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Global Warming's Human Preferences

An Experimental Investigation on the Interaction between Risk Attitude and Temporal Choice and the Effect on an Individual's Attitude towards Global Warming

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List with abbreviations

AR	Annual Interest Rate
AER	Annual Effective Interest Rate
BTS	Bayesian Truth Serum
CPT	Cumulative Prospect Theory
CRRA	Constant Relative Risk Aversion
CRT	Cognitive Reflection Test
CTB	Convex Time Budget
DMPL	Double Multiple Price List
DU	Discounted Utility
DV	Dependent Variable
EU	Expected Utility
EV	Expected Value
FED	Front-end Delay
IDR	Individual Discount Rate
IV	Independent Variable
MPL	Multiple Price List
OLS	Ordinary Least Squares
PSR	Preferred Societal Response
PT	Prospect Theory
RDU	Rank Dependent Utility
RIS	Random Incentive System
R2	R squared
sMPL	Sequential Multiple Price List
SSE	Sum of Squares for Error

Abstract

Understanding of how individuals discount and evaluate risks has priority in designing efficient and effective policies on how to mitigate global warming. A large body of experimental evidence has confirmed that people violate exponential discounting as well as expected utility. In fact, people's behaviour is better characterised by hyperbolic discounting and cumulative prospect theory. In the last-mentioned, an individual's risk attitude is determined jointly by the curvature in the utility value function and distortion of probabilities, or sub proportionality, in the probability weighting function. It is questioned what the relationship is between these risk and time preferences. Based on an incentivised experiment, it is demonstrated that subjects' risk aversion and discount rate are inversely related. This means that an individual's degree of probabilistic optimism - captured by overweighting of small probabilities in a person's inverted S-shaped probability weighting function - increases an individual's (constant) discount rate. By contrast, curvature of the utility function is not significantly correlated with an individual's time preference. As a result, subjects are categorised as either low or high patience types. Low patience types exhibit high discounting and optimism towards small probabilities, whereas high patience types demonstrate lower optimism and low discounting. Hyperbolic discounting is not as common as expected. Lastly, there is no support for the hypothesis that time or risk preferences are correlated with a subject's attitude towards global warming.

Keywords: Risk Preference; Time Preference; Risk and Time; Expected Utility Theory; Cumulative Prospect Theory; Exponential Discounting; Hyperbolic Discounting; Global Warming Attitude

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Introduction

“Climate change is no longer some far-off problem; it is happening here, it is happening now”
(Barack Obama, 2015)

Global warming is one of the most important problems of our century. Conversely, the following question is recurrently asked: “Why is thinking about and acting upon this issue that hard?” It might be that people’s focus is too short term and their risk vividness is low. In fact, to what extent an individual disregards the issue of global warming, may be partly explained by impatience and risk attitudes.

Preceding research points to heterogeneity in how individuals make risky choices and intertemporal decisions. Regarding risk, decision-makers are characterised as risk averse, risk seeking, or risk neutral. While a risk averse individual would rather settle for a certain, but lower amount of money, a risk seeking individual would opt for the chance of receiving a higher amount of money. It is often assumed that people are risk averse Expected Utility (EU) maximisers. Then, the rate of risk aversion is captured by curvature of the utility value function. Cumulative Prospect Theory (CPT) is recognised as being a better descriptor of people’s behaviour. The main characteristics of CPT are that people think of possible outcomes relative to a reference point, rather than to the final status (as in EU), have different risk attitudes towards gains and losses, and overweight extreme, but unlikely events (they are optimistic). This implies that an individual’s risk attitude is not only determined by curvature of the value function, but also by a probability weighting function.

Regarding time, there are differences to the extent, and manner, that people are able to delay gratification. While a patient individual attaches equal weight to the present as to the future, an impatient individual values their consumption in the present as relatively higher than additional consumption in the future. This rate of time preference is captured by the discount rate. It is often assumed that people are time consistent; that they have a constant discount rate. True, in practice, the rate of discounting falls over time, suggesting hyperbolic discounting.

Previously, risk and time preferences were either studied separately (the potential interaction was ignored) or it was assumed, in Discounted Expected Utility, that the two could be represented by a single parameter. However, given that discounting future outcomes is motivated by an element of risk introduced by the time delay, it is reasonable that risk and time preferences are driven by similar processes. Now, risk and time preference are believed to be inversely related to one another. This implies that risk averse agents are more patient. However, whether this risk aversion is explained by concavity in the utility function or curvature in the probability weighting function, is an open empirical question.

Moreover, as (economic) decisions are made under risk and affect the future as well as the present, basic features of human’s risk and time preferences may explain to what extent individuals exhibit different degrees of environmental awareness. Although some researchers have addressed this question, in what way these human preferences relate to people's attitudes towards climate change is still poorly understood.

To date, most work has been limited to the relationship between EU risk preferences and constant (time consistent) time preferences. By contrast, to the best of my knowledge, no study addressed the issue of how CPT risk preferences - accounting for different attitudes towards gains and losses and probability weighting - relate to hyperbolic time preferences. This lack may be due to the fact that a comparatively rich data set as well as a fairly sophisticated estimation strategy are needed to be able to disentangle curvature of the utility value function from probability weighting. In addition, in the light of the recent increased consequences due to climate change, there is considerable interest in knowledge about innate preferences in terms of policies to mitigate global warming.

This research has both scientific as practical relevance. First, in contrast to many previous studies, this research allowed for EU along with CPT risk preferences and exponential as well as hyperbolic time preferences. Therefore, it extends the literature on how they are related. Second, it is shown whether this correlation varies for people with different attitudes with regard to global warming. Risk and time preferences have also many applications, and thus, practical relevance. First, understanding heterogeneity in risk and time preferences may be critical in accurately predicting market outcomes. Also, as an illustration, lots of (environmental) policies involve near term costs, extend over long periods of time, and enjoy (to a large degree) uncertain future benefits. Hence, to understand and estimate how individuals discount and evaluate risks is of utmost important in order to design and evaluate efficient and effective policy on how and when to address global warming.

The core problem is that a CPT risk seeking and optimistic, but impatient and time inconsistent individual will reject a policy measure that is attractive to a decision-maker who is EU risk averse, patient, and time consistent. While public policies are often made to appeal to the last-mentioned type of decision-maker, policymakers should aim to appeal to the different patience types in order to make them care about climate change. Identifying decision-makers' risk and time preferences and adapting to their needs becomes important to ensure a wide acceptance of policy measures involving intertemporal and risky choices. In fact, cost-effectiveness of a policy can be enhanced if it is tailored to the preferences of the target population. Therefore this paper seeks to answer the following research question: Does the relationship between risk and time preferences differ for individuals with different attitudes towards global warming?

The purpose of the present study was twofold. First, the goal was to extend the knowledge concerning the relationship between risk and time preferences. Second was the aim to shed light on what this relationship tells us about attitudes towards global warming. In order to address these goals, I conducted an online experiment with mostly student subjects, using salient monetary incentives. It generated rich data, enabling me to estimate individual risk aversion coefficients and probability weights, and to relate them to the same subjects' revealed discount rates and global warming attitude.

This thesis is divided into six chapters. The remainder of the paper is structured as follows: Chapter 1 describes the theoretical framework. Chapter 2 highlights the methodology. Chapter 3 discusses the experimental design. Chapter 4 outlines the approaches to estimation and presents the results. Chapter 5 includes a discussion of the findings and concludes.

1. Theoretical Framework

This chapter discusses the theoretical framework. First, different frameworks for decision-making, over monetary outcomes, under risk and over time are examined. This results in the first two hypotheses. The purpose of H1 and H2 is to clarify the potential heterogeneity in risk and time preferences in order to express expectations towards one specific framework for risk and one for time. Heterogeneity in risk and time preferences is, among other things, affected by socioeconomic characteristics, such as gender, age, education level, and field of study, for which will be accounted as control variables. Second, the potential interaction between risk and time is reviewed, resulting in the third hypothesis. The (academic and methodological oriented) idea behind H3 is to find out about the relationship between risk and time preferences. Lastly, H4, H5, and H6 are presented to explore what the relationship between risk and time preferences (H3) tells us about attitudes towards climate change.

The hypotheses are prepared to account for the following research question: Does the relationship between risk and time preferences differ for individuals with heterogeneous attitudes towards global warming?

1.1. Risk preferences

This section introduces heterogeneity in risk preferences for Expected Utility (EU) maximisers as well as for Cumulative Prospect Theory (CPT) satisfiers. In economics, the EU hypothesis states that a decision-maker chooses between risky (or uncertain) prospects by comparing their expected utility values. However, a large body of empirical evidence challenges the validity of this EU framework. Instead, CPT is considered as an alternative theoretical framework. Importantly, in CPT, gains and losses are compared to a reference point. First, since in this paper investigated the relationship between risk and time preferences, it is of substantial importance to study empirically valid risk preferences. Also, because it was explored what this relationship has to say about attitudes towards climate change, which is often framed as a loss, allowing CPT was a necessity. Bartczak, Chilton and Meyerhoff (2015) confirm that environmental decisions are consistent with CPT. Also, Häckel, Pfosser and Tränkler (2017) state that CPT offers explanations for behavioural barriers in mitigating the impact of climate change and preserving non renewable resources. In fact, they illustrate how the extent of the energy efficiency gap - the gap between actual and optimal energy use - is influenced by behavioural biases such as loss aversion and probability weighting. Hence, there were good reasons, both theoretical and empirical, to hypothesise that CPT, compared to EU, was better in describing individual's risk preferences.

Independent of the utility model used, individuals are characterised as risk averse, risk seeking, or risk neutral. It is the hesitation (risk averse) or willingness (risk seeking) to agree to a situation with an unknown payoff rather than another situation with a more certain, but possible lower, expected payoff. A person shows greater risk aversion if, for every risk, their risk premium - the amount they are willing to pay to get rid of the risk - is larger than for another person. Lastly, a risk neutral individual is indifferent to risk and is, therefore, only concerned about the expected return (Pratt, 1964). Experimental evidence shows that most decision-makers are risk averse (Binswanger, 1980). In general, decision-making under risk is measured by means of choices between prospects, or gambles, with monetary outcomes.

In Von Neumann and Morgenstern's (1947) Expected Utility (EU) framework, risk attitudes are driven by differences in evaluations of outcomes (value function) and linear, objective probabilities. Consider decision-makers with (monetary) assets, *x,* and utility function, *u*. A risk averse individual has a concave utility function (decreasing marginal utility), a risk neutral person has a linear utility function, and a risk seeking person has a convex utility function (increasing marginal utility) (Pratt, 1964).

Since it is difficult and beyond the scope of this paper to compare alternative specifications of the EU utility function, only the favourite and most widely used, for reasons of plausibility and computational convenience, is presented. With constant relative risk aversion (CRRA) for money *x*, the utility function is: $u(x) = x^{1-\sigma}/(1-\sigma)$ with $x > 0$. The CRRA specification refers to decreasing absolute risk aversion; a higher income might result in lower risk aversion. The specification implies $\sigma > 0$ for risk aversion, $\sigma = 0$ for risk neutrality, and $\sigma < 0$ for risk seeking (Andersen, Harrison, Lau, & Rutström, 2008; Ferecatu & Önçüler, 2016; Holt & Laury, 2002; Pratt, 1964; Wakker, 2008).

However, a large body of empirical evidence challenges the validity of this EU framework. While EU is not able to capture optimism and pessimism, empirical evidence concerning sensitivity towards probabilities is overwhelming. In fact, CPT is considered as an alternative theoretical framework. Kahneman and Tversky (1979; 1992) claim that people place more weight on extreme outcomes in their decision process, violating the independence axiom. CPT allows for violations of the independence axiom, because it incorporates a probability weighting function and transforms objective probabilities into decision weights (Fennema & Wakker, 1997; Kahneman & Tversky, 1979, 1992; Wakker, 2010).

Kahneman and Tversky (1979; 1992) demonstrate that gains and losses are compared to a reference point. This way, they reject asset integration, but propose reference dependent utility; individuals do not necessarily care about their final wealth levels, but about changes from some status quo of wealth. Also, for the purpose of presenting preferences, contrary to EU, the risk attitude is not equal to curvature of the value function. In fact, the attitude is determined jointly by the value function (v) and the probability weighting function (π).

The S-shaped value function (v), which reflects the subjective value of an outcome, is concave for gains, $v''(x) < 0$ for $x > 0$, and convex for losses, $v''(x) > 0$ for $x < 0$. Thus, subjects are risk averse to gains, but risk seeking with respect to losses. Also, the function exhibits loss aversion (λ), shown by the steepness of the slope for losses compared to gains. This means that negative departures from one's reference consumption level decrease utility by a greater amount (roughly twice as much) than positive departures increase it (Tversky & Kahneman, 1992).

The probability weighting function (π), which replaces the linear, objective probabilities in EU with nonlinear decision weights, is an increasing function of p with $\pi(0) = 0$ and $\pi(1) = 1$. So, $\pi(p)$ reflects the impact of p on the overall value of the prospect and satisfies monotonicity, since the decision weights sum to one. Tversky and Kahneman (1992) prove that people's capacity to evaluate and understand extreme probabilities is limited. As a consequence, they suggest the inverted S-shaped weighting function that highlights overweighting of small probabilities, $(\pi(p) > p)$ or optimism, and underweighting of larger probabilities, $(\pi(p) < p)$ or pessimism. Wakker (2001) agrees that this inverse S-shaped weighting function, which captures optimism about unlikely good news and events and pessimism about unlikely bad news, is descriptively the most plausible pattern.

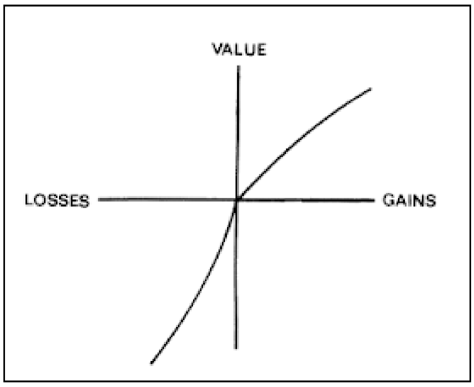

Figure 1. S-shaped value function (Kahneman & Tversky, 1979, p.279)

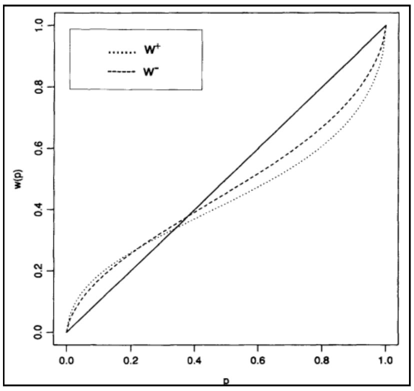

Figure 2. Inverted S-shaped weighting function for gains, w^{+}, and for losses, w^{-} (Tversky & Kahneman, 1992, p.313)

Taken together, the S-shaped value function (described by Figure 1) and the inverted S-shaped weighting function (described by Figure 2), result in a fourfold pattern of risk attitudes. People are typically risk seeking for small probability gains and large probability losses and, in contrast, risk averse for small probability losses and large probability gains (Abdellaoui, 2000; Tversky & Kahneman, 1992; Gonzalez & Wu, 1996).

In short, CPT seems to be more (descriptively and empirically) valid and more suited for analysing decision-makers' environmental decisions (regarding gains as well as losses), over the global climate (asset), *x*, and utility function, *u*. Therefore, in order to answer the main question, whether the relationship between risk and time preferences differs for individuals with heterogeneous attitudes towards global warming, the following first hypothesis is derived:

H1: Subjects are more likely to be cumulative prospect theory satisfiers rather than expected utility maximisers.

In addition to an inverted S-shaped weighting function, there is some evidence regarding a S-shaped weighting function. This implies underweighting of small probabilities, $(\pi(p) < p)$, and overweighting of large probabilities, $(\pi(p) > p)$. Since the methodology in this paper lends itself to account for this type of probability weighting as well, it is also included.

1.2. Time preferences

This section introduces heterogeneity in time preferences for exponential as well as for hyperbolic discounters. In economics, the exponential discounting hypothesis states that a decision-maker chooses between x_0, at time t_0, and a higher amount, x_n, at any point of time in the future t_n. Since future utility is discounted by the rate of time preference, or Individual Discount Rate (IDR), exponential discounting expects a positive and constant, and thus dynamically consistent, IDR. However, a large body of empirical evidence (experimental and field data) challenges the validity of this framework. Instead, hyperbolic discounting is considered as an alternative theoretical framework. Importantly, hyperbolic discounting challenges the assumption of constant discounting. Rather, observed discount rates tend to decline, implying time inconsistency. First, since the topic of this paper is the connection between risk and time preferences, it is of utmost importance to study empirically valid time preferences. To further explain, as environmental goods (and bads) often generate benefit (or cost) streams that may not occur until far into the future (and thus, their effects are intergenerational), analyses regarding climate change in relation to individual's preferences depend critically upon the discount rate. Also, because the second purpose is the examination of whether this relationship has something to say about attitudes towards global warming, and a behavioural bias such as time inconsistency has a lot to do with this, allowing hyperbolic discounting is essential. In fact, in contrast to exponential discounters, hyperbolic discounters are time inconsistent, and thus, may not carry out plans they make today. Indeed, Hepburn, Duncan and Papachristodoulou (2010) assert that, if an environmental (resource management) planner is unable to commit to a policy (absence of commitment mechanism), hyperbolic discounting generates temptation to re-evaluate the policy in the future. Consequently, this results in the collapse of a natural resource, and this way, hyperbolic discounting might exacerbate environmental problems. Copper and Laibson (1998) also propose to use hyperbolic discounting to evaluate payoffs under global warming. Hence, there are good reasons, both theoretical and empirical, to hypothesize that hyperbolic (contrary to exponential) discounting is better in describing an individual's time preference.

So, individuals have a time preference that is found on a continuum; there is no absolute distinction that separates high from low time preference. However, to simplify and explain, individuals can have a high time preference (high IDR), and value their consumption in the present relatively higher than additional consumption in the future, or they can have a low time preference (low IDR), and place more emphasis on utility in the future. Thus, the former being more impatient, they value an amount, x, at time t_0, (in terms of utility) higher than the same amount, x, at any point of time in the future t_n (Frederick, Loewenstein, & O'donoghue, 2002). Independent of the discount model used, future utility is discounted by the rate of time preference, or Individual Discount Rate (IDR).

The time preference is mathematically captured in the discount function. In Samuelson's (1937) original approach - the Discounted Utility (DU) framework or exponential discounting - time preferences are captured by the following formula: $f(D) = e^{-kD}$, in which D is the delay in the reward and k reflects the IDR. This model assumes that preferences do not change (*stationary instantaneous utility*) and are captured by a single, positive, and constant IDR (*constant discounting*). This implies that individuals are time consistent (Frederick et al., 2002; Samuelson, 1937).

Although the model was instantly accepted as both normative and descriptive valid for reasons of simplicity, elegance, and resemblance to the familiar compound interest formula, it is not accepted because of empirical validity (Frederick et al., 2002). In fact, a large body of empirical evidence challenges the validity of this framework. The most discussed (and relevant) anomaly (inconsistency related to the theoretical predictions of the model) is hyperbolic discounting[1]. In fact, instead of *constant discounting* and *time consistency,* empirically observed discount rates appear to decline over time, indicating dynamic inconsistency (Ainslie, 1975; Loewenstein & Prelec, 1992; Strotz, 1955; Thaler, 1981). This anomaly is relevant, because instead of a single discount rate, a discount function is specified. Furthermore, different time horizons matter in influencing an outcome and, because of time inconsistency, a decision-maker often does not have (unable or unwilling) well-formed plans about future consumption streams.

Hyperbolic discounting suggests that the discount rate varies inversely with the length of time to be waited. Thus, this framework is characterised by a declining discount rate, decreasing impatience, and time-inconsistency (Ainslie, 1975; Mazur, 1987; Prelec, 1992). In this paper, Mazur's generalized hyperbolic discounting formula (1987), $V_i = A_i/(1 + kD_i)$, where V is the present value, A is the future amount, D is the delay (in months/years), and k is a fitted parameter, was employed. The equations are solved for the discount parameter, *k*, which indicates how much someone values future outcomes relative to present outcomes. When a decision-maker has a *k* of zero, this implies that the present and the future are valued equally. Conversely, positive values of *k* indicate that future outcomes are discounted (the more so, the larger *k*). The specification was chosen because of its simplicity and considerable support (Frederick et al., 2002; Kirby, 1997; Mazur, 1987).

