this covariates are not statistically significant. For brevity they are not shown in this regression.

Turning to possibly different discount rates across tasks, we find that front-end delay is not associated with higher (or lower) elicited discount rate. On the other hand, tasks that consider a time horizon of 1 month exhibit, on average, higher elicited discount rates among the subjects. The latter result is consistent with a robust finding documented in

Table 4: Non-parametric test of the difference in means of discount rate between the treatment and control group

	Panel 1 - Discount Rates				Panel 2 - Discount Rates*			
	Sample	CG	TG	Rank-Sum Test	Sample	CG	TG	Rank-Sum Test
CRRA Index	-	-	-	-	0.96	0.71	1.21	$z = -0.934$ $p = 0.35$
Immediate Vs. Delayed Rewards (No FED)	39.34	39.31	39.38	-	33.89	35.86	31.91	-
Time Horizon: 1 Month	41.69	44.00	39.37	$z = 0.313$ $p = 0.754$	35.91	42.21	29.61	$z = 0.562$ $p = 0.574$
Time Horizon: 6 Month	37.66	38.46	36.86	$z = 0.503$ $p = 0.615$	32.46	33.66	31.25	$z = 0.398$ $p = 0.69$
Time Horizon: 12 Month	38.68	35.45	41.90	$z = -0.633$ $p = 0.527$	33.29	31.72	34.87	$z = -0.061$ $p = 0.952$
Delayed Vs. More Delayed Rewards (FED- 1 month)	44.31	41.97	46.65	-	37.74	37.69	37.78	-
Time Horizon: 1 Month	52.07	48.51	55.63	$z = -0.786$ $p = 0.432$	44.75	45.37	44.13	$z = -0.355$ $p = 0.723$
Time Horizon: 6 Month	39.62	39.84	39.39	$z = 0.174$ $p = 0.862$	32.39	33.12	31.65	$z = 0.311$ $p = 0.755$
Time Horizon: 12 Month	41.24	37.54	44.94	$z = -0.78$ $p = 0.435$	36.07	34.57	37.57	$z = -0.104$ $p = 0.917$
All Choices	41.83	40.64	43.01	-	35.81	36.78	34.85	-

Discount Rates* = Concave Utility with Individual Level of Expenditures; CG = control group; TG = treatment group; FED = Front-End Delay

the empirical literature about hyperbolic discounting. We stipulate that the reason why we did not find a positive effect of front-end delay, which is a common finding in empirical studies [e.g. Coller and Williams, 1999], is a peculiarity of our data: Many participants argued in the comment section of the tasks, that they associated a one-month front-end delay with summer vacations starting around 5 weeks after the time the experiment was conducted.

Moreover, we also noticed in the case of risk aversion, we find that cigarette consumption is negatively (partially) correlated with discount rates when assuming a linear utility function (column 1) while being positively correlated when allowing for a non-linear utility function. As we saw above, cigarette consumption corresponds to a lower average rate of risk aversion, which results in a higher

discount rate, even for the same observed choices in the tasks. Finally, we also observe higher discount rates for those participants that scored higher in the BSSS-4 scale.

5 Conclusion

The present study shows that there is indeed some evidence that people behave as being of two minds. In particular, we were able to show that subjects exhibited increased risk aversion after having completed a willpower depletion task which was supposed to affect the capacity for making choices in subsequent decision making. This is consistent with the dual self model of Loewenstein and O'Donoghue [2004], in that lower willpower is associated with

a more active affective system, which behaves in a very risk averse way (given the experimental design).

However, in the domain of time preferences, we were not able to find evidence in support of the predictions of the model – discount rates were not significantly higher in the treatment group. We speculate that this is due to the limitations of our experimental design. As explained in greater detail above, higher calibrated rates of risk aversion put a downward pressure on the elicited discount rates. Therefore, since we were not able to measure attitudes towards risk before *and* after the treatment, we had no means to disentangle the effect of willpower depletion on risk aversion from the effect on discount rates.

Therefore, we conclude that more tests is needed to ascertain validity of the model. Experimental design has to be improved to disentangle risk and time preferences. Precision issues should be dealt with a bigger sample, while incentive scheme supporting truthful reporting of the preferences should be implemented to dispense with measurement error concerns. Moreover, more controlled experimental setting in a lab would help with implementing more effective depletion treatment.