[1] In response to other anomalies, a wide variety of theoretical models has been developed.

This model lacks time-consistency; a subject's choice ordering changes over time. First, a subject prefers the smaller, sooner amount, x, to the larger, delayed amount, y. However, as this delay is increased, the preference for the earlier, smaller reward, x, declines, and the subject reverses its preferences, and prefers the larger, delayed amount, y (Frederick et al., 2002).

In short, hyperbolic discounting seems to be more (descriptively and empirically) valid and more suited for analysing decision-makers' environmental decisions (that involve long time horizons and high degrees of uncertainty). Therefore, in order to answer the main question, whether the relationship between risk and time preferences differs for individuals with heterogeneous attitudes towards global warming, the following second hypothesis is derived:

H2: Subjects are more likely to be hyperbolic discounters rather than exponential discounters.

In addition to hyperbolic discounting, there is some evidence regarding quasi-hyperbolic preferences that exhibit a 'present bias' (Ainslie, 1992; Laibson, 1997). Individuals might have a strong desire, ceteris paribus, for immediate gratification, but are more willing to wait for outcomes further in the future (Frederick et al., 2002). To the contrary, the topic of quasi-hyperbolic discounting is beyond the scope of this paper.

Notice that when it appeared, in this paper, that subjects were in fact exponential discounters, the simple exponential equation of Mazur (1987) was utilised: $V_i = A_i e^{-kD_i}$.

1.3. Relationship risk and time preferences

Although there is an abundance of research on socio-economic characteristics that affect heterogeneity in risk and time preferences, the *relationship* between risk and time preferences is somewhat unclear. As a consequence, the goal of this paper is to investigate the possible relationship. Since an element of risk is introduced in discounting future outcomes, due to the time delay, it is expected that some correlation between the domains of time and risk exists; they might be driven by similar processes.

Some studies solely describe the presence of an interaction between risk and time preferences; individuals become less patient as risk increases (Anderson & Stafford, 2009), while others focus on the absence of this interaction (Miao & Zhong, 2012). In the extant (empirical) literature, the relationship between risk and time preferences is examined from various different angles, yielding very different results. Some research suggests no significant correlation between an individual's risk aversion and discount rate (Abdellaoui, Bleichrodt, l'Haridon, & Paraschiv, 2013; Andreoni & Sprenger, 2012b; Coble & Lusk, 2010; Cohen, Tallon, & Vergnaud, 2011; Ioannou & Sadeh, 2016). Others find a significantly negative correlation, stating that risk averse agents are more patient and risk seeking agents are less patient (Booij & Van Praag, 2009; Cameron & Gerdes, 2007; Ferecatu & Önçüler, 2016). Lastly, also a significantly positive correlation is found, suggesting that risk averse agents are more impatient; they tend to discount the future more heavily (Anderhub, Güth, Gneezy, & Sonsino, 2001; Andersen et al., 2008; Eckel, Johnson, & Montmarquette, 2005; Chabris, Laibson, Morris, Schuldt, & Taubinsky, 2008; Leigh, 1986).Table I in Appendix A presents a complete literary overview of all studies.

Drawing conclusions from above studies is difficult. The analyses vary with different procedures (experimental designs, either field or laboratory, and estimation techniques), different elicitation methods of time and risk preferences (experimental tasks or questionnaires, joint or sequential elicitation), different subject pools (students or non-student subjects), and different types of payoffs (monetary or goods, real or hypothetical). Lastly, most studies assume subjects to be EU maximisers and exponential discounters, rather than (cumulative) prospect theory maximisers and hyperbolic discounters. In Section 1.1 and 1.2 it is pointed out that the assumptions of EU and constant discounting are commonly violated. Therefore, in this paper, these assumptions are avoided. Also, these contradictory results suggest that further assessment of the correlation between risk and time preferences is necessary.

Only some studies account for hyperbolic as well as for exponential discounting. Ferecatu and Önçüler (2016) claim that individuals have heterogeneous discounting patterns. 60% of the subjects discounts future rewards hyperbolically. Nevertheless, (save Abdellaoui et al., 2013; Epper et al., 2011), none of the studies account for probability weighting.

Abdellaoui et al. (2013) compare utility under risk and utility over time (while accounting for gains, losses, and loss aversion) to investigate whether the assumption of one unifying concept of utility, applicable to all decision problems, is realistic. Their general finding is that utility for risk and time are clearly different (and uncorrelated), for gains as well as for losses, and thus, require two utility functions. However, in the auxiliary analysis, they find (for one out of two experiments) a small negative and mildly significant correlation between risk aversion and impatience for gains, but not for losses. Although Abdellaoui et al. (2013) contributed by making it possible to estimate individual probability weights over varying delays, unfortunately, they were not able to easily identify the parameters.

Epper et al. (2011) address the question whether departures from exponential discounting are possibly correlated to departures from linear, objective probability weighting (as in EU). Indeed, they find a strong and significant correlation between the strength of decline in discount rates (extent of hyperbolic discounting) and probability distortions (non-EU risk preferences). More specifically, discount behaviour is directly linked to risk preference. Epper et al. (2011) explain this as follows: in decision-making, because of uncertainty, an individual gets the tendency to distort probabilities. This is called sub proportionality, as in Quiggins Rank Dependent Utility (1993) (RDU)[2], and as an effect, the more an individual discounts hyperbolically.

[2] RDU is explained below.

Interestingly, the correlation is not driven by one of the candidate factors such as the Cognitive Reflection Test (CRT) or other socioeconomic variables. Instead, Epper et al. (2011) argue that the correlation is driven by a common underlying factor that influences departures from linear probability weighting as well as departures from exponential discounting. In fact, the natural link between the domains of time and risk is explained by the uncertainty inherent in any future event. This explanation also accounts for previous evidence of interactions of time and risk. To illustrate, Keren and Roelofsma (1995) show that, when the present becomes risky, the percentage of subjects choosing the more delayed, but higher award, is increased. Weber and Chapman (2005) replicated these findings.

The claim of Epper et al. (2011) that hyperbolicity is generated by someone's proneness to probability distortions, is incorporated in this paper, but extended to CPT (instead of RDU) risk preferences. Although CPT and RDU risk preferences are closely related, they still differ from each other. In brief, Kahneman and Tversky's (1979) original Prospect Theory (PT) is further developed by the crucial idea of Quiggins (1993) RDU, leading to Tversky and Kahneman's (1992) CPT. Initially, PT assumed that people overweight *all unlikely*, or small probability, events. However, RDU adjusts this assumption; people overweight *only unlikely extreme* outcomes, rather than all unlikely events (Fennema & Wakker, 1997). As with all of nonexpected utility theories, RDU and CPT both permit nonlinear weighting of probabilities. RDU accounts for optimism and pessimism; whereas optimism means that, the better the outcome is relative to others, the more decision weight it gets, pessimism means that, the worse the outcome relative to others, the more decision weight it gets. The difference between RDU and CPT is that, while RDU accounts for optimism and pessimism, CPT includes payoffs that are measured as deviations from a reference point. So, CPT is a combination of RDU and PT; it justifies the fourfold pattern of risk behaviours, as explained in Section 1.1.

Although essential for building theoretical and empirical models for decision-making and public policy, to the best of my knowledge, there is no previous study that investigates the link between individuals' CPT risk preferences and hyperbolic discounting. This lack may be due to the fact that a fairly sophisticated estimation strategy is needed to be able to disentangle utility curvature and probability weighting. However, Tanaka, Camerer, and Nguyen (2010) solve this complication by an important methodological contribution. Through Multiple Price Lists (MPLs), the authors elicit three CPT parameters (utility curvature, probability weighting, and loss aversion) to estimate subjects' risk preferences. Also, they incorporate the discounting model of Benhabib, Bisin, and Schotter (2004) to compare exponential, hyperbolic, and quasi-hyperbolic discounting at once. They reject EU in favour of CPT and reject exponential discounting in favour of the quasi-hyperbolic discounting model (Tanaka et al., 2010). Although Tanaka et al. (2010) study how risk and time preferences are linked with wealth, the correlation between the two preferences is not assessed. Therefore, in this paper, the separate CPT parameters are derived and their correlation with the discount rate is studied.

In conclusion, various studies, assuming subjects to be EU maximisers and exponential discounters, demonstrate different results: an insignificant, significantly positive, or a significantly negative relationship between the risk aversion coefficient and the discount rate. Ferecatu and Önçüler (2016), who did account for heterogeneity in time preferences, find a significantly negative correlation, implying that risk averse agents are more patient. In the field of psychology, this negative correlation is already accepted for longer; the risk averse and more patient decision-maker sees greater opportunity costs to gambling (which is money spend now), while they value their savings more. By contrast, Ferecatu and Önçüler (2016) failed to include the measurement of non expected utility risk preferences. In fact, only Abdellaoui et al. (2013) and Epper et al. (2011) account for probability weighting. Curvature in the probability weighting function may also be the source of risk aversion.

Abdellaoui et al. (2013) assert a small and negative correlation between the discount rate and risk aversion, which suggests that risk averse agents are more patient, confirming the findings of Ferecatu and Önçüler (2016). To be fair, Abdellaoui et al. (2013) address that in nonlinear estimation, the parameters cannot be easily identified. So, the risk aversion can be explained by concavity in the utility function as well as by convexity, indicating pessimism, of the probability weighting function. Epper et al. (2011) point to a significant positive correlation between probability weighting and the degree of hyperbolic discounting. It is important to note that Epper et al. (2011) take the extent of hyperbolic discounting into account and not necessarily the absolute value of the discounting parameters.

Hence, these results demand further investigation. Apparently, in line of Epper et al. (2011), it is possible that the discount rate is (significantly) correlated with the probability weighting function, but not with curvature of the value function, or vice versa. Partly following Ferecatu and Önçüler (2016), the decision-makers are clustered as being either a high or a low patience type[3]. However, since Ferecatu and Önçüler (2016) did not account for heterogeneous risk preferences, adaptations to the clustering were made. In CPT, the risk attitude exists of a value function as well as probability weighting. Riddel (2012) introduces the distinction between outcome and probabilistic risk attitude. It was expected that either the concavity of the value function (outcome risk attitude) or the curvature of the probability weighting function (probabilistic risk attitude: optimism or pessimism) negatively correlated with the discount rate. Increased risk aversion could have implied increased outcome risk or increased pessimism, resulting in more patience.

[3] Ferecatu and Önçüler (2016) cluster subjects into three types: high patience (low discounting and risk averse), low patience (high discounting and risk-seeking), and moderate patience types. This paper compares low patience with high patience types. Therefore, in this study, the moderate type is left out.

	Risk attitude		Time preference
Patience Type	*Risk aversion (outcome risk attitude)*	*Probability weighting (probabilistic risk attitude)*	*Hyperbolic time preference*
High patience (type I)	More risk averse / less risk seeking	More pessimistic / less optimistic	Low discounting
Low patience (type II)	Less risk averse / more risk seeking	Less pessimistic / more optimistic	High discounting

Table 1. CPT maximisers with hyperbolic time preferences: high and low patience types[4]

Table 1 explains the difference between high and low patience types. The high patience type is medium to highly risk averse to gains (but risk seeking or less risk averse with respect to losses), is pessimistic (less optimistic) towards small probabilities, has a lower discount rate and is thus more patient. By contrast, the low patience type is mediocre to medium risk averse to gains (but risk seeking or less risk averse in the field of losses), is less pessimistic (more optimistic) towards small probabilities, has a higher discount rate and is thus more impatient.

In order to answer the main question, the following general hypothesis is derived:

> **H3.** In the domain of gains, there is a negative correlation between an individual's risk aversion and discount rate, classifying the population into high patience and low patience types.

In addition, to account specifically for an individual's curvature in the utility function (outcome risk attitude) or probabilistic optimism (probabilistic risk attitude), H3.1. and H3.2. are in place. Since CPT assumes an inverted S-Shaped weighting function, which captures probabilistic optimism (overweighting of small probabilities), pessimism is captured as ''less probabilistic optimism'', suggesting a positive correlation with the discount rate.

> **H3.1.** In the domain of gains, there is a negative correlation between an individual's curvature in the utility function and discount rate, classifying the population into high patience and low patience types.
>
> **H3.2.** In the domain of gains, there is a positive correlation between an individual's degree of probabilistic optimism and discount rate, classifying the population into high patience and low patience types.

Notice that the hypotheses only account for the gains domain, while additionally, the correlation might be different in the field of losses. In fact, the literature also points to a positive correlation between risk aversion and the discount rate, suggesting that risk averse agents are more impatient. According to Wakker (2010, p.6): *"Most of the risk aversion empirically observed is probably not caused by concave*

[4] If no support was found for H1 and/or H2, the grouping in Table 1 was not completely validated. However, it was made sure that the grouping could also account for EU risk preferences and exponential time preferences.

utility as classical studies have it, but by loss aversion". First it was intended to hypothesise that, in the domain of losses, a positive correlation between an individual's risk attitude (loss aversion) and their discount rate would be found. However, due to practical limitations, discussed in Chapter 3 and 4, this was beyond scope of research.

1.4. Domain differences risk and time preferences

In utility measurements of risk and time preferences, the concept of monetary equivalency requires that the marginal utility of an additional euro worth of an environmental good is the same as the marginal utility of an additional euro. So, consequently, an individual's risk attitude and discount rate must be the same whether measured in euros (monetary domain) or in euro-denominated environmental goods (environmental domain).

The evidence regarding this is mixed. On one hand, the claim is that people's risk attitudes are different across the monetary and environmental domain (Ioannou & Sadeh, 2016; Riddel, 2012). On the other hand, research demonstrates that attitudes are not statistically different across domains (Bartczak, et al., 2015; Dohmen et al., 2011; Weber, Blais, & Betz, 2002). Furthermore, some authors suggest differences in a person's discounting behaviour across domains; environmental outcomes are discounted less than financial outcomes (Gattig and Hendrickx, 2007; Nicolaij & Hendrickx, 2003). Then again, others state that there are no statistical differences (Ioannou & Sadeh, 2016).

Unfortunately, the studies show some important limitations, of which a few are discussed. First, Weber et al. (2002) present a psychometric scale; subjects self-report their willingness to take risk. Thus, risk preferences are inferred, not directly measured, and not incentive compatible. The problem is that subjects might not be encouraged to give truthful answers. Another caveat is that Ioannou and Sadeh (2016) and others assume EU risk preferences; this under- or overestimates people's indifference points. Lastly, Riddel (2012) only compares *hypothetical* monetary and environmental lotteries, which makes the results less valid and difficult to generalise.

So, although a green frame might increase external validity, since the evidence regarding domain differences (monetary versus financial) is mixed, a context-neutral frame is chosen to avoid loss of control and confounding factors. In fact, environmental framing within the online experiment would bring about other disturbances. To illustrate, accounting for an environmental gamble that involves the success of a mitigation policy towards global warming, is hypothetical per definition because it can never be played out for real. While subjects can still be paid for participation, no rewards can be given for truthful answers. The consideration of incentive compatibility won. Also, a risk attitude for environmental preferences might differ from that of financial preferences just because people are more familiar with financial gambles than environmental gambles, and therefore, uncertainty picks up the risk effect.

1.5. Relationship risk and time preferences and attitude type

Although time and risk preferences appear to be *context-independent*, Viscusi, Huber, and Bell (2008) find that time preferences do differ for regular recreational visitors to lakes, rivers, and streams, compared to those who do not. Therefore, time (and risk) preferences might be different for subjects with different degrees of environmental awareness.

Ioannou and Sadeh (2016) exactly studied this relation, but find no support for a subject's time or risk preference to be correlated with their environmental awareness. Nevertheless, one might doubt the construct validity of their measure of environmental awareness, because out of 221 questions of the Segmentation Model, they only took 17 questions to divide their sample into seven behavioural groups[5]. Since the authors do not mention anything about the correctness and accuracy of the shorter version of the questionnaire, and the choice for the 17 questions almost looks random, the construct validity is doubted.

Therefore, this paper's focal point is more specific: an individual's attitude towards global warming. Since the measurement of actual environmental friendly behaviour is very impractical and hypothetically deriving behaviour comes with its own problems, a person's attitude is measured. Laroche, Bergeron, and Barbaro-Forleo (2001) argue that a (consumer's) attitude is a good determinant of environmental friendly behaviour.

Attitudes describe more dimensions than either being positive or negative. In fact, an attitude consists of three ABC components: affective (emotional), behavioural (action), and cognitive (knowledge), and as such, can be mixed. As a result, the audience segmentation typology of Maibach, Leiserowitz, Roser-Renouf, and Mertz (2011) makes it possible to classify subjects into six distinct segments. The attitude types form a continuum, from the *Alarmed* to the *Dismissive*. In brief, the *Alarmed* are people whose ABC components are in line. They are the ones most engaged in the issue of global warming. They are well informed, convinced it is happening, and believe it is human-caused (cognitive), are highly worried and feel it is serious and urgent (affective), and are supportive of policy responses and try to take action themselves (behavioural). The *Dismissive* are also people whose ABC components are in line. These people are also engaged with the issue, but on the opposite end of the spectrum. They are sure it is not happening (cognitive), are completely unconcerned (affective), and are strongly opposed to policy responses and do not act upon it (behavioural). The four middle groups, the *Concerned, Cautious, Disengaged,* and *Doubtful*, have either weaker behavioural and/or affective

[5] Ioannou and Sadeh (2016) employ a part of the Segmentation Model, created by the Department for Environment, Food and Rural Affairs (DEFRA), to categorise the population into seven behavioural groups. The segments - Positive Greens (PG), Waste Watchers (WW), Concerned Consumers (CC), Sideline Supporters (SS), Cautious Participants (CP), Stalled Starters (StSt), and Honestly Disengaged (HD) - are classified according to their propensity to undertake twelve key behaviours, such as avoiding unnecessary flights, wasting less food, increasing recycling, and buying more energy efficient products. In the original questionnaire, 221 questions (divided over eight different categories) need to be answered to make the classification. However, Ioannou and Sadeh (2016) only take 17 questions to divide their sample into seven groups.

components. In this paper, due to practical limitations, the six groups are merged into three groups: the 1) *Alarmed* & *Concerned,* 2) *Cautious* & *Disengaged,* and 3) *Doubtful* & *Dismissive*.

It is assumed that time and risk preferences differ among population groups depending on their attitude towards global warming. Risk aversion (measured by curvature in the utility value function and in weighting function) is expected to contribute to a higher level of (environmental) urgency, and thus, environmental awareness. Indeed, Yapici, Ögenler, Kurt, Koçaş, and Şaşmaz (2017) find that subject's environmental risk perceptions (ERPS risk factors) of ecological risks, chemical waste risk, resource depletion, and global environment risk are positively correlated with environmental attitudes (EAS scores). Environmental risk perception does not necessarily equal risk attitude or preference, because the perception is influenced by psychological factors such as how available the risk is (i.e. how easy it is to imagine or recall the possible outcome of the risk) and cultural factors such as public awareness of the risk (Upham, et al., 2009). Still, Weber et al. (2002) demonstrate that people's risk-taking tendency is strongly associated with the perception of risk. Furthermore, it might be that not only risk aversion, measured by curvature in the utility value function, but also probability weighting, is correlated to environmental awareness. Therefore, in order to answer the main question, the following hypotheses are derived:

> **<u>H4.</u>** Risk aversion decreases the probability of being a *Doubtful* or *Dismissive* type and increases the probability of being an *Alarmed* or *Concerned* type.

Again, to account specifically for an individual's curvature in the utility function (outcome risk attitude) or probabilistic optimism (probabilistic risk attitude), H4.1 and H4.2. are in place. Again, risk aversion means increased pessimism, and thus ''less probabilistic optimism'', and a lower probability of being *Doubtful* or *Dismissive*. As a result:

> **<u>H4.1.</u>** An individual's curvature in the utility function decreases the probability of being a *Doubtful* or *Dismissive* type and increases the probability of being *Alarmed* or *Concerned*.
> **<u>H4.2.</u>** An individual's degree of probabilistic optimism increases the probability of being a *Doubtful* or *Dismissive* type and decreases the probability of being *Alarmed* or *Concerned*.

Viscusi et al. (2008) find that regular, recreational visitors to water bodies have lower discount rates, but exhibit hyperbolic discounting, compared to those who are no regular visitors. The latter have consistently high discount rates. From this, the derived expectation is that people who in general have little concern with the future simply do not place great value on environmental amenities, while people with greater environmental awareness exhibit lower discount rates.

> **<u>H5</u>**: The discount rate coefficient increases the probability of being a *Doubtful* or *Dismissive* type and decreases the probability of being an *Alarmed* or *Concerned* type.

H4 and H5 are in place to investigate the individual relationships between either the risk attitude or the discount rate and the attitude type. Furthermore, if support is found for H3, the population is classified in high patience types and low patience types. These high and low patience types might have different attitudes towards global warming. The expectation is that the *Alarmed*, compared to the *Dismissive*, exhibit more environmental awareness because they realise that decisions regarding global warming affect a longer time scale, are more ambiguous, and affect multiple people. As this implies that the *Alarmed* should have lower discount rates (they are more patient), be more risk averse and less optimistic, in order to answer the main question, the last hypothesis is derived:

> **H6**: Being a high patience type, compared to a low patience type, decreases the probability of being a *Doubtful* or *Dismissive* type and increases the probability of being an *Alarmed* or *Concerned* type.

2. Methodology

The focus of this research is the relationship between risk and time preferences and the correlation with an individual's attitude towards global warming. These relationships were analysed by means of an online survey. This chapter discusses and explains the different elements of the online survey.

The survey consists of three parts, of which the first two are decision tasks. First, the time discounting variables are measured through the methodology of Ferecatu and Önçüler (2016). Second, the risk variables are measured through the methodology of Tanaka et al. (2010). Third, the attitude type is measured through the methodology of Maibach et al. (2012). Changes made with respect to the original methodologies are discussed. Lastly, additional info is gathered to measure the control variables. The socioeconomic control variables that are included are: gender, age, education level, student, field of study, nationality, and geographic living situation.

For my methodological choices, the positivist school of thought is followed, since I was interested in quantifiable observations that resulted in statistical analyses, to explain and possibly predict. As a consequence, as an observer, I was independent, concepts were operationalised so that they could be measured, and generalisations were done through statistical probability. However, the explanations in a positivist paradigm would demonstrate causality, while my topic is more explorative and aims to increase understanding in general terms.

In the two decision tasks, in order to cut down subjects' cognitive effort, similar MPLs were employed to elicit risk and time preferences. In this procedure, individuals need to make decisions between two (lottery) choices, Option A and Option B. Although it is beyond the scope of this paper to explain all estimation and elicitation procedures for time and risk preferences, in short, the MPL methodology is used for several reasons. First, the MPL is more valid than a non-incentivised questionnaire. Also, it is easy to explain, implement, and understand, so that error is decreased, compared to a method such as the Becker-deGroot-Marschak (BDM) procedure. Lastly, it does not assume EU, so lotteries involving both gains and losses are possible (Andersen, Harrison, Lau, &

Rutström, 2006). The disadvantages of the method concern a framing and inconsistent switching effect. First, since people are psychologically biased towards the middle, the middle rows might be chosen more. Although randomisation, or scrambling, of rows is a possible solution, I decided that this will add a lot of noise, since it would make the tasks way harder, from a cognitive perspective, for subjects to understand. Second, although the MPL is less complex than other methods, still a significant number might fail to understand the procedure, or, due to the nature of the online survey, might not carefully read and follow the instructions. As a result of this, instead of switching only once, they can switch back and forth from row to row, resulting in possibly inconsistent preferences, violating the principle of monotonic switching (Dave, Eckel, Johnson, & Rojas, 2010; Holt & Laury, 2002). Since these inconsistent answers would reduce the reliability of the MPL, and can potentially bias the results, I decided to enforce monotonicity by applying the sequential MPL (sMPL) approach. Subjects were simply asked at which row they would switch from Option A to Option B, imposing strict monotonicity (more is preferred to less), and enforcing transitivity in revealed preferences (Gonzalez & Wu, 1996).

Subjects were told they can switch to Option B starting with the first question and that they did not have to switch to Option B at all. The instructions gave three examples. In one example, the subject chooses Option A for all questions and in another example, the subject chooses Option B for all questions. In the last example, the subject switches at the seventh question. These examples are given to help ensure that subjects do not feel that they are forced to switch. The exact explanation given to subjects is discussed in Chapter 3.

Next, the measurement of the time and risk preferences is examined. Thereafter, the measurement of the attitude type is addressed. Table I, II, and III in Appendix D present a complete overview of the (un)transformed variables.

2.1. Time preferences

The measurement of the IDRs follows Ferecatu and Önçüler (2016), but changes made with respect to the original methodology are discussed.

The basic experimental design of Ferecatu and Önçüler (2016) was introduced by Coller and Williams (1999). Individuals need to make decisions between Option A and Option B. Option B is the future income option. The sequence is defined in such a way that Option B increases, while Option A remains constant. The more impatient the individual, the longer he or she chooses Option A before switching to Option B. The switching point provides a bound on the individual's discount rate, δ.

Coller and Williams (1999) argue that studies that examined IDRs often suffered from (uncontrolled) factors, because decisions in the laboratory are influenced by possibilities in the field. They propose to provide the Annual Interest Rate (AR) and the Annual Effective Interest Rate[6] (AER) to ease comparison with other investment opportunities outside the lab. Where the AR is the nominal interest rate (the stated rate on a financial product), the AER is the interest rate which is actually

[6] The formula is the following: AER = (1 + AR/n)^n - 1 with n = the number of compounding periods.

earned on an investment due to the result of compounding over a given time period (Investopedia, 2017). Providing the AR and AER helps subjects to better evaluate their options, resulting in less experienced difficulty and fewer random errors (Coller and Williams, 1999). They also introduce the front-end delay (FED). Instead of offering one immediate payment and one future income option, both payment options are delayed. The FED avoids the problem of subjective transactions costs. Regardless of the option chosen, the participant faces similar experimental uncertainty, because he or she must keep track of the payment guarantee and devote the same time and energy in reclaiming the money. Contrary to other studies, in which contract enforcement was weak or absent and participants were maybe not sure whether they would receive the promised reward, inducing extreme short-run impatience (Andersen et al., 2008; Ferecatu & Önçüler, 2016).

The approach of Ferecatu and Önçüler (2016) embeds exponential discounting as well as hyperbolic discounting. This is necessary for testing H2. Epper et al. (2011) show that the discount rate depends on the pure time preference, the level of uncertainty, and the probability weighting function. They find that a nonlinear weighting function generates hyperbolicity and that uncertainty increases the absolute level of the discount rates.

Compared to Ferecatu and Önçüler (2016), only two (instead of four) time horizons were tested, due to practical (time-related) limitations. However, the amount of choices per choice task was extended, to derive a more specific interval for the discount rate. In fact, although lots of the discount rates are upwardly biased (because of the assumption of risk neutrality), a key range is found varying between 10.1% to 26% (Andersen et al., 2008; Ferecatu & Önçüler, 2016; Laury, McInnes, & Swarthout, 2012). Therefore, a wider variety of ARs and AERs is included, to make it possible to account for more heterogeneity in discount intervals. In addition, instead of Ferecatu and Önçüler's (2016) flat-fee incentive (an Amazon gift-card of 20 euros), real incentives that are based upon choices were given, to make the experiment incentive compatible. This to satisfy the precept of saliency (Smith, 1982). The original principal of 300 euros was divided by thirty. This to be sure that the amounts are equivalent, except for their timing, and that it are reasonable amounts to pay out for real. Furthermore, Andersen et al. (2006) and Ferecatu and Önçüler (2016) included the option for subjects to indicate indifference between Option A and Option B, but in this study, this option is excluded, because the amounts are already really low. Lastly, because Ferecatu and Önçüler (2016) only allow for EU (CRRA) risk preferences, their hierarchical Bayes methodology could not be employed. Therefore, for the calculation of the IDRs, either Mazur's hyperbolic specification of the discount rate, $V_i = A_i/(1 + kD_i)$, or Mazur's exponential specification, $V_i = A_i e^{-kD_i}$, could be utilised. The fitted parameters *k*, which indicated how much someone valued future outcomes relative to present outcomes, were calculated, resulting in *IDR1*[7]. Appendix C presents the calculations and tables to elicit the time discounting parameters.

[7] Whether time preferences were hyperbolic or exponential was not the focus of this research. Instead, it mattered whether subjects were high or low discounters. Also, because the majority discounted exponentially, for simplification reasons it was decided to (for all subjects) only calculate *IDR1* after the exponential specification of Mazur.

2.2. Risk preferences

The measurement of the risk parameters follows Tanaka et al. (2010), but changes made with respect to the original methodology are discussed[8].

The method of Tanaka et al. (2010) to elicit an individual's risk attitude is originally popularised by Holt and Laury (2002). In Holt and Laury's (2002) influential paper, individuals need to make decisions between lotteries. As one proceeds down the matrix, the expected value (EV) of both lotteries increases, but the EV of Lottery B becomes greater relative to the EV of Lottery A. All individuals, except from the most risk-seeking, start by choosing Option A, and switch over to Option B at some point. Hence, this crossover point, together with the assumption of CRRA, define a range to construe the coefficient of risk aversion. Tanaka et al. (2010) extend the MPL approach to allow for heterogeneous risk preferences that nest both EU and CPT, without rejecting EU immediately.

Consider a two-outcome gamble defined over x, occurring with probability p, and outcome y, occurring with probability q. Also, assume a piecewise power function for value, $u(x)$, separate for gains and for losses, which is found in Table 2. Lastly, the probability weighting function (π), also found in Table 2, satisfies all four target properties; it is asymmetric, (inverted) S-shaped, reflective, and regressive (Prelec, 1998, p.499). The property of regressiveness generates the fourfold pattern of risk attitudes; it accounts for overweighting and underweighting of probabilities.

Table 2 compares the values for σ, α, and λ for EU maximisers as well as for CPT satisfiers. First, the σ represents concavity of the value function; a σ larger than zero refers to a concave value function and a σ smaller than zero refers to a convex value function. Second, the α shows the curvature of the probability weighting function. The weighting function is linear, as it is in EU, when α is equal to one. If α is smaller than one, the weighting function is inverted S-shaped; it shows overweighting of small probabilities and underweighting of larger probabilities. The smaller the value for α, the more sub proportional the curve is, which means that it departs more strongly from linear weighting. Lastly, the λ embodies the degree of loss aversion; it defines the curvature below zero relative to the curvature above zero. If λ is equal to one, there is no kink in the curve, but if it is larger than one, the subject is loss averse (Tanaka et al., 2010; Tversky & Kahneman, 1992).

Admittedly, an exhaustive discussion of other possible weighting functions is beyond the scope of this paper. Still, since heterogeneity in individual's probability weighting functions cannot be ignored and the method allowed for it, for underweighting of small probabilities and overweighting of larger probabilities is also accounted. This implies that, if α is larger than one, the weighting function is S-shaped.

[8] The method is (a.o.) also employed (and validated) by Liu and Huang (2012), Liu (2013), and Riddel (2012).

Parameter	EU with CRRA (risk averse)	EU with CRRA (risk seeking, or less risk averse)	CPT (inverted S-shaped weighting function)
σ (concavity of value function)[9]	$\sigma > 0$	$\sigma < 0$	$\sigma > 0$ for gains[10]
α (curvature of probability weighting function)	$\alpha = 1$	$\alpha = 1$	$0 < \alpha < 1$
λ (degree of loss aversion)	$\lambda = 1$	$\lambda = 1$	$\lambda > 1$
Value function[11]	$u(x) = x^{1-\sigma}/(1-\sigma)$	$u(x) = x^{1-\sigma}/(1-\sigma)$	$v(x) = x^{1-\sigma}$ for gains, $x > 0$ $v(x) = -\lambda(-x)^{1-\sigma}$ for losses, $x < 0$
Weighting function	Linear	Linear	$\pi(p) = exp[-(-lnp)^{\alpha}]$

Table 2. Values of parameters σ, α, and λ for different functional forms

Serie 1 and 2 jointly determine the values for σ (concavity of value function) and α (curvature of probability weighting function). The loss aversion parameter λ is determined by the switching point in Serie 3. Section 3.2 presents an example from this study and Appendix B presents the calculations (including Mathematica Script) and tables to elicit the CPT parameters.

Compared to the original study of Tanaka et al. (2010), the probabilities are kept the same and the amounts are almost the same, since the authors carefully designed the choices so that any combination in the three series determines a particular interval of CPT parameters. However, in Serie 1, Choices 12 to 14 are left out, because it was impossible to make these incentive compatible. Also, these choices resulted in values of α larger than one, indicating S-shaped probability weighting, which is not the focus of this research. All original amounts, varying from 5,000 to 400,000 Vietnamese dong, are converted to euros[12], multiplied by two, and rounded up to one decimal place. The multiplication took place, because some amounts were too low in euros for the target population of European students, compared to poor Vietnamese farmers.

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[9] In this research, sigma could display values between 0 and 0.9. This implied that there was only a distinction between risk averse and less risk averse.

[10] Sigma should have been < 0 for losses. However, in Series 1 and 2, only lottery choices in the positive domain were made.

[11] Tanaka et al. (2010) present a different piecewise power function and weighting function compared to the ones in Table 2. However, the current functional forms were presented to ease comparison with the EU under CRRA function. This followed Liu (2013).

[12] The exchange rate between the Vietnamese dong and European euro has not fluctuated that much. In July-August 2005, risk and time discounting experiments were conducted in Vietnam by Tanaka et al. (2010). In July 2002, the household surveys were conducted in Vietnam by Tanaka et al. (2010). In August 2017, the lottery amounts were calculated for this paper. On July 23 2002, the exchange rate was 15192 dong for one euro. On July 23 2005, the exchange rate was 19284 dong for one euro. On July 23 2017, the exchange rate was 26474 dong for one euro (XE, 2017). So, in the time passed (2002 to 2017), the exchange rate has changed with 11282 dong for one euro, what comes down to a change of 0.42 euro.

2.3. Attitude type

The original questionnaire of Maibach et al. (2011) classifies subjects into six groups on the basis of beliefs, emotions, perceived risks, talking and hearing about global warming, taking action, perceived effectiveness of taking action, and conceptualisation of global warming. Since the original questionnaire takes 26 minutes to complete, only part of the questions were included. As a matter of fact, a shorter version of the questionnaire (15-item instrument), that still classifies 84% of the sample correctly, but varies in accuracy per attitude type (60% to 97%), is used (Maibach, Leiserowitz, Roser-Renouf, Mertz, & Akerlof, 2012).

Compared to the original questionnaire, a few changes are made. First, a smaller change, regarding the use of language (adjustment to European citizens, next to American, or US, citizens) is made. Also, I replaced a question about *changing your mind concerning global warming* by another behavioural question about an individual's meat and fish consumption (Dagevos, Voordouw, Van der Weele, de Bakker, 2012). This choice is motivated by the outcome of the pilot survey. A few pilot survey participants did not understand the original question, and at the same time, in my opinion, there were too little behavioural questions included. Instead of choosing another behavioural question from the original questionnaire, regarding energy efficiency or transport, which would have resulted in uninteresting answers, I decided to incorporate the question about *frequency of meat and fish consumption*. Answers concerning energy efficiency and transport would have been unexciting, because the majority of participants is student and thus, does either not decide about isolation or energy supplier (energy efficiency) or has no choice but taking public transport, because they do not have enough money to own and drive a car (transport). To the contrary, regarding meat and fish consumption, the Food and Agriculture Organization of the United Nations (FAO, 2006) investigate how the livestock sector is one of the most significant contributors to the most serious environmental problems, at every scale, from local to global. In addition, fish consumption connects to global warming (Scarborough et al., 2014). Already in 2008, UN's IPCC chairman Dr. Rajendra Pachauri described eating less meat as ''the most attractive opportunity'' for making immediate changes to climate change (Jowitt, 2008). The assumption is made that subjects are aware of the connection between the consumption of meat and fish and global warming.

3. Experimental design

This chapter discusses the experimental design. It elaborates upon recruitment and description of the sample subjects, the pilot survey, and the incentive compatibility of the design.

3.1. Subjects

117 subjects were recruited online (37.61% female, average age of 30.26 years, range of 12-100 years)[13]. The sample was made up by acquaintances and friends (participants with their age below 35) and others. To ensure heterogeneity in the attitude types, besides Facebook, the survey is also distributed on the social news and media aggregation Reddit.com[14]. Therefore, also subjects of higher ages have participated. The survey was online for fourteen days: from September 11, 2017 to September 25, 2017. The experiment was single blind, so that the subjects are anonymous to other subjects, but they are not anonymous towards the experimenter. More specifically, since the experiment does not involve social preferences, the condition of double-blind was not necessary; the participants are known to the experimenter through their email address (to include them in the random lottery).

3.2. Stimuli

The online survey consisted of three parts: time preference experiment (Part I), risk preference experiment (Part II), attitude type questionnaire and control questions (Part III). Every subject faced the same decision context. The experiment consisted of one-shot observations (single period), so that there is a strong incentive for the decisions, it is easy to perform, and limited in time (short). Subjects first had to read the instructions and were shown examples to make sure they understood the experimental tasks. Appendix E elaborates upon the (introductory) instructions and examples.

The disadvantage of this design is the possibility of complicated interactions between tasks, or order effects. This would imply that participating in the first condition affects performance in the other condition, due to fatigue (negative effect on performance in later conditions) or practice (positive effect on performance in later conditions) (List, Sadoff, & Wagner, 2011). Therefore, the experiment took up only 12-15 minutes to make sure that fatigue was no problem. Also, practice was unlikely. The time preference questions were asked first, because often, no order effects and fewer inconsistencies are observed for time, compared to risk, suggesting that the time questions are cognitively easier (Abdellaoui et al., 2013; Ferecatu and Önçüler, 2016; Laury, et al., 2012). Then, the risk preference questions were asked. Lastly, although it seemed unlikely that was an experimenter-demand effect

[13] More information about the subject population is given in Section 4.2.1.
[14] After granted permission of the moderators, the online survey was distributed via the following subreddits of Reddit.com: *climate_science*, *climateskeptics*, and *climate change*.

regarding the questionnaire, the classification into the six attitude types was done in the last stage, to remove any unintentional impact these questions might have had on the measurement of the intertemporal choices and risk aversion of subjects. Part I, Part II, and Part III are discussed below.

Part I - Time preference: Subjects completed two choice sequences, containing 38 choices in total. In both series, Option A was an amount of 10 euros, paid half a month from now, and Option B was an amount of $10 + x$ euros, paid either two and a half (Serie 1) or four and a half (Serie 2) months from now[15]. The amount x was computed given a discount rate of 5% to 50% on the principal of 10 euros, compounded quarterly. The quarterly compounded interest rate was chosen because of ecological validity and time horizons of less than a year. The more impatient the individual, the longer he or she chooses Option A before switching to Option B. Serie 1 is presented, while Appendix C shows Serie 2.

Hence, subjects indicated their two switching points in Serie 1 and 2, making it possible to identify two discount rates: δ_1 and δ_2. To illustrate, Screenshot 1 highlights that, if a subject switched in Row 7 in Serie 1, his or her discount rate, δ_1, lies in the interval 17.50% - 20.00%, yielding the midpoint 18.75%. Then, if the same subject switched in Row 6 in Serie 2, which is found in Appendix C, his or her discount rate, δ_2, lies in the interval 15.00% - 17.50%, yielding the midpoint 16.75%. This might have been evidence for hyperbolic discounting, because $\delta_1 > \delta_2$, and, if preferences are hyperbolic, elicited discount rates decline as the time horizon is increased.

To work with discounted utility instead of discount rates and since the majority of the sample exhibited exponential discounting, Mazur's (1987) exponential equation, $V_i = A_i e^{-kD_i}$, was employed. The belonging fitted parameter k was calculated for all subjects[16].