We believe that with further empirical verification the dual self model might prove to be a useful new tool for modeling choices related to risk and time preferences. Model provides a number of interesting fields of future research, on the one hand, novel methods for activating the affective system could be explored, and on the other many more heuristics suggested by the literature in the past, could be introduced.

References

Steffen Andersen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. Eliciting risk and time preferences. *Econometrica*, 76(3):583–618, May 2008. ISSN 1468-0262. doi: 10.1111/j.1468-0262.2008.00848.x. URL <http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0262.2008.00848.x/abstract>. 3, 3

Steffen Andersen, Glenn W. Harrison, Arne Risa

Hole, Morten Igel Lau, and E. Elisabet Rutström. Non-Linear Mixed Logit. *Theory and Decision*, 2011. URL http://www.cear.gsu.edu/files/Non-Linear_Mixed_Logit.pdf. 4.2

Alan D. Baddeley. Working Memory: Looking Back and Looking Forward. *Nature reviews. Neuroscience*, 4(10):829–39, October 2003. ISSN 1471-003X. doi: 10.1038/nrn1201. URL <http://www.ncbi.nlm.nih.gov/pubmed/14523382>. 1

Roy F. Baumeister, Ellen Bratslavsky, Mark Muraven, and Dianne M. Tice. Ego depletion: is the active self a limited resource? *Journal of Personality and Social Psychology*, 74(5):1252–65, May 1998. ISSN 0022-3514. URL <http://www.ncbi.nlm.nih.gov/pubmed/9599441>. 2.4, 3, 3, 4

Roy F. Baumeister, Erin A. Sparks, Tyler F. Stillman, and Kathleen D. Vohs. Free will in consumer behavior: Self-control, ego depletion, and choice. *Journal of Consumer Psychology*, 18(1): 4–13, January 2008. ISSN 10577408. doi: 10.1016/j.jcps.2007.10.002. URL <http://linkinghub.elsevier.com/retrieve/pii/S1057740807000034>. 1, 2.4

Jess Benhabib and Alberto Bisin. Self-control and consumption-saving decisions: Cognitive perspectives. Technical report, New York University, New York, 2002. 1

Daniel J. Benjamin, Sebastian A. Brown, and Jesse M. Shapiro. Who is Behavioral? Cognitive Ability and Anomalous Preferences. 2006. 2.3

B. Douglas Bernheim and Antonio Rangel. Addiction and cue-triggered decision processes. *The American Economic Review*, 94(5):pp. 1558–1590, 2004. ISSN 00028282. URL <http://www.jstor.org/stable/3592834>. 1

A. Colin Cameron and Pravin K. Trivedi. *Microeconometrics: Methods and Applications*. Cambridge University Press, New York, 2005. 4.2

Maribeth Coller and Melonie B. Williams. Eliciting Individual Discount Rates. *Experimental Economics*, 2(2):107–127, December 1999. ISSN 1386-4157. doi: 10.1007/

- BF01673482. URL <http://www.springerlink.com/index/10.1007/BF01673482>. 3, 3, 4.3
- Jonathan St B T Evans. Dual-processing accounts of reasoning, judgment, and social cognition. *Annual Review of Psychology*, 59:255–78, January 2008. ISSN 0066-4308. doi: 10.1146/annurev.psych.59.103006.093629. URL <http://www.ncbi.nlm.nih.gov/pubmed/18154502>. 1
- Peter C. Fishburn and Ariel Rubinstein. Time preference. *International Economic Review*, 23(3):677–694, 1982. ISSN 00206598. URL <http://www.jstor.org/stable/2526382>. 2, 9
- Ana M. Franco-Watkins, Timothy C. Rickard, and Hal Pashler. Taxing executive processes does not necessarily increase impulsive decision making. *Experimental Psychology*, 57(3):193–201, January 2010. ISSN 1618-3169. doi: 10.1027/1618-3169/a000024. URL <http://www.ncbi.nlm.nih.gov/pubmed/20178926>. 2.3
- Shane Frederick, George Loewenstein, and Ted O’Donoghue. Time discounting and time preference: A critical review. *Journal of Economic Literature*, 40(2):351–401, June 2002. URL <http://ideas.repec.org/a/aea/jeclit/v40y2002i2p351-401.html>. 1
- Drew Fudenberg and David K. Levine. A Dual-Self Model of Impulse Control. *American Economic Review*, 96(5):1449–1476, December 2006. ISSN 0002-8282. doi: 10.1257/aer.96.5.1449. URL <http://pubs.aeaweb.org/doi/abs/10.1257/aer.96.5.1449>. 1
- Glenn W. Harrison, Morten I. Lau, and Melonie B. Williams. Estimating Individual Discount Rates in Denmark: A Field Experiment. *American Economic Review*, 92(5):1606–1617, December 2002. ISSN 0002-8282. doi: 10.1257/000282802762024674. URL <http://pubs.aeaweb.org/doi/abs/10.1257/000282802762024674>. 3
- Stephanie S Hart. *The role of cognitive resources and individual differences in risk preferences of children and adults*. Ph.d. thesis, The University of Iowa, 2005. 2.3
- John M. Hinson, Tina L. Jameson, and Paul Whitney. Impulsive decision making and working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29(2):298–306, 2003. ISSN 0278-7393. doi: 10.1037/0278-7393.29.2.298. URL <http://doi.apa.org/getdoi.cfm?doi=10.1037/0278-7393.29.2.298>. 2.3
- Charles A. Holt and Susan K. Laury. Risk aversion and incentive effects. *American Economic Review*, 92(5):1644–1655, 2002. URL <http://www.nber.org/~rosenbla/econ311-04/syllabus/holtlaury.pdf>. 2.2, 3, 4
- Gideon Keren and Yaacov Schul. Two is not always better than one: A critical evaluation of two-system theories. *Perspectives on Psychological Science*, 4(6):533–550, 2009. URL http://pluto.mssc.huji.ac.il/~mschul/yaacov_schul_files/2sys-final-090126doc.pdf. 1
- Arie W. Kruglanski and Gerd Gigerenzer. Intuitive and deliberate judgments are based on common principles. *Psychological Review*, 118(1):97–109, January 2011. ISSN 1939-1471. doi: 10.1037/a0020762. URL <http://www.ncbi.nlm.nih.gov/pubmed/21244188>. 1
- Arie W. Kruglanski and Edward Orehek. Partitioning the domain of social inference: dual mode and systems models and their alternatives. *Annual Review of Psychology*, 58:291–316, January 2007. ISSN 0066-4308. doi: 10.1146/annurev.psych.58.110405.085629. URL <http://www.ncbi.nlm.nih.gov/pubmed/16968211>. 1
- Matthew D. Lieberman, Ruth Gaunt, Daniel T. Gilbert, and Yaacov Trope. Reflexion and reflection: A social cognitive neuroscience approach to attributional inference. *Advances in Experimental Social Psychology*, 34:199–249, 2002. ISSN 00652601. doi: 10.1016/S0065-2601(02)80006-5. URL <http://linkinghub.elsevier.com/retrieve/pii/S0065260102800065>. 1
- George F. Loewenstein and Ted O’Donoghue. Animal Spirits: Affective and Deliberative Processes in Economic Behavior. 2004. 1, 2, 2, 2.1, 2.2, 2.4, 4, 5