[15] I considered it to be important that subjects received payments in 2-18 weeks. First, the FED of two weeks was implemented to avoid subjective transaction costs and because of the impossibility of making the immediate option incentive compatible. Also, the FED was implemented because Laibson's (1997) quasi-hyperbolic discounting was beyond the scope of this paper. The maximum time horizon of 18 weeks was chosen so that transaction costs were the same for all subjects. If some expected to graduate or leave university after the fall semester, they might have encountered higher subjective transaction costs, making comparison of results more difficult.

[16] Appendix C shows the values for k.

Serie 1

For instance, if you choose Option B in the first row, you will earn an annual interest rate of 5% on the 10 euros available in 0.5 month from today, but which you choose to receive 2.5 months from today. Since this is compounded quarterly, your annual effective interest rate is 5.09%.

Please choose between the following options:

SERIE 1

Question	Option A (amount to be paid in 0.5 month)	Option B (amount to be paid in 2.5 months)	AR	AER
1	€10	€ 10.08	5.00%	5.09%
2	€10	€ 10.12	7.50%	7.71%
3	€10	€ 10.17	10.00%	10.38%
4	€10	€ 10.21	12.50%	13.1%
5	€10	€ 10.25	15.00%	15.87%
6	€10	€ 10.28	17.50%	18.68%
7	€10	€ 10.33	20.00%	21.55%
8	€10	€ 10.37	22.50%	24.47%
9	€10	€ 10.41	25.00%	27.44%
10	€10	€ 10.45	27.50%	30.47%
11	€10	€ 10.49	30.00%	33.55%
12	€10	€ 10.53	32.50%	36.68%
13	€10	€ 10.58	35.00%	39.87%
14	€10	€ 10.62	37.50%	43.11%
15	€10	€ 10.66	40.00%	46.41%
16	€10	€ 10.70	42.50%	49.77%
17	€10	€ 10.74	45.00%	53.18%
18	€10	€ 10.77	47.50%	55.95%
19	€10	€ 10.82	50.00%	60.19%

AR is Annual Interest Rate and AER is Annual Effective Interest Rate

I switch at Question (type a number, 2-19)

I choose Option A for all questions (I never switch)

I choose Option B for all questions (I switch at question 1)

Screenshot 1. Serie 1 (Part I) in Qualtrics (Erasmus University Qualtrics, 2017).

Part II - Risk preference: Subjects completed three choice sequences, containing 32 choices in total. In all three series, Option A and Option B are lotteries. Serie 1 and 2 concern gains, while Serie 3 concerns gains as well as losses. Screenshot 2 shows Serie 1, while Appendix B presents Serie 2 and 3. In Serie 1 and 2, the payoffs for Option A are less variable, compared to the payoffs for Option B. The sequence is defined in such a way that the EV of Lottery A remains constant, while the EV of Lottery B increases. Eventually, the EV difference (A-B) decreases and becomes negative. In Serie 1 and 2, the more risk averse the individual, the longer he or she chooses Lottery A before switching to Lottery B. In Serie 3, the more loss averse the individual, the longer he or she chooses Lottery A before switching to Lottery B.

Part II.

For 3 series of questions, you are asked to indicate your choice for Option A or Option B. The questions consider lotteries.

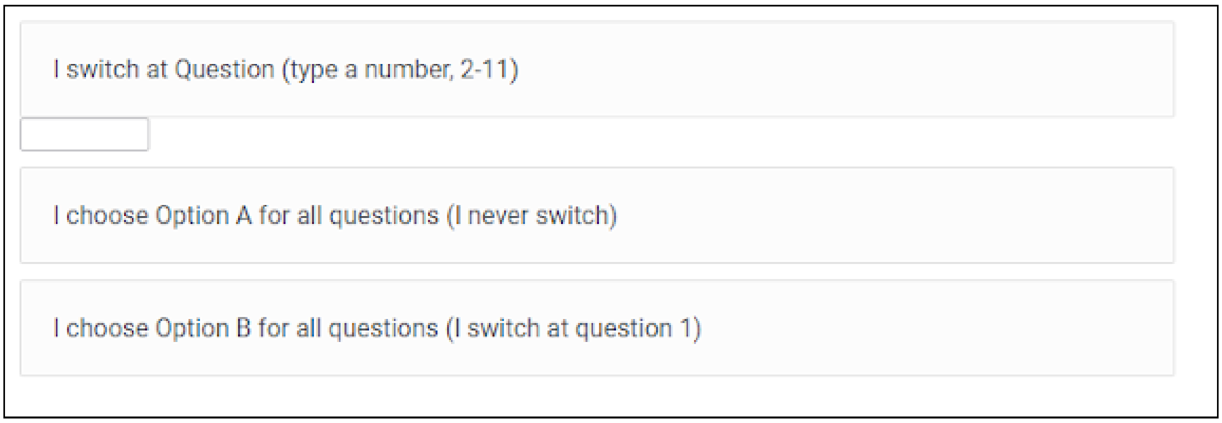
Remember: you can only switch (go from A to B) once, but you do not need to switch.

Serie 1

Please choose between the following options:

SERIE 1

Question	Option A				Question	Option B			
1	3/10 of	€ 3.00	7/10 of	€ 0.80	1	1/10 of	€ 5.10	9/10 of	€ 0.40
2	3/10 of	€ 3.00	7/10 of	€ 0.80	2	1/10 of	€ 5.60	9/10 of	€ 0.40
3	3/10 of	€ 3.00	7/10 of	€ 0.80	3	1/10 of	€ 6.20	9/10 of	€ 0.40
4	3/10 of	€ 3.00	7/10 of	€ 0.80	4	1/10 of	€ 7.00	9/10 of	€ 0.40
5	3/10 of	€ 3.00	7/10 of	€ 0.80	5	1/10 of	€ 7.90	9/10 of	€ 0.40
6	3/10 of	€ 3.00	7/10 of	€ 0.80	6	1/10 of	€ 9.40	9/10 of	€ 0.40
7	3/10 of	€ 3.00	7/10 of	€ 0.80	7	1/10 of	€ 11.20	9/10 of	€ 0.40
8	3/10 of	€ 3.00	7/10 of	€ 0.80	8	1/10 of	€ 13.80	9/10 of	€ 0.40
9	3/10 of	€ 3.00	7/10 of	€ 0.80	9	1/10 of	€ 16.40	9/10 of	€ 0.40
10	3/10 of	€ 3.00	7/10 of	€ 0.80	10	1/10 of	€ 22.40	9/10 of	€ 0.40
11	3/10 of	€ 3.00	7/10 of	€ 0.80	11	1/10 of	€ 29.80	9/10 of	€ 0.40



Screenshot 2. Serie 1 (Part II) in Qualtrics (Erasmus University Qualtrics, 2017).

So, the choice sequences in Serie 1 and 2 jointly determined σ and α. In fact, the parameter pair (σ, α) was not uniquely determined, but one could solve for a set of pairs that was consistent with the following inequalities. Table 3 considers a participant that switched in the seventh row in Serie 1 as well as in Serie 2. Thus, for both series, he/she preferred Option A to Option B in Row 6, but preferred Option B to Option A in Row 7:

Serie 1. The subject prefers Option A to B (A>B) in rows 1-6:	$0.80^{1-\sigma} + exp[-(-ln0.3)^{\alpha}](3^{1-\alpha} - 0.80^{1-\sigma}) > 0.40^{1-\sigma} + exp[-(-ln0.1)^{\alpha}](9.40^{1-\alpha} - 0.40^{1-\sigma})$
Serie 1. The subject prefers Option B to A (B>A) in the seventh to last row:	$0.80^{1-\sigma} + exp[-(-ln0.3)^{\alpha}](3^{1-\alpha} - 0.80^{1-\sigma}) < 0.40^{1-\sigma} + exp[-(-ln0.1)^{\alpha}](11.20^{1-\alpha} - 0.40^{1-\sigma})$

Serie 2. The subject prefers Option A to B (A>B) in rows 1-6:	$2.30^{1-\sigma} + exp[-(-ln0.9)^{\alpha}](3^{1-\alpha} - 2.30^{1-\sigma}) > 0.40^{1-\sigma} + exp[-(-ln0.7)^{\alpha}](4.90^{1-\alpha} - 0.40^{1-\sigma})$
Serie 2. The subject prefers Option B to A (B>A) in the seventh to last row:	$2.30^{1-\sigma} + exp[-(-ln0.9)^{\alpha}](3^{1-\alpha} - 2.30^{1-\sigma}) < 0.40^{1-\sigma} + exp[-(-ln0.7)^{\alpha}](5.10^{1-\alpha} - 0.40^{1-\sigma})$

Table 3. Inequalities for the elicitation of the parameters σ and α from Serie 1 and 2

So, this subject's *Alpha* amounts to $0.66 < \alpha < 0.74$, or $\alpha = 0.7$, and *Sigma* amounts to $0.27 < \sigma < 0.36$, or $\sigma = 0.3$ [17]. The loss aversion parameter λ was determined by the switching point in Serie 3. Yet, λ could not be uniquely inferred from the switching in Serie 3 because it depended upon σ and α.

Part III - Attitude and personal questions: The 15-item attitude questionnaire that measures an individual's attitude towards global warming consists of six questions regarding beliefs and perceived risks, four questions about issue involvement and emotions, two questions concerning behaviour, and three questions about the Preferred Societal Response (PSR). Thereafter, some personal questions are posed to measure socio-economic characteristics. Appendix D presents the 15-item questionnaire, as well as the control questions.

[17] The estimates for alpha and sigma are validated in Liu (2013).

3.3. Pilot survey

To test for effectiveness and understandability of the online survey, seven persons of different genders, ages, fields of study, and nationalities answered a pilot survey and a questionnaire (about this pilot survey). Because of the online character of the experiment, control over participants is limited, required cognitive ability should be kept to a minimum level, and duration could not be too long. The pilot participants felt that Parts I, II, and III were clear, easy to understand, credible, interesting, and not too long (on average, 14 minutes). Some smaller suggestions were processed, but, unfortunately, although two people suggested to increase the money amounts to ‘‘make people care more’’, this is not adapted, due to practical (budgetary) constraints. Lastly, as explained in Section 2.3, one question is replaced by the behavioural question regarding fish and meat consumption.

3.4. Incentives

A random incentive system was employed to compensate for subjective costs of the transaction and to fulfill the criterion of nonsatiation. The participants were told that their earnings depended on their decisions made, and, this way, they were incentivised to reveal their true preferences in Parts I and II, meeting the criterion of saliency (Smith, 1982). Specifically, a hybrid Random Incentive System (RIS) was applied in which both tasks and subjects were selected to ensure the experiment was incentive compatible (Baltussen, Post, Van den Assem, & Wakker, 2012). At the end of the experimental period, the RIS determined *who* received a real payment of *what amount*. Two participants received a real payment. To them, the show up fee of 10 euros was assigned, and thereafter, randomly, it was decided how much commission they earned or lost. Saliency was satisfied; if you made a profit in the experiment, you earned more, but if you made a loss in the experiment, you earned less (Smith, 1982). The website random.org, which generates random numbers, was used to randomly select the two participants and randomly select the task that was paid out.

3.5. Payment

The participants were told that they would be paid according to one of their decisions. Ex post, two participants and one of their decisions in either Part I or Part II was randomly chosen. For Part I, the option they had selected could be paid out for real. For Part II, the lottery they had selected could be played for actual stakes, with the outcome of that lottery determining their monetary payoff. However, in Part III, they answered questions so that the affective, behavioural, and cognitive component of the attitude type, or control characteristics, were revealed. Therefore, in Part III, the questions were not defined as a decision or preference, and thus, could not satisfy saliency, and were not incentivised.

Those participants who were chosen to be paid out for real were provided with an initial endowment of 10 euros. Then, it was decided which Part (I or II), which choice (row), and the actual payoff (lottery or option) that was paid out. This way, incentives were given while participating. The flat-rate show up fee of 10 euros gave an incentive to participate and provided a buffer in case losses were made, since it is considered to be unethical to let participants pay the experimenter money[18]. After, the actual payment was added to or extracted from the 10 euros, so that the gain from participating was always positive.

Although Thaler and Johnson (1990) warn for the house money effect, stating that subjects have a larger willingness to accept a gamble with a prior gain, this was not really likely, since the show up fee was not too large. Another issue is that, for both tasks, the payment involved a time delay. The survey was online for fourteen days and after these two weeks, the RIS determined the payouts.

In this experiment, the two chosen participants were paid out according to their decision in Part II. Therefore, the longer time delay posed no difficulties. The two weeks could simply be added to their recorded date (the date they they filled in the survey, *t*) and the money was transferred on that date, *t + 14 days*[19]. In fact, the participants received an email with their payoff determination and demand for their bank account details and the transfer was done immediately, since both already waited for fourteen days. A difficulty in eliciting time preferences (and risk preferences with a delay) with monetary incentives is the credibility of payment. Therefore, to ensure subjects that the money would be delivered, a print screen of an automatic bank transfer to the subject (specified on a specific date) was sent, to increase credibility of actual payment.

Usually, if subjects perform multiple tasks, and each task is for real, they accumulate earnings over the tasks. So, this way, income effects may be a problem, since diminishing returns to money may change a subject's behaviour. However, because of the RIS, out of all tasks performed, only one is randomly chosen, and the problem of possible wealth effects is avoided (Baltussen et al., 2012).

Subjects were not informed about the likely number of participants in the online survey; they were not able to compute their chances of winning the lottery. In this study, subjects could earn minimally €8.40 (€10 - €1.60) up to a maximum of €39.80 euros (€10 + €29.80). The two participants who were paid out for real earned respectively €12.30 and €10.80. Appendix E displays the exact determination of the paid amounts and emails sent to the winners and losers.

[18] Admittedly, since these losses were framed losses, they might have still been treated differently from real losses. This is a typical problem in economic experiments involving monetary losses. The subjects were told that this show up fee was paid as a buffer, but it could still be that they valued the 10 euros as a ''windfall gain''.
[19] Decisions in Part I involved a time delay of two and a half (Serie 1) or four and a half (Serie 2) months.

4. Data Analysis

This chapter elaborates upon the data analysis. The data were obtained using Qualtrics Survey Software, the calculation of σ and α, λ is executed through Wolfram Mathematica 11.2, the values for k were calculated using Wolfram Alpha, and statistical significance was analysed through the use of STATA/MP Version 14.1. First, the data cleaning and transformation are discussed. Thereafter, the descriptive statistics and correlation matrices are reported. Lastly, the relationship between the dependent variable (DV) and independent variables (IVs) is further analysed by means of regression analyses.

4.1. Data cleaning and transformation

4.1.1. Data cleaning

First, the data was cleaned. In general, the sample was carefully checked for: validity, accuracy, completeness, consistency, and uniformity. Specifically, three subsamples were created: S_1, S_2, and S_3. The sample S_3 was the original sample and consisted of 117 subjects. The sample S_2, which consisted of 99 subjects, was the sample of which the outliers (regarding age, duration, and switching points) were removed. Two participants (aged 12 and 100 years old) were deleted from the sample. Also, the speeders, those who finished the survey in an absurd short amount of time (150 or 192 seconds), were deleted. In addition, it was checked whether there were subjects whose answers differed by more than three standard deviations from the mean. By contrast, with regards to the risk variables and the time variables, there were none and thus, no subjects were excluded on the basis of this criterium. Also, for consistency and validity, people who only chose Lottery A or B in all three the risk measurement series, were deleted. These extreme switches could have been due to low commitment, bad comprehension of the experiment, or too little cognitive ability. Lastly, the sample S_1 also excluded subjects that have a S-shaped weighting function. This cleaning left 88 subjects (S_1) in the final analysis.

4.1.2. Data transformation

First, the interval ranges for σ, α, and λ were calculated using Wolfram Mathematica 11.2[20], the scopes for δ_1, and δ_2 were determined with a simple calculator, and the belonging k_1 and k_2 were calculated using Wolfram Alpha.

[20] Appendix B presents (part of) the script in Wolfram Mathematica 11.2. Appendix B also includes tables regarding the elicitation of sigma and alpha.

If subjects opted for the same option in all rows, the lower/upper bound of the interval was arbitrarily determined[21]. Thereafter, following Tanaka et al. (2010), the midpoint of the intervals was taken, rounded to one decimal place, and used as a point estimate. Since the bounds were relatively narrow, this offered a good guess. The exact data transformation of the variables is discussed next. Please refer to Appendix D for an overview of the (un)transformed variables.

Part I - Time preference: The switching points in Serie 1 and Serie 2 resulted in two intervals of which the midpoints were taken, resulting in an average δ_1 and δ_2 for every subject. However, the true underlying discount weights D(t) were defined in terms of utilities, not payoffs. Therefore, Mazur's exponential specification was applied and the fitted parameters k_1 and k_2 were calculated for all subjects. Since there was no evidence for hyperbolic discounting, only k_1 (*IDR1*) was employed to distinguish people with a high discount rate from a low discount rate. The distinction was made using cluster analysis, which is explained in Section 4.3.

Part II - Risk preferences: The combination of switching points in Serie 1 and Serie 2 produced two inequalities, that determined the intervals for σ and α. Thereafter, for σ as well as for α, the midpoints of the intervals were taken, resulting in an average σ and an average α for every subject. In addition, the switching point in Serie 3 determined the interval of λ. As explained in Section 2.2., the methodology of Tanaka et al. (2010) allows for EU as well as CPT risk preferences. It tolerates part of the sample to be characterised by EU preferences and part of the sample to be characterised by CPT preferences. The parameters for curvature of the probability weighting function, α, and loss aversion, λ, capture this. Furthermore, dummies were created to capture whether a subject was *Optimistic* or *Pessimistic*.

Part III - Attitude and personal questions: The analysis could not run with missing data. Since answering was forced, the only missing data was the answer "don't know", which I replaced with the mean value for each of the variables in this part (for *Belief1, Belief3, Belief4, Behaviour1, PSR3*). In addition, the variables *Belief2, Belief3*, *Belief4*, *Behaviour1*, and *PSR3* were recoded into dummy variables; other/only a little/once/only if other industrialised countries reduce were the omitted response categories. Thereafter, the scores on each segment were calculated and it was determined, by the highest score, to what segment a subject belonged. Also, to make sure to have enough participants in each category, and to make richer deduction of the data possible (using ordered logistic regressions), instead of six segments, subjects were categorised into three segments: the 1) *Alarmed* & *Concerned,* 2) *Cautious* & *Disengaged,* and 3) *Doubtful* & *Dismissive*.

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[21] This was in line with Epper et al. (2011), Liu and Huang (2012), Liu (2013), and Tanaka et al. (2010). For the risk preference measurement, this meant that, for the ones who never switched (choose A for all options) or switched at Row 1 (choose B for all options), there was only one inequality in Serie 1, 2, and/or 3. Therefore, it was necessary to arbitrarily determine the lower or upper bound. In Serie 3, the lower and upper bound were determined on the basis of alpha = 0.5 and interval length of 0.90.

Concerning the control variables, not much transformations took place. The variable *Student* was recoded into *Economics student*, *Living* was modified to *LivingNL* (for those who lived in the Netherlands), and from *Age* the new variable *Age2* (age squared) was created. Regarding *LivingNL*, Section 4.2.1. comments that the majority of the sample was Dutch and, in addition, lots of the non-Dutch actually live in the Netherlands. Therefore, instead of including *Nationality*, the variable *LivingNL* is created and adopted.

4.2. Descriptive Analysis

First, to better understand the data, the collected data was analysed using descriptive statistics and graphics analysis. The key variables of interest, as well as descriptive support for H1 and H2, are discussed.

4.2.1. Key variables of interest

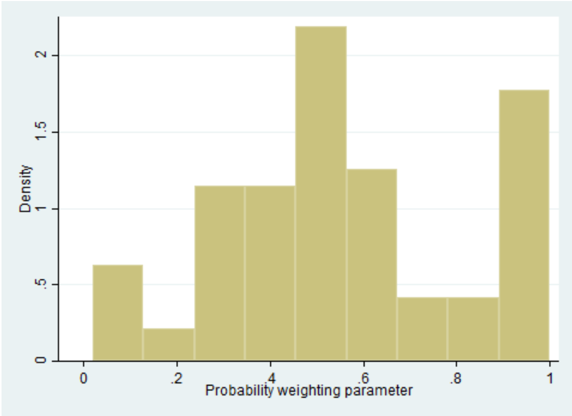
There were five primary variables of interest: *Alpha*, *Sigma*, *Lambda*, *IDR1*, and *Attitude type*. The secondary variables of interest were: *Age*, *Female*, *Student*, *Schooling*, and *LivingNL*. Including these made control for individual characteristics possible.

Like Tanaka et al. (2010) and Liu (2013), only an alpha of exactly 1 was considered evidence for EU. For only 11.11% of the sample, the alpha was exactly 1, reflecting EU. This meant raw evidence of nonlinear probability weighting. In fact, 11.11% of the sample had an alpha of larger than 1, indicating a S-shaped weighting function. These individuals underweight small probabilities and overweight large probabilities, and thus, are pessimistic. Also, an overwhelming 77.77% of the subjects had an alpha of smaller than 1. This reflected an inverted S-shaped weighting function, meaning that they overweight small probabilities and underweight large probabilities, and thus, are optimistic.

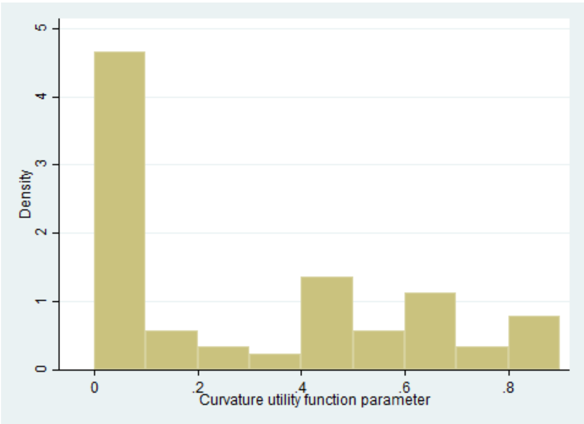
However, because inclusion of pessimistic persons (with an alpha of larger than 1) would have meant a violation of monotonicity, only those with alpha <=1 were included in the analyses, reducing the sample to N=88. Then, for 12.5% of the sample, the sample was exactly 1, reflecting EU[22]. Furthermore, for 87.5% of the sample, alpha was smaller than 1.

[22] Admittedly, minimal deviations from 1 could have been considered as practically the same as EU. Therefore, persons with alphas of 0.93 and 1.03 were taken into account in auxiliary analyses. These are reported in the robustness checks (Section 4.4.), but did not change the results.

Alpha: The variable *Alpha* was measured in Serie 1 and 2 in the risk preference experiment. Histogram 1 shows that, for N=88, the average was 0.56. The standard deviation was 0.28[23]. The minimum was 0.02 and the maximum was 1.23. Having an alpha of close to 1 means that you act more in accordance with EU, compared to people with a lower alpha or a higher alpha[24].



Histogram 1. *Alpha* (probability weighting parameter)

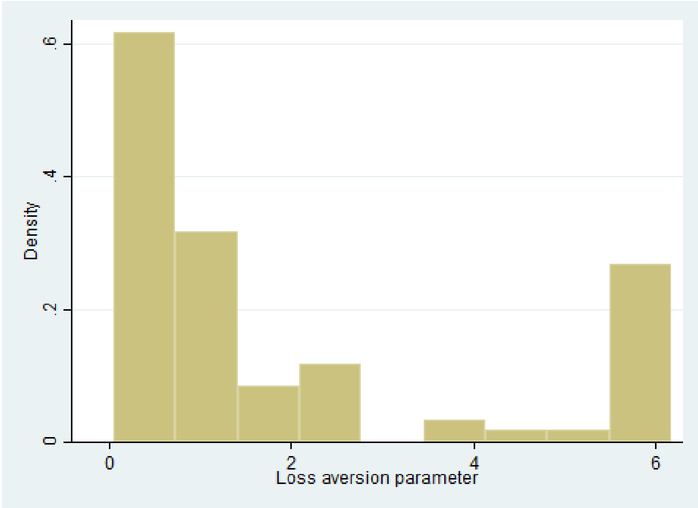


Histogram 2. *Sigma* (curvature utility function)

Sigma: The variable *Sigma* was measured in Serie 1 and 2 of the risk preference experiment. Histogram 2 shows that, for N=88, the average was 0.30. The standard deviation was 0.31[25]. The minimum was 0 and the maximum was 0.9. Having a high sigma means that you are more risk averse (for gains). Approximately, a sigma from 0 to 0.02 implies that a subject is risk seeking (or less risk averse), whereas a sigma of 0.02 to 0.9 means that a subject is risk averse. For N=88, 68.18% of the sample is characterised as risk seeking (or less risk averse), compared to 31.82% risk averse.

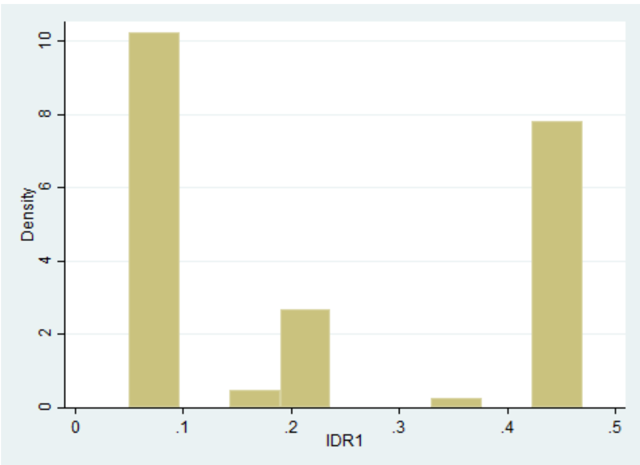
[23] For N=99, the average was 0.63. The standard deviation was 0.33.
[24] The drawback of the sMPL method for measuring risk preferences is anchoring towards the middle. Therefore, the distribution of switching points is discussed in the robustness checks. Little to no correlation between the switching points in Serie 1, 2 and 3 was found. This implied that the pattern of responses was consistent with choices made, based on actual preferences. It lessened the possibility that subjects were biased towards either the middle or extreme rows.
[25] For N=99, the average was 0.29. The standard deviation was 0.30.

Lambda: The variable *Lambda* was measured in Serie 3 of the risk preference experiment. Histogram 3 shows that, for N=88, that the average was 1.84. The standard deviation was 2.07. The minimum was 0.05 the maximum was 6.18[26]. Having a high lambda means that you are more loss averse. For N=88, 38.64% of the sample is characterised as loss averse.



Histogram 3. *Lambda* (loss aversion)

Regarding the discount rate, two discount rates were calculated (δ_1 and δ_2). Initially, I intended to investigate the strength of (and portion of the sample who showed) declining discount rates ($\delta_1 - \delta_2 > 0$), in line with Epper et al. (2011), and additionally, to adopt *IDR1* (Mazur's discount rate) in regressions. First, this would have given me information about the extent of hyperbolic discounting (per individual and for the sample as a whole). Also, employing *IDR1* (which is an one-shot answer with strong incentives that did not involve any learning) would have given me information about the absolute value of the time preference (high or low). When in fact, the evidence for hyperbolic discounting is mediocre, only *IDR1* is studied.

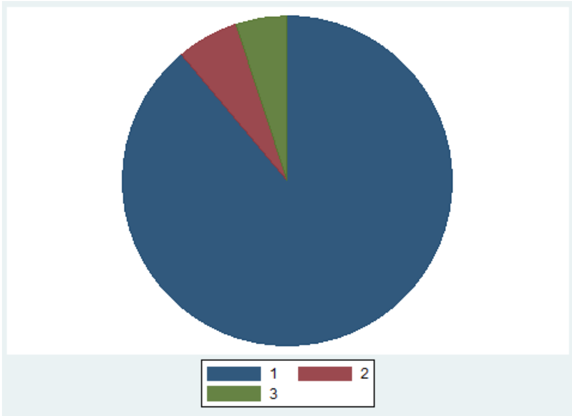


Histogram 4. *IDR1* (Mazur's discount rate)

IDR1: This discount rate was measured using Serie 1 of the time preference experiment. These k-values were calculated through Mazur's exponential discounting formula. Histogram 4 shows that, for N=88, the average was 0.23. The standard deviation was 0.19[27]. The minimum was 0.05 and the maximum was 0.47. Having a high (low) discount rate means that you value present outcomes as much more (less) important than the future.

[26] For N=99, the average was 1.97. The standard deviation was 2.15.
[27] For N=99, the average was 0.22. The standard deviation was 0.19.

Attitude3: The variable *Attitude6* was measured through the attitudes questionnaire. Then, the variable *Attitude6* was recoded into the variable *Attitude3*. Pie chart 1 shows that 89.77% (N=79) of the sample is categorised as *alarmed* (1) or *concerned* (2) and 3.41% (N=3) of the sample is categorised as *doubtful* (5) or *dismissive* (6).



Pie chart 1. *Attitude3* (attitude type in 3 categories)

117 subjects participated, data cleaning resulted in a sample (S_2) of 99 participants, from which 33.33% was female. The median age was 26 years[28], the majority (65.66%) was Dutch or had another European nationality[29] (21.21%) and most people lived in the Netherlands (80.61%). 89.89% was a student or graduated less than six months ago against 10.10% which was working. The sample was highly educated: 44.44% held a degree of the University of Applied Sciences (HBO if they are Dutch) and another 34.34% held a Bachelor's degree (WO if they are Dutch).

Also, as expected, 31.48% of the sample consisted of Behavioural/Social Sciences students and 29.63% consisted of Economics/Business students (and recent graduates). This was consistent with the way how I gathered the data. In the data, I encountered a possible selection bias, since of the 293 subjects who started the survey, only 117 completed the online survey. However, the majority of the people who started, but did not finish the survey, ended the survey after 1-2 minutes, indicating that they either realised that the survey was not easy to fill in on their phone, and therefore, quit, or they encountered the time preference questions and found them too difficult. Although this can be interpreted as a selection bias, I actually interpreted this as a positive given, since it also implies that the people who finished the online survey, were motivated till the very end[30].

The overall picture revealed by my data was partly consistent with the typical empirical findings. On average, subjects systematically violated linear probability weighting. However, regarding intertemporal choices, the average behaviour exhibited constant discount rates (exponential discounting), although decreasing discount rates were expected. Sometimes, even, subjects discounted less remote outcomes less than more remote ones (increasing discount rates).

[28] The data was skewed; the youngest and oldest participants were 19 and 76 years of age. Seeing the difference between the mean age of 29.26 years and the median age of 26 years, the median and interquartile range (upper - lower quartile) were more appropriate. The interquartile range was the following: 29 (Q2) - 24 (Q1) = 5 years of age.

[29] Either French, Italian, or Irish for other European nationalities and Australian as an answer to the 'other' category.

[30] Appendix F presents more details on the summary statistics of the variables.

4.2.2. Descriptive analysis of H1 and H2

This section reveals the results regarding H1 and H2 only in a descriptive matter, because these results are not crucial for the core analysis (H3, H4, H5, and H6). The ongoing debate between CPT and EU as best descriptor of individual' s decisions was not this paper's focus. In fact, given my methodology, it was not of importance, or even meaningful, to test whether alpha was significantly different from 1. The fact was that any deviation from $\alpha = 1$ already indicated a clear violation of EU, because if subjects were EU maximisers, they would have picked the choice consistent with EU.

Hypothesis 1: Risk preferences

As expected, Table 4 shows that the mean values of α and λ were different from 1. The average derived value of α was smaller than 1, implying a rejection of EU risk preferences, in favour of CPT risk preferences, and so, the inverted S shaped probability weighting. Also, the average derived value of λ was larger than 1, implying loss aversion. Also, there was some evidence of a S shaped weighting function; some individuals had an α which was larger than 1. Either way, it is far beyond the scope of this paper to take stand on whether EU or CPT is better. I could only cautiously conclude that in this particular sample, it was rejected that people are expected utility maximisers. CPT describes people's decisions better than EU does.

Risk attitude	**Frequency**	**Percentage**
EU with CRRA with $\alpha = 1$, $\lambda = 1$ and $0 \leq \sigma < 0.02$ (risk seeking, less risk averse) or $0.02 \leq \sigma < 0.9$ (risk averse)	11	11.11%
CPT (inverted S-shaped weighting function) with $0 < \alpha < 1$, $\lambda > 1$ and $\sigma \geq 0$	77	77.77%
S shaped weighting function with $\alpha > 1$, $\lambda \neq 1$ and $\sigma \geq 0$	11	11.11%
Total	99	100%

Table 4. Heterogeneous risk preferences

Hypothesis 2: Time preferences

Epper et al. (2011) find that sub proportionality in the probability weighting function generates a larger decline in discount rates between periods. Therefore, it was expected that the difference in discount rates, $(\delta_1 - \delta_2)$, was positive, implying declining discount rates, and thus, a rejection of exponential discounting, in favour of hyperbolic discounting. However, after exploration of the data it was clearly rejected that the majority follows hyperbolic discounting. Table 5 shows that only 12 out of 88 subjects (13.64%) showed signs of hyperbolic discounting, against 65 exponential discounters. There were even, against expectations, 11 subjects who had increasing discount rates[31].

[31] Notice that N=88 is studied. Inclusion of persons whose alpha is larger than 1 would have violated monotonicity. However, for the descriptive discussion of H1, they were included, because the findings concerning an alpha of greater than 1 support the evidence for probability weighting.

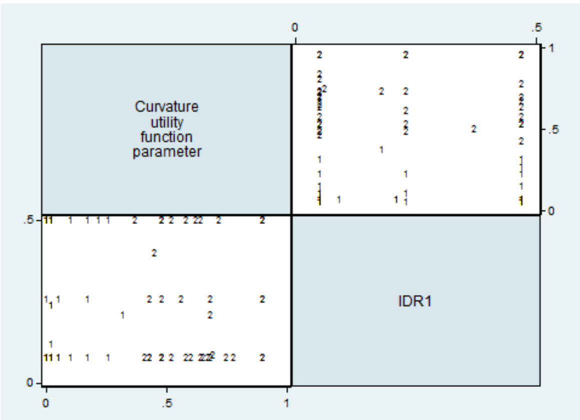
Time preference	Frequency	Percentage
Increasing discount rates $(\delta_1 - \delta_2 < 0)$	11	12.50%
Exponential discounting $(\delta_1 - \delta_2 = 0)$	65	73.86%
Hyperbolic discounting $(\delta_1 - \delta_2 > 0)$	12	13.64%
Total:	88	100%

Table 5. Heterogeneous time preferences.

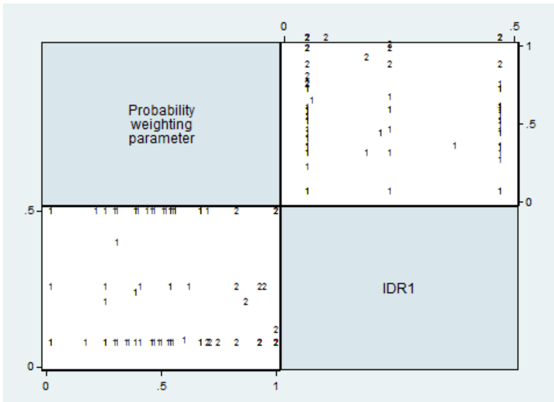
In conclusion, these descriptive data statistics showed that (cumulative) prospect theory was as common as expected, causing H1 to be rejected, and exponential discounting was more common than expected, whereby H2 was not rejected.

4.3. K means cluster analysis

Following Ferecatu and Önçüler (2016), k means cluster analysis was applied to determine the natural groupings of observations, or homogeneous groups, based on selected characteristics. K means clustering essentially makes no assumptions, but minimises the Sum of Squares for Error (SSE), which is the sum of the squared differences between each observation and its group's mean, and thus, is a measure of variation within a cluster. K means clustering employs an iterative procedure in which each observation is assigned to the group whose mean is closest.



Graph 1. Clustering on basis of *Sigma* and *IDR1*



Graph 2. Clustering on basis of *Alpha* and *IDR1*

Where Graph 1 reflected on the possible correlation between the curvature of the utility function (*Sigma*) and Mazur's discount rate (*IDR1*), Graph 2 took a closer look at the probability weighting functio*n* (*Alpha*) and *IDR1*. The graphs gave some indication that there were distinct groups[32]. Then, k means clustering was employed to classify the sample into two groups: high and low patience types.

[32] I attempted three means clustering as well as two means clustering, since the groups in two means clustering were of unequal size. However, increasing the number of clusters only made the unequal group size problem worse. Furthermore, two means clustering was chosen because of ease of interpretation and willingness to divide the sample into high and low patience types, instead of high, moderate, and low patience types.

Table 6 presents the cluster analysis on basis of *Sigma* and *IDR1* for subjects who are EU maximisers or *Optimistic*, while excluding the *Pessimistic* subjects. High patience types (N=55) with low IDRs and high sigmas and low patience types (N=33) with high IDRs and low sigmas were distinguished. This implied that high patience types were risk averse and patient, while low patience types were less risk averse (relatively risk seeking) and impatient.

Patience Type	**Sigma**	**IDR1**
High Patience (N=55)	Mean value: 0.3107273	Mean value: 0.0918182
Low Patience (N=33)	Mean value: 0.2693939	Mean value: 0.4669697
Total (N=88)		

Table 6. Categorisation patience types on basis of *Sigma* and *IDR1*

However, the problem with the categorisation in Table 6 was that the risk aversion coefficients of the low and high patience types did not differ enough to make comparison possible. Therefore, Table 7 displays the categorisation into high patience types (N=27) with low IDRs and high alphas and low patience types (N=61) with high IDRs and low alphas. This implied that high patience types that acted closer to EU, were less optimistic towards small probabilities, and were patient, while low patience types were more optimistic and impatient.

Patience Type	**Alpha**	**IDR1**
High Patience (N=27)	Mean value: 0.8937037	Mean value: 0.1403704
Low Patience (N=61)	Mean value: 0.4163934	Mean value: 0.2732787
Total (N=88)		

Table 7. Categorisation patience types on basis of *Alpha* and *IDR1*

Risk attitude in non expected utility is not equal to curvature (*Sigma*) alone, but depends on other factors, such as probability weighting (*Alpha)* as well. Therefore, in the domains of gains, support for H3.1 implied a significantly negative correlation between an individual's curvature in the utility function and the discount rate, while support for H3.2. indicated a positive correlation between an individual's degree of probabilistic optimism and the discount rate. This suggested the following: the higher the discount rate (the more impatient), the lower the risk aversion coefficient, (the less risk averse), the more overweighting of small probabilities and underweighting of large probabilities (the more optimistic). Table 6 and 7 endorse this.

In line with Epper et al. (2011), who find that hyperbolicity is significantly correlated with *Alpha* (but not with *Sigma*) and that uncertainty increases the absolute level of the discount rate, the cluster analysis was based on *IDR1* and *Alpha*, as in Table 7. This choice was also motivated by the given that the risk aversion coefficients of the high versus the low patience type in Table 6 did not differ enough for comparison.

4.4. Results

First, the assumptions of *normality*, *homogeneity of variance,* and *independency,* that need to be met for a parametric test, were reviewed. To be sure of non-normal data, a Shapiro-Wilk test was performed to test for normality. Indeed, I rejected the null hypothesis (p-value < 0.01 and p-value < 0.10) that the sample comes from a population which has a normal distribution[33]. However, the problem with this test is that it is only recommended for smaller samples (N<50), because it might be too sensitive. Therefore, I also present the histograms of the DVs in Appendix F[34]. The histograms did not show any peaks in the middle and were not approximately symmetrical about the mean. Therefore it was concluded that the data was not normally distributed[35].

4.4.1. Tests of association

At first sight, from summing *Alpha*, *Sigma*, and *Lambda* for the three different attitude types, the following relationships seemed to appear[36]: the *Alarmed & Concerned* have the lowest *Alpha*, the average *Sigma* and the lowest *Lambda*, while the *Doubtful & Dismissive* show the highest *Alpha*, the lowest *Sigma*, and the highest *Lambda*.