- E. J. Masicampo and Roy F. Baumeister. Toward a physiology of dual-process reasoning and judgment: lemonade, willpower, and expensive rule-based analysis. *Psychological Science*, 19(3):255–60, March 2008. ISSN 0956-7976. doi: 10.1111/j.1467-9280.2008.02077.x. URL <http://www.ncbi.nlm.nih.gov/pubmed/18315798>. 2.3
- Samuel M. McClure, David I. Laibson, George F. Loewenstein, and Jonathan D. Cohen. Separate neural systems value immediate and delayed monetary rewards. *Science*, 306(5695):503–7, October 2004. ISSN 1095-9203. doi: 10.1126/science.1100907. URL <http://www.ncbi.nlm.nih.gov/pubmed/15486304>. 2.3
- Samuel M. McClure, Keith M. Ericson, David I. Laibson, George F. Loewenstein, and Jonathan D. Cohen. Time discounting for primary rewards. *The Journal of Neuroscience*, 27(21):5796–804, May 2007. ISSN 1529-2401. doi: 10.1523/JNEUROSCI.4246-06.2007. URL <http://www.ncbi.nlm.nih.gov/pubmed/17522323>. 2.3
- Michael P. Milham, Marie T. Banich, and Vikram Barad. Competition for priority in processing increases prefrontal cortex’s involvement in top-down control: an event-related fMRI study of the stroop task. *Cognitive Brain Research*, 17(2):212–222, July 2003. ISSN 09266410. doi: 10.1016/S0926-6410(03)00108-3. URL <http://linkinghub.elsevier.com/retrieve/pii/S0926641003001083>. 4
- Allen Newell. You can’t play 20 questions with nature and win. In W.G. Chase, editor, *Visual information processing*, pages 287–307. Academic Press, New York, NY, US, 1973. URL <http://www-psychology.concordia.ca/fac/deAlmeida/COGSCI/Newell-1973-TwentyQuestions.pdf>. 1
- Efe A. Ok and Yusufcan Masatlioglu. A theory of (relative) discounting. *Journal of Economic Theory*, 137(1):214 – 245, 2007. ISSN 0022-0531. doi: DOI:10.1016/j.jet.2007.01.008. URL <http://www.sciencedirect.com/science/article/B6WJ3-4NC5T8M-2/2/3c25a95f853c259f3d6c3a1bbe4ca995>. 2
- Jennifer A. Richeson, Abigail A. Baird, Heather L. Gordon, Todd F. Heatherton, Carrie L. Wyland, Sophie Trawalter, and J. Nicole Shelton. An fMRI investigation of the impact of interracial contact on executive function. *Nature neuroscience*, 6(12):1323–8, December 2003. ISSN 1097-6256. doi: 10.1038/nn1156. URL <http://www.ncbi.nlm.nih.gov/pubmed/14625557>. 5
- Ariel Rubinstein. *Lecture notes in microeconomic theory*. 2010. URL <http://arielrubinstein.tau.ac.il/Rubinstein2007.pdf>. 4
- M.T. Stephenson, R.H. Hoyle, Philip Palmgreen, and M.D. Slater. Brief measures of sensation seeking for screening and large-scale surveys. *Drug and Alcohol Dependence*, 72(3):279–286, 2003. URL <http://linkinghub.elsevier.com/retrieve/pii/S0376871603002382>. 3
- J.R. Stroop. Studies of interference in serial verbal reactions. *Journal of Experimental Psychology: General*, 121(1):15, 1992. URL <http://psycnet.apa.org/journals/xge/121/1/15/>. 3
- Kan Takeuchi. Non-parametric test of time consistency: Present bias and future bias. *Games and Economic Behavior*, 71(2):456–478, March 2011. ISSN 08998256. doi: 10.1016/j.geb.2010.05.005. URL <http://linkinghub.elsevier.com/retrieve/pii/S0899825610000904>. 4.3
- Kathleen D. Vohs and Ronald J. Faber. Spent Resources: Self Regulatory Resource Availability Affects Impulse Buying. *Journal of Consumer Research*, 33(4):537–547, March 2007. ISSN 0093-5301. doi: 10.1086/510228. URL <http://www.journals.uchicago.edu/doi/abs/10.1086/510228>. 2.4
- Kathleen D. Vohs and Todd F. Heatherton. Self-regulatory failure: a resource-depletion approach. *Psychological Science*, 11(3):249–54, May 2000. ISSN 0956-7976. URL <http://www.ncbi.nlm.nih.gov/pubmed/11273412>. 2.4
- Kathleen D. Vohs, Roy F. Baumeister, Brandon J. Schmeichel, Jean M. Twenge, Noelle M. Nelson, and Dianne M. Tice. Making choices impairs subsequent self-control: a limited-resource account of decision making, self-regulation, and active initiative. *Journal of Personality and Social Psychology*, 94(5):883–98, May 2008. ISSN 0022-3514.

doi: 10.1037/0022-3514.94.5.883. URL <http://www.ncbi.nlm.nih.gov/pubmed/18444745>. 2.4

Paul Whitney, Christa A. Rinehart, and John M. Hinson. Framing effects under cognitive load: the role of working memory in risky decisions. *Psychonomic Bulletin & Review*, 15(6):1179–84, December 2008. ISSN 1069-9384. doi: 10.3758/PBR.15.6.1179. URL <http://www.ncbi.nlm.nih.gov/pubmed/19001587>. 2.3

Marvin Zuckerman, D.M. Kuhlman, Jeffrey Joireman, Paul Teta, and Michael Kraft. A comparison of three structural models for personality: The Big Three, the Big Five, and the Alternative Five. *Journal of Personality and Social Psychology*, 65(4):757–768, 1993. URL <http://psycnet.apa.org/journals/psp/65/4/757/>. 3