Because the assumption of the Spearman Rank Order Correlation Test (ρ) that the variables are linearly related was not met (the scatterplots showed that this was not the case), pairwise correlation coefficients are displayed. The pairwise correlation matrix for the risk and time variables (Table F) - found in Appendix F - showed that, for N=88, the correlation between *Sigma* and *Alpha* was -0.4500 (p-value: 0.0000), between *Lambda* and *Alpha* was -0.0945 (p-value: 0.3813), and between *Lambda* and *Sigma* was -0.0714 (p-value: 0.5088). The correlation between *Alpha* and *IDR1* was -0.0952 (p-value: 0.3775). The correlation between *Sigma* and *IDR1* is -0.0272 (p-value: 0.8012).

So, consequently, because the correlation coefficient of *Alpha* and *IDR1* was insignificant, the first evidence characterising the relationship between risk and time preferences indicated that there was no relationship[37]. The correlation coefficient between *Sigma* and *Alpha* was significant, indicating some underlying relationship between the curvature of the value function and probability weighting. In fact, the negative correlation shows that someone who is more optimistic towards small probabilities, is more risk averse. This was against expectations, because risk aversion was expected to be displayed

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33 *Attitude3* (p-value: 0.000) and *IDR1* (p-value: 0.08498) for N=88.
34 For a smaller sample, a QQ-plot would have been more appropriate.
35 Since non-normality was already demonstrated, I did not employ Levene's test to test for homogeneity of variances. Also, independency was not taken into account.
36 The following values were found for N=88: for the *Alarmed & Concerned, Alpha's* mean was 0.55 with a standard deviation of 0.28, *Sigma* was 0.30 with a standard deviation of 0.31, and *Lambda* was 1.75 with a standard deviation of 2.02. For the *Doubtful & Dismissive, Alpha* was 0.78 with a standard deviation of 0.19, *Sigma* was 0.01 with a standard deviation of 0.01, and *Lambda* was 4.06 with a standard deviation of 2.65.
37 Notice that the high p-value for the correlation coefficient of *Sigma* and *IDR1* further supported the notion that the cluster analysis was based on *Alpha* and *IDR1*.

by risk aversion and lower optimism. It was also not in line with Liu (2013), who finds a low but positive correlation between *Alpha and Sigma.*

Also, the relationship between risk and time preferences and the correlation with the attitude types was examined. Against expectations, the pairwise correlation matrix showed that the correlation between *Alpha* and *Attitude3* was 0.1280 (p-value: 0.2348) and insignificant. Also against expectations, the correlations between *Sigma* or *IDR1* with *Attitude3* were low and insignificant. Lastly, although not hypothesised, the correlation between *Attitude3* and *Lambda* was positive (0.1790) and significant at a 10% significance level (p-value: 0.0951).

4.4.2. Regression analyses

To further analyse the relationship between the DV and IVs, Ordinary Least Squares (OLS) and Tobit regressions, elaborating upon H3.1. and H3.2., and three ordered logistic regression equations, elaborating upon H4-H6, were estimated with Maximum Likelihood.

The control variables that were included standardly are: *Age*, *Female*, *Student*, *Schooling*, and *LivingNL*. The pairwise correlation matrix was studied and since correlations between some control variables appeared to be high, the following variables were left out because of multicollinearity: *Age2, Nationality, Field study,* and *Econ student*[38]*.* Multicollinearity needed to be avoided and the logistic regressions could not be overfitted. Still, the regression analyses were carried out stepwise, to study the effects on model fit[39]. Incorporating the last mentioned variables instead of the other variables did not really change the results.

H3. In the domain of gains, there is a negative correlation between an individual's risk aversion and discount rate, classifying the population into high patience and low patience types.

H3.1. In the domain of gains, there is a negative correlation between an individual's curvature in the utility function and discount rate, classifying the population into high patience and low patience types.

H3.2. In the domain of gains, there is a positive correlation between an individual's degree of probabilistic optimism and discount rate, classifying the population into high patience and low patience types.

It was expected that a significantly negative correlation between the discount rate and an individual's risk aversion - measured by *Sigma* or *Alpha* was found, classifying the population into high patience and low patience types[40]. Regarding H3.2., a positive correlation between an individual's degree of

[38] *Age2* showed a high and significant correlation with *Age*, *Nationality* showed a high and significant correlation with *LivingNL*, *Field study* showed a medium and significant correlation with *Schooling* and *Econ student* showed high and significant correlations with *Student* and *Field study*.

[39] Please refer to Appendix F (Table G) for the pairwise correlation matrix of the control variables.

[40] The hypothesis concerning the expected positive correlation between loss aversion and the discount rate in the domain of losses could not be investigated separately, since the time preference parameters were not elicited in the domain of losses. Furthermore, the measurement of loss aversion suffered from inadequacies, which are discussed in the last chapter.

probabilistic optimism and discount rate was expected, which implied the following: an increase in risk aversion meant an increase in pessimism, and thus, the lower the degree of probabilistic optimism, the higher *Alpha*, the lower *IDR1*.

Where the OLS has difficulties with this type of regression (biased and inconsistent), Tobit - using the Maximum Likelihood method - generates a model that predicts the DV to be within the specified range (Amemiya, 1984; Tobin, 1958). The Tobit model assumes that there is a latent variable (desired discount rate) underlying the observed variable (actual discount rate). The two are equal when the latent variable is greater than zero (and smaller than 50% in this case), but the observed value amounts to zero when the latent variable is negative. As a result, there is a corner solution in the utility maximisation program; if an individual's optimal value of the discount rate is negative, the value is rounded to zero because of the non negativity constraint. That being the case, in this study, the discount rate could vary between 0% (Mazur's: 0.05) and 50% (Mazur's: 0.47), which meant that the DV was censored from left and from right[41]. As a consequence, measurements were cut off on the lower and the upper side. Two participants that had a discount rate of 50%, or 0.47, were equal according to my scale, but they might have been not truly equal in discounting behaviour.

Remember that, as Table 8 shows, the sample was categorised as *Optimistic* (inverted S-shaped weighting function, N=77), *Pessimistic* (S-shaped weighting function, N=11), or *EU maximisers* (linear, objective weighting function, N=11).

Optimistic ($\alpha < 1$)	**Frequency**	**Percentag e**		**Pessimistic** ($\alpha > 1$)	**Frequency**	**Percentage**
No	22	22.22%		**No**	88	88.89%
Yes	77	77.78%		**Yes**	11	11.11%
Total	99	100.00%		**Total**	99	100.00%

Table 8. Heterogeneous probability weighting function parameters

Since the *Pessimistic* subjects violated monotonicity, they were excluded from the analyses. The discount rate (DV) was a function of the IVs and an error term to capture the noise. The relationship was estimated by means of the following regression:

$$IDR = \beta_0 + \beta_1(\textit{probability weighting}) + \beta_2(\textit{curvature value function}) + \beta_3(\textit{loss aversion}) + \textit{Controls} + \varepsilon$$

	Model 1 (Linear OLS)	**Model 2 (Linear OLS)**	**Model 3 (Tobit)**	**Model 4 (Tobit)**
DV		***IDR1***		
Alpha	-0.0627	-0.0829	-0.2748	-0.3566
Sigma	-0.0299	-0.0521	-0.1043	-0.2304
Lambda	0.0218**	0.0208**	0.1031*	0.0959*

[41] In the sample N=88, there were 40 left-censored observations at IDR1 < 0.05, 32 right-censored observations at IDR > 0.47, and 16 uncensored observations.

Age		-0.0010		-0.0084
Female		-0.0360		-0.1147
Student		-0.0469		-0.2811
Schooling		-0.0083		-0.0411
LivingNL		0.0028		0.0427
Constant term	0.2365***	0.4057	0.1509	1.1219
Observations	88	88	88	88
F test (Prob > F)	0.1262	0.2549		
R2	0.0674	0.0964		
Adjusted R2	0.0341	0.0049		
Log Likelihood			-74.844533	-73.457003
Chi2 test			0.2065	0.5003
Pseudo R2			0.0296	0.0476
* p-value < 0.1	** p-value < 0.05	*** p-value < 0.01		

Table 9. OLS and Tobit regression results for estimating H3.

The OLS model was compared to the Tobit model. The empirical results from Table 9 showed that the signs for the variables of key interest stayed the same, but the significance decreased. Both OLS and Tobit have their disadvantages. Whereas OLS was biased and inconsistent because the DV was censored (from above and below at the same time) and non-normal, Tobit was also inconsistent because of the non-normal DV. Although Tobit was appropriate because of the censoring, the added value of the Tobit model is also frequently debated by researchers. In fact, positive discount rates are generally accepted, causing the floor effect to be less of a problem. Also, because some coefficients became less significant in the Tobit model, it was decided to use OLS instead[42]. Based on the following results, although insignificant, preliminary evidence (in the same direction as the literature) indicated that the connection between risk and time preferences was possibly present.

From Model 1 to Model 2, stepwise adding controls (*Age, Female, Schooling, Student,* and *LivingNL*) increased the R squared (R2) from 0.0674 to 0.0964, but decreased the adjusted R2 (from 0.0341 to 0.0049). Where R2 shows how close the data is to the fitted regression line (calculating the explained variance), the adjusted R2 corrects this explained variance for the amount of IVs, being a better measurement of goodness of fit. Also, the F test, which measures whether the adding of variables helps to explain variance, increased to a large extent. Therefore, judging the model fit measures, the simple Model 1 without controls was studied. The coefficient of *Alpha* was -0.0627 and insignificant[43]. The negative coefficient of *Alpha* indicated that someone who was more optimistic with respect to small probabilities, has a higher discount rate, and is thus, more impatient. Although

[42] Although the null hypothesis of the Breusch-Pagan test for heteroscedasticity (indicating whether a DV's variability is unequal across values of an IV, or, whether the variance of error terms is variable), was not rejected, robust standard errors were still reported. Using robust standard errors has become common practice in economics in an effort to be conservative, or cautious.

[43] The analyses with N=99 showed the same signs for coefficients. However, the negative coefficient for *Alpha* was significant at the 10% level.

insignificant, this was some first evidence for the existence of a categorisation into low patience and high patience types. Besides, the coefficient of *Sigma* carried the expected sign, but was also insignificant. Lastly, the positive sign for *Lambda* (significant at the 5% level) was not really hypothesised. Still, the sign was as expected, indicating that someone who was more loss averse, had a higher discount rate, and was thus, more impatient.

Because there existed a possibility that the effect of *Alpha* was different for *Optimistic, Pessimistic* and *EU satisfying* persons, other OLS regressions were estimated with *IDR1* as DV and the risk variables *(Optimistic, Pessimistic, Alpha, Sigma,* and *Lambda*) as IVs.

	Model 1 (Linear OLS)	**Model 2 (Linear OLS)**	**Model 3 (Linear OLS)**
DV		***IDR1***	
Optimistic	0.0640	0.0843*	
Pessimistic	-0.0334		
Alpha			-0.0309
Sigma	-0.0340	-0.0571	-0.0349
Lambda	0.0204**	0.0190**	0.0209**
Age		-0.0026	
Female		-0.0183	
Student		-0.0514	
Schooling		0.0004	
LivingNL		0.0035	
Constant term	0.1485**	0.3012**	0.2278***
Observations	99	99	77
F test (Prob > F)	0.1060	0.1291	0.1807
R2	0.0787	0.1096	0.0643
Adjusted R2	0.0395	0.0304	0.0285
	* p-value < 0.1	** p-value < 0.05	*** p-value < 0.01

Table 10. OLS regression results for estimating H3

Table 10 presents the following: there might have been a different effect of *Alpha* for those subjects being optimistic (*Alpha* < 1) and pessimistic (*Alpha* > 1), indicated by the positive coefficient for *Optimistic* (p-value: 0.340) and the negative coefficient for *Pessimistic* (p-value: 0.688). Moving from Model 1 to Model 2, stepwise adding controls (*Age*, *Female*, *Schooling*, *Student*, and *LivingNL*) and only accounting for *Optimistic*, decreased model fit (Adjusted R2). However, the positive coefficient (p-value: 0.085), which was weakly significant, showed that someone who was more optimistic with respect to small probabilities, was more impatient. Lastly, because of the small data set of pessimistic subjects, Model 3 investigated the relationship between *IDR1* as DV and the risk variables *Alpha*, *Sigma*, and *Lambda* as IVs for the subsample of subjects who satisfied the criterion *Alpha < 1*. The negative coefficient for *Alpha* (p-value: 0.748) confirmed the direction of earlier results. However, seeing the far from significant p-values (save Model 2), no further conclusions could be derived from these results.

Hypotheses 4-6 were tested by means of ordered logistic regressions; the IVs show the effect on the probability of being a certain attitude type. Since it was not possible to interpret the magnitude of the coefficients, but only possible to state something about the outer categories, three (instead of six) attitude types were analysed. Ordered logit models were estimated, and not ordered probit models, because a probit model assumes a normal distribution, while this assumption is not met. In fact, Long and Freese (2006) prove that a logistic regression makes no assumptions about: linearity, normality, and homoscedasticity. However, there are a few assumptions that need to be met. First, the DV must be ordinal. Second, the model should be fitted correctly (no over- or underfitting and only inclusion of meaningful variables). Third, the error terms should be independent and there should be little to no multicollinearity (Long & Freese, 2006). It was made sure that these assumptions were met. Marginal effects - which would have shown how the probabilities of each outcome (DV) change with respect to a change in the IVs - were not calculated because this paper was only an explorative research. Thus, interpreting the coefficients of the logit regression was not necessary. Also, the categorisation of the subjects into the three attitude type groups was very uneven, and therefore, the marginal effects would have been biased. As a result, only the sign and significance of the coefficients were examined. The coefficients of H4-H6 are estimated using Maximum Likelihood .

H4 was tested employing an ordered logistic regression. It was estimated to what extent the attitude type (*Attitude3)* was influenced by the risk preference IVs of *Alpha*, *Sigma*, and *Lambda*[44]. Also, controls were added.

> **H4.** Risk aversion decreases the probability of being a *Doubtful* or *Dismissive* type and increases the probability of being an *Alarmed* or *Concerned* type.
>
> **H4.1.** An individual's curvature in the utility function decreases the probability of being a *Doubtful* or *Dismissive* type and increases the probability of being *Alarmed* or *Concerned*.
>
> **H4.2.** An individual's degree of probabilistic optimism increases the probability of being a *Doubtful* or *Dismissive* type and decreases the probability of being *Alarmed* or *Concerned*.

It was expected, supporting H4.1, that a significantly negative correlation between an individual's attitude type (*Attitude3)* and risk aversion (*Sigma*) was found. Also, as hypothesised in H4.2, a significantly positive correlation between an individual's attitude type (*Attitude3)* and an individual's degree of probabilistic optimism was expected. Similar to H3.2., this positive correlation meant the following: a decrease in risk aversion represented a decrease in pessimism and thus, a higher degree

[44] In addition, for robustness, an ordered logistic regression was estimated with *Attitude3* as DV and *Optimistic* and *Pessimistic* as IVs. However, again, since the sample (for pessimistic subjects) was small and p-values far from significant, no conclusions could be derived from this. Also, in the ordered logistic regression with *Attitude3* as DV and *Optimistic* as only IV, model fit was not increased.

of probabilistic optimism, the lower *Alpha*, the higher the probability of being a *Doubtful* or *Dismissive* type. Therefore, a negative coefficient for *Alpha* was expected.

	Model 1 (oLogit)	**Model 2 (oLogit)**	**Model 3 (oLogit)**	**Model 4 (oLogit)**
DV		**Doubtful & Dismissive (*Attitude3*)**		
Alpha	1.2070	1.3025	0.8408	0.5895
Sigma		-0.4179	-0.8692	-1.1446
Lambda		0.2315	0.1990	0.2159
Age			-0.1736	-0.2406
Female			-1.5373	-1.7992
Student			-0.6337	-0.6399
Schooling			0.7194	0.6732
LivingNL			-0.5716	0.2607
Observations	88	88	88	77
Log Likelihood	-34.331137	-33.255856	-29.3850	-23.383485
Pseudo R2	0.0127	0.0436	0.1549	0.1541
Chi2 test	0.3473	0.3864	0.2147	0.3841
AIC	74.66227	76.51171	78.76991	66.76697
BIC	82.09429	88.8984	103.5433	90.20502
	* p-value < 0.1	** p-value < 0.05	*** p-value < 0.01	

Table 11. Ordered logistic regression results for estimating H4

Against expectations, already from the pairwise correlation coefficients could a possible (positive) relationship between probability weighting parameter (*Alpha)* and attitude type *(Attitude3)* be deducted. Table 11 shows the estimation results. Model 1 consisted of the simple model with *Attitude3* as DV and *Alpha* as IV, without any controls. However, the risk attitude in CPT exists of the probability weighting function parameter (*Alpha*), curvature of the value function (*Sigma*), and the loss aversion parameter (*Lambda*). Moving from Model 1 to Model 2, adding *Sigma* and *Lambda*, model fit was increased (Log Likelihood and Pseudo R2 improved), but also decreased (Chi2, AIC, and BIC deteriorated). Neither Model 1 or Model 2 shows significant coefficients. From Model 2 to Model 3, stepwise adding controls (*Age*, *Female*, *Schooling*, *Student*, and *LivingNL*) increased the model fit (Log Likelihood, Pseudo R2, Chi2 Test), but also decreased it (AIC and BIC deteriorated). None of the coefficients of was significant. Lastly, for robustness, Model 4 investigated the relationship between the risk variables *Alpha, Sigma,* and *Lambda* for the subsample of *Optimistic* subjects. Again, a positive, but insignificant coefficient of *Alpha* was found.

The negative coefficient for *Sigma* (although insignificant) followed expectations. Someone who was more risk averse for gains was less likely to be *Doubtful & Dismissive*. At the same time, this person was more likely to be *Alarmed & Concerned*. However, the signs of the coefficients of *Alpha* and *Lambda* did not follow expectations. Whereas a negative coefficient for *Alpha* was expected, suggesting that someone who exhibits a higher degree of probabilistic optimism (the lower *Alpha*) has a higher probability of being a *Doubtful* or *Dismissive* type, a positive coefficient was found, suggesting that someone who was less optimistic with respect to small probabilities (more pessimistic) was more likely to belong to the category *Doubtful & Dismissive* (*Attitude3)*. So, this implied that someone who was more optimistic with respect to small probabilities was more likely to be *Alarmed & Concerned*. Lastly, the positive coefficient of *Lambda* indicated that someone who was more loss averse was more likely to be *Doubtful & Dismissive* and less likely to be *Alarmed & Concerned*. The sign of this coefficient was against expectations. Still, it is not completely implausible. In fact, imagine that a person who belonged to the *Doubtful & Dismissive* believes that global warming happens with low probability. Simply put, this person had two options: either incurring a small loss now to prevent global warming or incurring a massive loss (climate change) later. Since the *Doubtful & Dismissive* person believed that global warming will happen with very low probability, this person might have rather taken the risk of the big loss in the future (which will, according to them, happen with small probability) if it allowed them to avoid the small loss now. Both options are losses. So, consequently, *Lambda*, which measures the degree of loss aversion, does not necessarily account for this behaviour. In fact, this behaviour is related to the shape of the value function for losses, which was not investigated in detail in this paper.

The signs of the coefficients for the control variables were not the main topic of interest. Still, they are briefly discussed. The negative coefficients of *Age, Female,* and *Student* implied that a female student, who was a few years older, was less likely to be *Doubtful & Dismissive*. At the same time, the positive coefficient of *Schooling* implied that someone with more years of schooling was more likely to belong to the category *Doubtful & Dismissive*. The coefficient of *LivingNL* is negative in Model 3, but positive in Model 4. A negative coefficient was expected. The signs of the control variables were, except from *Schooling*, in accordance with the expectations. In fact, it was expected that years of schooling would increase the likelihood to belong to the category *Alarmed & Concerned*, but the contrary appeared to be the case. However, the data concerning these control variables was not so reliable, since there is not a lot of variance (see descriptive statistics variables)[45]. Also, with regards to *Schooling*, it should be noted that the survey was also distributed on Reddit.com, where, on several subreddits, discussions took place between highly educated (PhD or higher) Geology / Climatology / Physics professors who were sceptic towards climate change. Since they were categorised as belonging to the category *doubtful & dismissive*, this might have biased the results.

H5 was tested with an ordered logistic regression. It was estimated to what extent the attitude type (*Attitude3)* was influenced by the time preference (*IDR1*). Also, controls were added.

[45] The sample was highly educated. 44.44% held a degree of the University of Applied Sciences (HBO if they were Dutch) and another 34.34% held a Bachelor's degree (WO if they were Dutch).

H5: The discount rate coefficient increases the probability of being a *Doubtful* or *Dismissive* type and decreases the probability of being an *Alarmed* or *Concerned* type.

It was expected that a significantly positive correlation between an individual's attitude type (*Attitude3)* and discount rate (*IDR1*) was found.

	Model 1 (oLogit)	**Model 2 (oLogit)**
DV		**Doubtful & Dismissive (*Attitude3*)**
IDR1	1.5721	0.0798
Age		-0.1574
Female		-1.4159
Student		-0.8367
Schooling		0.7515
LivingNL		-0.3682
Observations	88	88
Log Likelihood	-34.401332	-30.632256
Pseudo R2	0.0107	0.1191
Chi2 Test	0.3887	0.2182
AIC	74.80266	77.26451
BIC	82.23467	97.08321
* p-value < 0.1,	**p-value < 0.05,	***<p-value < 0.01

Table 12. Ordered logistic regression results for estimating H5

Table 12 shows the regression results. Model 1 consisted of the simple model with *Attitude3* as DV and *IDR1* as IV, without any controls. Although insignificant, a positive coefficient (p-value: 0.390) for the discount rate was found. Then, in Model 2, controls were added and model fit increased (Log Likelihood, Pseudo R2, and Chi2 Test improved), but it also deteriorated (AIC and BIC). Also, although positive, the coefficient of the discount rate became even more insignificant (p-value: 0.969). Seeing the far from significant p-values, no further conclusions could be derived from these results.

With regards to the control variables, the same signs of the coefficients for the control variables were found as in H4. This partly - apart from the coefficient for schooling - followed expectations.

Lastly, H6 was tested using an ordered logistic regression. It was estimated to what extent the attitude type (*Attitude3)* was influenced by the patience type (*HighPatience)* or by the risk and time preference IVs (*Alpha, Sigma, Lambda, IDR1)*, separately. Also, controls were added.

<u>H6</u>: Being a high patience type, compared to a low patience type, decreases the probability of being a *Doubtful* or *Dismissive* type and increases the probability of being an *Alarmed* or *Concerned* type.

It was expected that a significantly negative correlation between an individual's attitude type (*Attitude3*) and the probability of being a high patience type (*HighPatience)* was found.

	Model 1 (oLogit)	**Model 2 (oLogit)**	**Model 3 (oLogit)**	**Model 4 (oLogit)**
DV		**Doubtful & Dismissive (*Attitude3*)**		
HighPatience	0.7055	0.7443		
Alpha			1.4425	0.8395
Sigma			-0.4119	-0.8686
Lambda			0.1988	0.1993
IDR1			1.2816	-0.0136
Age		-0.1823		-0.1738
Female		-1.3397		-1.5387
Student		-0.8264		-0.6353
Schooling		0.7545		0.7198
LivingNL		-0.3834		-0.5711
Observations	88	88	88	88
Log Likelihood	-34.301022	-30.201488	-33.041077	-29.384936
Pseudo R2	0.0136	0.1315	0.0498	0.1549
Chi2 Test	0.3313	0.1657	0.4834	0.2914
AIC	74.60204	76.40298	78.08215	80.76987
BIC	82.03406	96.22167	92.94617	108.0206
	* p-value < 0.1,	**p-value < 0.05,	***<p-value < 0.01	

Table 13. Ordered logistic regression results for the estimation of H6

Already earlier, a possible (positive) relationship between *Alpha* and the *Attitude3* could be deducted. However, there was no clear relationship between *Attitude3* and *IDR1*. Still, following the cluster analysis, the sample was divided into high patience types (low IDRs and high alphas) and low patience types (high IDRs and low alphas).

Table 13 shows the regression results. Model 1 consisted of the simple model with *Attitude3* as DV and *HighPatience* as IV, without any controls. The (against expectations) positive coefficient of *HighPatience* (p-value: 0.323) indicated that someone who was a high patience type was more likely to belong to the category *Doubtful & Dismissive* (*Attitude3).* Moving from Model 1 to Model 2, adding *Age, Female, Student, Schooling* and *LivingNL* as control variables, the coefficient of *HighPatience* stayed positive and remained insignificant (p-value: 0.346). The model fit partly increased (Log Likelihood, Pseudo R2, and Chi2) and partly decreased (AIC and BIC). To the contrary, none of the coefficients of the IVs was significant. Seeing the far from significant p-values, no further conclusions could be derived from these results.

The problem with Model 1 and Model 2 was that only the dummy *HighPatience* was included, which caused a loss of data. Therefore, Model 3 consisted of the *Attitude3* as DV and the risk and time preference parameters *(Alpha, Sigma, Lambda,* and *IDR1*) as IVs. Nevertheless, from Model 2 to Model 3, overall, the model fit (Log Likelihood, Pseudo R2, Chi2, and AIC) deteriorated. *Sigma* and *IDR1* carried the expected signs, but were far from significant. Therefore, no further conclusions could be derived from these results. Lastly, from Model 3 to Model 4, stepwise adding controls (*Age, Female, Schooling, Student,* and *LivingNL*) partly increased the model fit (Log Likelihood, Pseudo R2, Chi2 Test) and partly decreased it (AIC and BIC). None of the coefficients became significant and only *Sigma* carried the expected sign. Again, seeing the far from significant p-values, no further conclusions could be derived from these results.

The control variables were not the main topic of interest. Since their coefficients were already briefly discussed in the estimations of H4 and H5, and the signs of the coefficients stayed the same, these are not elaborated upon any further.

In conclusion, partly supporting H3, it followed that a positive, weakly significant relationship existed between *Optimistic* and *IDR1*, supporting the notion of high and low patience types. To the contrary, the results were not convincing enough to find support for H3. Furthermore, although the sign of the relationship between *Sigma* and the attitude type pointed in the expected direction, *Alpha* was, against expectations, positively (but insignificantly) associated with the attitude type. As a result, H4 was not supported either. In addition, in estimating H5, although the positive coefficient for *IDR1* was as expected, the values were far from significant, not supporting H5. So, consequently, since H6 only held under the condition that H4 and H5 held, also no support for H6 was found.

4.5. Robustness checks

Some robustness checks were done to validate the methodology and the results. Internally, robustness of results, for OLS, logistic, and Tobit models, was taken care of by the statistical analysis program STATA. In addition, some other checks are discussed. First, the distribution of switching points from the risk preference task is discussed, then the clustering analysis is elaborated upon, and lastly, some auxiliary analyses are done.

4.5.1. Distribution of switching points

Since people are psychologically biased towards the middle, the middle rows might have been chosen more in the sMPL elicitation method. However, Table 14 shows that the highest percentage of subjects (N=88) switched at Row 1 (34.09%, 31.82%, or 26.14%), and lower percentages switched at the middle rows or the last row[46]. Moreover, except from the positive correlation between *Risk1* and *Risk2* (p-value: 0.0108), low and insignificant correlations were reported[47]. The variation in switching points for the time preference tasks was not calculated, because of response error, hyperbolic discounting, and increasing discount rates. In conclusion, there was no evidence that subjects anchored towards the middle, and therefore, it was concluded that the pattern of responses was consistent with choices made based on actual preferences.

	Switching point in		
Row	**Serie 1**	**Serie 2**	**Serie 3**
1	34.09%	31.82%	26.14%
2			30.68%
3	3.41%	1.14%	5.68%
4	9.09%	2.27%	4.55%
5	3.41%	4.55%	7.95%
6	12.50%	2.27%	3.41%
7	18.18%	6.82%	2.27%
8	4.55%	3.41%	19.32%
9	2.27%	6.82%	
10	2.27%	5.68%	
11	1.14%	2.27%	
12	9.09%	6.82%	
13		1.14%	
14		2.27%	
15		22.73%	
Total	100.00%	100.00%	100.00%

Table 14. The percentage of people per row and serie that made the switch in that row

4.5.2. Cluster analysis

K means clustering was employed to divide the sample into two groups: high patience types (low *IDR1* and high *Alpha*) and low patience types (high *IDR1* and low *Alpha*). Instead, a k median cluster analysis could have been applied to make sure absolute deviations were minimised. The decision for k means clustering was made upon the fact that *Alpha* was not influenced by many outliers, and therefore, minimising within-cluster variance was preferred. Still, the results did not change much when k median cluster analysis was applied.

Also, k means clustering could have been employed to divide the sample in the following two groups: high patience types (low *IDR1* and high *Sigma*) and low patience types (high *IDR1* and low *Sigma*). Section 4.3 justifies the choice for a cluster analysis on the basis of *IDR1* and *Alpha*. The encountered problem with a cluster analysis on the basis of *IDR1* and *Sigma* was that the risk aversion

[46] For the risk preferences task (N=88), in Serie 1, the mean switching point was 5.01 and its variance was 3.59 decision rows. In Serie 2, the mean was 7.68 and its variance was 5.56 decision rows. In Serie 3, the mean was 3.53 and its variance was 2.65 decision rows.

[47] The correlation between *Risk1* and *Risk2* was 0.2704 (p-value: 0.0108), between *Risk1* and *Risk3* -0.1651 (p-value: 0.1242), and between *Risk2* and *Risk3* was -0.0532 (p-value: 0.6228).

coefficients of the low and high patience types did not differ enough to make comparison possible. Also, since the correlation between *Sigma* and *IDR1* was only -0.0272 (p-value: 0.8012), and in line of reasoning of Epper et al. (2011), it was expected to find a relationship between *Alpha* and *IDR1*, there was no reason to carry out the cluster analysis on the basis of *Sigma* and *IDR1*.

4.5.3. Other robustness checks

Admittedly, minimal deviations from 1 could have been considered as practically the same as EU. In fact, five persons, with alphas of 0.93 or 1.03, were taken into account in auxiliary analyses. They were treated as if their alpha equalled 1. This increased the sample to N=89. The results for the cluster analysis are reported in Appendix F.3. However, treating them as EU maximisers did not really change the results. Also, the results regarding the regression analyses only changed to a very small amount. Therefore, these are not included in this paper.

Also, in estimating H6, it was investigated whether the patience type was significantly related to an individual's attitude towards global warming. In addition, the Fisherś Exact Test is employed. The null hypothesis for the Fisher's Exact Test was that the groups did not affect the outcome; rejection of the null hypothesis would have indicated that the outcome depended upon the group. To the contrary, Table 15 shows that the null hypothesis was not rejected (value: 0.355) and it was concluded that the groups are independent.

Patience type	**Attitude type**			
	Alarmed & Concerned	**Cautious & Disengaged**	**Doubtful & Dismissive**	**Total**
High patience	23	2	2	27
Low patience	56	4	1	61
Total	79	6	3	88

Table 15. Correlation between patience type and individual's attitude towards global warming

Lastly, the results of S_1 (N=88) were compared with those from S_2 (N=99). To the contrary, not many striking differences were found. Therefore, the analyses are not included.

5. Discussion and Conclusion

This chapter first discusses the research limitations. Then, the results are discussed in combination with related literature. Lastly, a conclusion, including suggestions for further research and practical implications, is presented.

5.1. Research limitations

Several caveats are in order when interpreting the results. Section 5.1.1. discusses the limitations regarding the methodologies measuring risk and time preferences and the attitude towards global warming. Section 5.1.2. discusses the limitations regarding the online experiment.

5.1.1. Limitations methodology

First, regarding risk as well as time, the assumption was made that preferences were exogenous and captured by parameters in utility functions, while alternatively, they could have been treated as endogenous. The implication of this assumption and recommendations for further research are further discussed in Section 5.3.1. Also, I enforced monotonic switching because this reduced the noise. On the other hand, it might have also biased results, since confused subjects were included now, actually increasing the noise. Although I tried my best to decrease unclarities, I did not include a sample task for increased understanding (because of time constraints). Therefore, it is possible that subjects just randomly made decisions. Moreover, it was assumed that risk and time preferences were the same in the environmental and monetary domain, excluding the necessity for environmental framing in the online experiment. To the contrary, evidence also specifies that these preferences are volatile and subject to framing. Therefore, I could have relied on a hypothetical environmental outcome such as a mitigation policy towards climate change. However, I decided that this was less valid and would result in loss of control. In fact, the argument to make the experiment incentive compatible overruled[48]. Still, it is possible that different values would have been measured in the environmental compared to the monetary domain. Section 5.3.1. elaborates on this point.

Second, concerning risk, the assumption was made that an individual's risk attitude could be derived by means of an experiment. This was done because measuring people's risk-taking tendency in real life was impractical (and would have resulted in confounding factors) and measuring it in a hypothetical way was judged to be unreliable and invalid. However, it can be argued that risk attitude is not equal to risk perception. Therefore, a risk seeking individual might still perceive global warming as

[48] To illustrate, I could have presented the choice between two mitigation policies (Option A and Option B) towards climate change. The *risky* policy could have offered a small chance of total mitigation, but a large chance that it would not have an effect at all. The *safe* mitigation policy could have guaranteed some mitigation, but would have had no chance of complete mitigation. Notice that the gambles are could have been framed in terms of mitigation, and thus environmental gains could have been evaluated. However, since the policies are hypothetical per definition, they could not be made incentive compatible.

a considerable risk, and therefore, act risk averse. Unfortunately, the inclusion of extra measurements (for example individual's self-reported willingness to take risks or perception of risks), which would have possibly increased validity, was impossible due to time constraints.

Third, regarding time, the assumption was made that subjects have a positive time preference. That this assumption is questionable if sequences are concerned, is discussed in Section 5.3.1. However, in this paper, subjects choose between two outcomes, which made only allowing of positive discount rates more acceptable. Also, the methodology to measure time preferences, combining Ferecatu and Önçüler (2016) and Mazur (1987), was possibly less valid than the methodology of Tanaka et al. (2010). However, the problem with the last mentioned was that subjects were required to make way more choices, increasing time spent, while this was constrained.

Lastly, because of time constraints, since the original survey takes approximately 26 minutes to complete, the shorter version of the attitude questionnaire was employed to classify subjects into the attitude types. However, the shorter version implied lower validity (only 84% of the sample was classified correctly, which varied in accuracy per attitude type). In addition, changing one of the questions into another behavioural question, it was assumed that subjects have knowledge and are aware about how meat and fish consumption are associated with global warming. By contrast, if people were not aware of this connection, the answer to the question did not add anything relevant. Still, especially seeing the recent (media and political) attention devoted to this topic and knowing my sample is highly educated, it was likely that this assumption held. Lastly, individual's attitudes were measured, and the assumption was made that this attitude is a good predictor of behaviour. Still, attitude is not necessarily identical to behaviour; numerous papers focus on the attitude-behaviour gap between the possession of environmental knowledge and awareness and displaying pro-environmental behaviour (Kollmuss and Agyeman, 2002).

5.1.2. Limitations experiment

The results need to be interpreted with caution, because the following limitations reveal the difficulties of collecting data online via Qualtrics. Ideally, the experiment was implemented in the lab, so that more control over subjects was practiced. However, due to limited time and money available, the data collection was pursued through Qualtrics. Using Smith's (1982) five precepts (nonsatiation, saliency, dominance, privacy, parallelism), I will discuss some experimental limitations that might have influenced the results. Since the goal of this study was to explore theoretical models, the first four precepts are all that is needed.

The first precept, nonsatiation, is likely to be met, since it assumes that subjects value more over less (Smith, 1982). Indeed, control is achieved by inducing monetary values to actions.

Second, saliency, which implies that earnings depend on decisions made and subjects are not deceived, is made sure to be met (Smith, 1982). For Part I and II, a profit in the online experiment resulted in higher earnings for the subjects, while a loss made in the experiment resulted in lower earnings. Also, the instructions stated that promised earnings would be paid out to two participants, and indeed, two participants were paid for real. However, with regard to the risk preference measurement, since it was unethical to measure real losses, framed losses were measured. Although the show up fee was only small (10 euros), subjects might have perceived it as a ‘‘windfall gain’’, causing them to have treated it differently[49]. With regard to the time preference measurement, only gains were discounted, while in fact, there is substantial evidence that people have the tendency to discount gains more than losses (Frederick et al., 2002; Loewenstein & Prelec, 1992; Thaler, 1981). This paper did not account for the valence of discounting, because otherwise, a similar problem as with the framed losses in the risk preference measurement had occurred. Also, the payoffs after Part I and II included a two week delay, which might have resulted in subjects feeling deceived. In a real lab, credibility would have been higher, because then, subjects are immediately paid out. Lastly, the questions in Part III regarding the attitude and socioeconomic characteristics were not incentive compatible, and thus, saliency was not satisfied (because choices did not really affect earnings). Although Prelec (2004) showed with his Bayesian Truth Serum (BTS) how we can incentivise people to reveal the truth, even when this truth is subjective, unobservable, or only observed in the distant future, the BTS was not employed because of time-related limitations.

Third, dominance, which is only partly met, indicates that a subject’s subjective costs of participating - their mental effort - is dominated by the earnings (Smith, 1982). Since subjects could earn minimally €8.40 up to a maximum of €39.80 euros, while the average time spent was 12-15 minutes, the possibly hourly earnings were fairly high. Also, the RIS was applied to select two participants whose decision in ether Part I or Part II was paid out. While Charness, Gneezy, and Imas (2013) argue that there is no difference in choice behaviour when all decision rows are paid out or when one is chosen at random, this still suggests that all participants are paid out (according to one of their decisions). However, it was not possible to perfectly replicate a fully incentivised lab experiment; in this study, only two (of 117 participants) were paid out, which decreased the expected monetary payoffs. So, because of the smaller choice that their decision was selected, subjects might have experienced reduced task motivation and might have not taken the tasks seriously. Of course, with more resources available, more control could have been accomplished. Still, it may be concluded that, since 293 people started the online survey, the 117 people (minus the speeders) who finished it were determined to finish and answered in a concentrated and truthful way. Alternatively, similar to Ferecatu and Önçüler (2016), I could have studied higher stakes (of factor thirty f.e.), without actually paying these amounts (but paying the smaller stakes). In that case, however, the instructions about how incentives were paid out would have been considerably more difficult.

Furthermore, the precept of privacy, which demands that participants only receive information about their own payoff alternatives, is met in all probability (Smith, 1982). However, since time and location that subjects filled in the online survey were not controlled for, the only exception could be that subjects may have filled in the survey with someone else, resulting in biased answers.

[49] Windfall gains might have resulted in more risky and less patient choices.

In conclusion, nonsatiation and saliency are sufficient conditions for a microeconomy. Since these are satisfied to a large extent, this experiment is called an economic experiment. However, dominance and privacy should hold for control. To increase internal validity, (mostly demographic) control variables were included to keep other factors constant, earlier research and a pilot experiment were employed to ensure face validity, and it was made sure that participants were not aware of what I was researching. Validated measures (time and risk preference, attitude questions) were used to increase reliability. Still, since dominance and privacy were not met and the study also failed to include treatments, correlation, instead of causal inference, was investigated (List & Sadoff, 2008).

5.2. Discussion of results

The main goals of this paper were to investigate the possible relationship between risk and time preferences and to what extent this relationship states something about an individual's attitude towards global warming. This section discusses the main findings and relates them to connected literature.

First, since H1 and H2 were not statistically tested, it could not be derived whether the hypotheses should be rejected or not. However, descriptively it was endorsed that cumulative prospect theory was as common as expected (H1), because almost all subjects were loss averse and weighted probabilities nonlinearly[50]. My findings corroborate with previous results of Abdellouai et al. (2013), Conte, Hey, and Moffat (2011), and Epper et al., (2011) who find that the minority of subjects is EU maximiser. In fact, the majority exhibits significant probability weighting in their preference functions. Lower values for *Alpha*, *Sigma*, and *Lambda* were found with respect to those reported by Bocqueho, Jacquet and Reynaud (2011), Liu (2013), and Tanaka et al. (2010), indicating that subjects in this sample were less risk averse (but more risk seeking), more optimistic (more overweighting of small probabilities), and less loss averse. This contradiction may be due to the sample of subjects; while the former authors studied farmers in France, China, or Vietnam, this study investigated (mostly highly educated Dutch student) subjects from the Netherlands[51]. The findings with regard to H1 validate the usefulness of allowing for heterogeneous (also CPT) risk preferences. Normally, Willingness To Pay (WTP) estimations for environmental risk reductions assume EU risk preferences. But, as Riddel (2012) also reasons, ignoring probability weighting may lead to biased estimates individual's WTP. This is the case because subjects exhibit significantly more risk aversion in the environmental domain (Ioannou & Sadeh, 2016), while at the same time, the probability weighting function is more pronounced (Riddel, 2012).

Second, in contrast to earlier findings of Ainslie (1975), Mazur (1987), and Prelec (1992), exponential discounting was more common than expected (H2). In fact, (in S_1) only 13.64% of the

[50] Admitted, nonlinear probability weighting might indicate evidence for RDU as well. However, since also evidence for loss aversion was found, it was assumed that CPT better describes subject's preferences than EU does.
[51] Tanaka et al. (2010) find that people who live in villages with higher mean income are less loss averse and more patient. Also, Rosenzweig and Binswanger (1993) find that wealthier people are willing to take more risk than poorer people.

subjects followed the hyperbolic discounting hypothesis, compared to 73.86% that discounted exponentially. Unlike Epper et al. (2011), I was unable to account for the *extent* of hyperbolic discounting $(\delta_1 - \delta_2 > 0)$. However, this paper failed to account for several factors. Normally, declining discount rates (and preference reversals) are found when two choice problems are offered at different points in time. Then, subjects first prefer the smaller and closer outcome, but switch to the larger and remote outcome when both are remote. In this study, the decision was made at the same time, which might have induced weaker inconsistency. Also, only two very short time horizons were studied and Option A and B only differed by very small amounts (making deferrance of the reward actually not that worthwhile). Indeed, Mazur (1987) argues that a brief procedure (like in this experiment), which encompasses short periods with a few choices, is less informative, because near-exclusive preferences are often observed. Higher values for δ_1 and δ_2 were found than Ferecatu and Önçüler (2016), indicating that subjects in this study were more impatient. Admittedly, Frederick et al. (2002) explain that time preference measurements often suffer from an upward bias; the assumption of risk neutrality causes discount rates to be overestimated when the subject is in fact risk averse. Therefore, it is proposed that joint estimation strategies such the Convex Time Budget (CTB) approach of Andreoni and Sprenger (2012a) or the Double Multiple Price List (DMPL) methodology of Andersen et al. (2008), which is adapted and utilised by Ferecatu and Önçüler (2016), should be employed to use the estimated curvature of the utility function to correct, or condition, the discount rate. Now, the problem with these methodologies is that they cannot infer utility curvature under non-expected utility theory (they assume a CRRA EU function), which made them of no practical value for my research. Therefore, time and risk preferences in my research were sequentially elicited. In case the CTB or DMPL approach was used, it is expected to find lower discount rates. Although it would have been still possible to account for hyperbolic discounting, non-expected utility preferences would have been ignored.

Third, a positive, but insignificant, correlation between an individual's degree of probabilistic optimism and discount rate was found. However, in an auxiliary analysis, a weakly positive coefficient for *Optimistic* was found, supporting H3.2. This confirmed that someone who was more optimistic with respect to small probabilities, had a higher discount rate, and was thus, more impatient. As a result, the population was classified into high patience (low IDRs, high alphas) and low patience types (high IDRs, low alphas). This result shares similarities with Epper et al. (2011), Halevy (2008), and Saito (2009). It is argued that the correlation is driven by a natural link between the domains of time and risk. Every future consequence is associated with uncertainty, which implies that the decision-maker's valuation of a delayed outcome not only depends on pure time preference, but also on perception of uncertainty, and thus, risk preferences. Although Epper et al. (2011) find hyperbolic preferences to be more pronounced for more sub proportional probability weighters, this result was not replicated, because the sample of hyperbolic discounters was too small.

Furthermore, no evidence of a correlation between an individual's curvature in the utility function and discount rate was found, failing to find support for H3.1. This finding partly disproves previous results reported by Booij and Van Praag (2009), Cameron and Gerdes (2007), and Ferecatu and Önçüler (2016), who find that risk averse agents are more patient. However, these authors did not account for nonlinear probability weighting. However, Epper et al. (2011) also find that curvature per se is not directly related to the strength of decreasing discount rates.

Notice that this paper explored in more depth the effect of risk and time preferences on the probability that someone belonged to a certain attitude type. Unlike Leiserowitz, Maibach, Roser-Renouf, Feinberg, and Rosenthal (2016), who find that only 17% of the Americans is *Alarmed* and 28% is *Concerned* , against 21% who is *Doubtful & Dismissive*, much less variability is found in the attitude type. In fact, in this study, out of 99 subjects (S_2), 88.89% was categorised as *Alarmed & Concerned*, against 5.05% as *Doubtful & Dismissive*. As a result, the number of observations in each group was actually too low to make statements about. Partly, this was expected, because the sample exists of highly educated, European - mostly Dutch - students. In that sample, especially my friends and acquaintances, people who believe global warming is not happening and are thus, not worried at all, belong to a very small minority. However, I tried to capture the heterogeneity in attitude types by distributing the online survey via Reddit.com (instead of only via Social Media to friends and acquaintances) and by merging the six attitude types into three categories. This lack of variability in attitude types made it difficult/less valid to estimate H4-H6, because every group should have consisted of at least 10 to 15 observations. However, on the positive side, by far the majority is categorised as *Alarmed & Concerned*, indicating that their attitude is strong, consistent, and explicit (their ABC components are aligned). Since this influences their behaviour, beliefs, and in which experts or facts they believe in, and the group appeared to be quite homogenous, designing effective communication strategies becomes easier. This is explained in Section 5.3.2.

Fourth, H4 showed the correlation between the risk parameters and an individual's attitude towards global warming. Although curvature in the utility function (outcome risk aversion) seemed to decrease the probability of being a *Doubtful & Dismissive* type, H4.1. failed to find support. Furthermore, against expectations, the degree of probabilistic optimism (overweighting of small probabilities) seemed to decrease the probability of being a *Doubtful & Dismissive*. So, H4.2. also failed to find support. It was expected that risk aversion and overweighting of small probabilities contributed to a higher level of environmental urgency (and the willingness to insure themselves), and therefore, would increase the probability of being *Alarmed & Concerned* (and decrease the probability of being *Doubtful & Dismissive)*. However, as Upham, et al. (2009) suggest, risk aversion is not necessarily equal to risk perception and it might be different in different domains. Also, the probability weighting might be different after all for financial and environmental decisions. Riddel (2012) finds that subjects overemphasise low probability, extreme environmental outcomes compared to low probability, extreme financial ones. She argues that, because environmental damages are largely public (not private), these losses may make socially conscious individuals more concerned, cautious, and risk averse, whereas a self-interested person may be largely dismissive and therefore, act more risk loving.

Fifth, the results concerning the correlation between an individual's time preference and attitude towards global warming were unclear and could not be interpreted. Therefore, H5 failed to find support as well. It was expected, elaborating on Viscusi et al. (2008), to find a significantly positive correlation between an individual's discount rate and attitude type, suggesting that people who in general have little concern with the future simply do not place great value on environmental amenities, while people with greater environmental awareness exhibit lower discount rates. However, as discussed in the second paragraph of this section, the results regarding the time preferences should be treated with caution.

Furthermore, H6 described the relationship between being a certain patience type and an individual's attitude towards global warming. It was expected to find a significantly negative correlation. However, a positive coefficient was found and since the coefficients were far from insignificant, H6 was not supported either. Still, the categorisation into high and low patience types was made. The far from insignificant results can be explained by different factors, such as the partly invalid time preference measurement and the lack of dispersion in global warming attitudes.

In conclusion, this paper has given an account of the relationship between risk and time preferences and how this differs for individuals with different attitudes towards global warming. Although the first evidence concerning the relation between risk and time preferences indicates that someone who is more optimistic, is more impatient, the evidence is not very conclusive. Therefore, further research (discussed in Section 5.3.1.) is needed. Furthermore, there is no evidence that this relationship is different for individuals with various attitudes towards global warming.

5.3. Recommendations

5.3.1. Further research

I propose that further research should be undertaken in the following four areas. First, as discussed in Section 5.1.1., this paper took preferences of time and risk as exogenous, or given, while an area of future research is to think about how you can change these preferences, since they are, in effect, endogenous. So, recognising that these preferences are influenced by psychological and sociological factors, one might focus recommendations of policy on changing these preferences. Further work, taking a constructivist and in depth approach, might be performed to investigate the endogeneity of risk and time preferences.

Second, as discussed in Section 5.1.1., the assumption was made that time and risk preferences were the same across domains. However, it is argued that risk and time preferences are different in the environmental and monetary domain. Still, especially regarding risk preferences, various authors do not necessarily agree about the exact difference. While Ioannou and Sadeh (2016) argue that risk aversion is higher in the environmental domain compared to the monetary domain, Riddel (2012) finds that subjects overemphasise low probability, extreme environmental outcomes compared to low probability, extreme financial ones. Although unstudied, the finding of Ioannou and Sadeh (2016) might indicate more concavity of the utility function or convexity in the probability weighting function. At the same time, Riddel (2012) demonstrates more concavity (optimism) in the probability weighting function. So, consequently, further experimental investigations are needed to assess the risk attitude (utility and probability weighting function) in the environmental as well as the monetary domain in order to gain a better understanding of how individuals evaluate risks across domains. Even convex utility can be consistent with risk aversion if combined with convex probability weighting.

Third, as discussed in Section 5.1.1., this study investigated individual's attitudes towards global warming, while it did not directly measure pro-environmental behaviour. Future studies should examine how risk and time preferences relate to real economic decision making with regards to climate change, such as households' adoption of solar panel technology.

Lastly, as discussed in Section 5.1.1. and 5.1.2., the current study was not specifically designed to investigate time preferences in depth. In fact, the sign effect (gains are discounted more than losses), loss aversion in time preference, other than positive discount rates, and improving sequences were not researched in detail. However, it is recommended that further research is undertaken to address these issues. Since environmental problems, e.g. global warming, are often framed as losses, they might lead to valuable results that help in designing better environmental policies. To illustrate, Frederick et al. (2002) show that people can display different preferences when considering sequences or considering isolated outcomes. Guyse, Keller, and Eppel (2002) argue that decisions in the environmental domain affect streams of consequences (a sequence) rather than a lump sum; they find negative discount rates in the environmental domain. Moreover, Fleurbaey and Zuber (2012) justify a negative discount rate for climate policies. Therefore, further research should allow negative discounting as well. Also, although the methodology of Tanaka et al. (2010) accounts for CPT risk preferences, it still sequentially elicits time and risk preferences, which biases discount rates. Therefore, more research is necessary to assess which methodology is more suited to assess curvature in discounting models. Laury, Mcinnes, Swarthout and Nessen (2012) introduce the simultaneous Probability Discounting Elicitation Method to elicit curvature controlled discount rates, that are invariant to the form of utility function. However, while this method allows probability weighting, it is not possible to distinguish between gains and losses and to estimate a loss aversion parameter.

5.3.2. Practical implications

This work has a few implications, especially in designing efficient and effective policies on how to mitigate global warming. First, as discussed in Section 5.2., failure to account for probability weighting may lead to biased estimates of individual's WTP. In the valuation of environmental goods, risk aversion information is incorporated to estimate how much individuals are willing to pay to reduce the likelihood of a risk. However, the inappropriate assumption of EU risk preference is often made.

Therefore, by validating the usefulness of allowing for the outcome as well as the probabilistic risk attitude, this research can be beneficial in improving the predictive powers of WTP and to guide WTP analysis.

Also, as discussed in Section 5.2., in the risk preference measurement it was found that people judge outcomes relative to a certain reference point rather than to a final status. This results in different outcomes towards gains and losses. Frederick et al. (2002) argue that this finding also holds for intertemporal choices. Since climate policies are mostly framed in terms of losses, costs, and sacrifices, but people exhibit various degrees of loss aversion, this shaming and call for taking individual responsibility might be way too much to bear for people. To the contrary, it is important for policy makers to encourage supportive framings (from sacrifice to opportunity) that do not backfire.

Third, as discussed in Section 5.2., despite the problems with regards to the measurement of time preferences, relatively high discount rates were found. The failure to invest for long-time-horizon objectives, such as combating climate change, may be due to a strong present orientation or a failure to plan for the future. Since the issue of global warming appears very remote (in distance and time) to lots of people, it is discounted to a large extent. So, rather than talking about the negative consequences for the long term, policymakers are encouraged to frame the message more near, human, and personal.

Lastly, as discussed in Section 5.2., the majority of the sample is characterised as *Alarmed & Concerned*, what implies that their ABC components are in line. Still, a minority is categorised as *Cautious, Disengaged,* or *Doubtful*; their ABC components are not in line. Yet, their attitude helps them organise knowledge and inform decisions. Thus, an individual might be well informed about global warming, convinced it is happening, and believe it is human-caused (cognitive), being highly worried and feeling it is serious and urgent (affective), but not trying to take action themselves and unsupportive of policy responses (behavioural). Then, if only more information is sent, targeting the cognitive component of the attitude, while not influencing the behavioural and the affective component, cognitive dissonance is provoked. In fact, since this individual performs actions that contradict their knowledge and beliefs, they experience internal inconsistency and feel uncomfortable. As a result, they are motivated to reduce the dissonance; people will deprioritise the issue and justify their behaviours, instead of changing them. However, attitudes are not static, but dynamic, and influenced by a range of factors. To reduce dissonance, policy makers should focus on simple solutions, e.g. green defaults, to make climate friendly behaviour easy and convenient, in order to elicit consistent and visible action. With regard to the *Alarmed*, designing effective communication strategies is easier, because their ABC components are in line and not mixed, and thus, more easy to target.

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Appendices

Appendix A. Table with literary overview relationship risk and time preferences

Study	Method	Risk preference	Time preference	Findings on correlation risk aversion coefficient and discount rate
Abdellaoui et al. (2013)	MPLs to elicit: Utility for gains: certainty equivalents (risk) and present equivalents (time) Utility for losses: certainty equivalents (risk) and present equivalents (time) Loss aversion: indifference points to connect losses and gains	EU with CRRA and Prospect Theory	Discounted Expected Utility	General finding: no correlation utility over time and risk Two experiments: 1) negative correlation between risk aversion and discount rate for gains in one, 2) but no correlation in second experiment
Anderhub et al. (2001)	Joint estimation strategy: Simple lottery decisions (different timings)	EU	Discounted Expected Utility, no evidence for hyperbolic discounting	Significant positive correlation Risk averse people are less patient.
Andersen et al. (2008)	Joint estimation strategy: Double Multiple Price List (DMPL) Methodology: procedure of Coller and Williams (1999) for time preferences and procedure of Holt and Laury (2002) for risk preferences	EU with CRRA	Discounted Expected Utility, some evidence for hyperbolic discounting	Significant positive correlation
Anderson and Stafford (2009)	Joint estimation strategy: Variant on Anderhub et al. (2001): simple lottery decisions (different timings, difference in presence and degree risk, differences in scale of payoffs)	EU	Discounted Expected Utility	Interactions: 1) individuals become less patient as risk increases, 2) increased risk decreases subjects' patience levels. But, further examination needed.
Andreoni and Sprenger (2012b)	Joint estimation strategy: Convex Time Budget (CTB)	EU with CRRA	Discounted Expected Utility, no evidence for	No significant correlation

			hyperbolic discounting	
Booij and Van Praag (2009)	Joint estimation strategy: Survey study: six hypothetical simple lotteries, that differed in prizes ($500 - $500,000), probabilities (0.01 - 0.20), and timing	EU with CRRA	Discounted Expected Utility	Moderate negative correlation Risk averse people are more patient.
Cameron and Gerdes (2007)	Joint estimation strategy: Lottery playing behaviour (risk) and guesses about life expectancy (time)	EU with CRRA	Exponential discounting or Discounted Expected Utility	Significant negative correlation
Chabris et al. (2008)	Risk and time preferences sequentially elicited: Questions about field behaviours such as exercise, BMI, and smoking (risk) and a choice-delay discounting task (time) created by Kirby et al. (1999)	EU	Discounted Expected Utility, some evidence for hyperbolic discounting	Weak to none, but positive correlations (none exceeds 0.28, many are near 0).
Coble and Lusk (2010)	Joint Estimation Strategy with Kreps-Porteus preferences: Task 1 involved choices between certain outcomes paid out in different time periods (following Harrison et al., 2002) Task 2 involved choices between risky outcomes paid out in the present (following Holt and Laury, 2002) Task 3 involved choices between risky outcomes paid out in different time periods	EU with CRRA	Discounted Expected Utility is rejected as an adequate descriptor of people's choices in favour of the Kreps-Porteus model	Interaction: Time and risk preferences are not governed by a single parameter: time preferences are not defined by risk preferences or vice versa
Cohen et al. (2011)	Risk and time preferences sequentially elicited: Hypothetical simple lotteries in the risk, time, and ambiguity domain Self-reported survey questionnaire about field behaviours and attitudes towards risk/uncertainty and impatience	EU	Discounted Expected Utility	No correlation
Eckel et al. (2005) Data taken from laboratory experiment of Eckel et al. (2002)	Risk and time preferences sequentially elicited: Variant of the Eckel- Grossman test, simple lottery decisions (risk) and decisions about smaller, sooner and larger, later amounts of money (time)	EU with CRRA	Discounted Expected Utility, some evidence for hyperbolic discounting	Significant positive correlation Risk averse people are less patient.

Epper et al. (2011)	Joint estimation strategy: Elicitation of certainty equivalents for non-delayed risky prospects to estimate individual probability weighting functions Elicitation of future equivalents involving guaranteed payments to estimate individual discount rates	EU with CRRA (utility function) and Rank Dependent Utility, RDU (probability weighting function)	Hyperbolic discounting	Negative correlation between sub proportionality (probability weighting) and the strength of decline in discount rates (hyperbolicity) Curvature of utility function not related to hyperbolicity.
Ferecatu and Önçüler (2016)	Joint estimation strategy: DMPL in combination with hierarchical Bayes methodology	EU with CRRA	Discounted Expected Utility, some evidence for hyperbolic discounting	Significant negative correlation
Ioannou and Sadeh (2016)	Risk and time preferences sequentially elicited: Variant of the Eckel- Grossman test, simple lottery decisions (risk) in monetary and environmental domain and fixed-sequence choice titration (time)	EU	Discounted Expected Utility, evidence for hyperbolic discounting	No significant correlation
Leigh (1986)	Panel Study of Income Dynamics (PSID) for 1972: Average preferences (position of indifference curve), instead of marginal preference (slope), & behaviours with respect to future plans: risk preferences & time preferences			Significant positive correlation
Miao and Zhong (2012)	Joint estimation strategy: Convex Time Budget (CTB) with 2 time menus and four risk-related treatments	EU	Discounted Expected Utility is rejected in favour of recursive form of Kreps-Porteus model (Epstein and Zin, 1989), also evidence for hyperbolic discounting	Interaction: Time and risk preferences are not governed by a single parameter: time preferences are not defined by risk preferences or vice versa

Table I. Overview of studies that look at the correlation or interaction between risk and time preferences

Appendix B. Eliciting CPT Parameters

Appendix B.1. Serie 1, 2, and 3

Serie 1 and 2 jointly determine the values for σ and α, and Serie 3 determines λ.

SERIE 1

Question	Option A				EV(A)	Option B				EV(B)	Expected payoff difference (A-B)
1	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 5,10	9/10 of	€ 0,40	€ 0,87	€ 0,59
2	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 5,60	9/10 of	€ 0,40	€ 0,92	€ 0,54
3	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 6,20	9/10 of	€ 0,40	€ 0,98	€ 0,48
4	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 7,00	9/10 of	€ 0,40	€ 1,06	€ 0,40
5	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 7,90	9/10 of	€ 0,40	€ 1,15	€ 0,31
6	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 9,40	9/10 of	€ 0,40	€ 1,30	€ 0,16
7	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 11,20	9/10 of	€ 0,40	€ 1,48	-€ 0,02
8	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 13,80	9/10 of	€ 0,40	€ 1,74	-€ 0,28
9	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 16,40	9/10 of	€ 0,40	€ 2,00	-€ 0,54
10	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 22,40	9/10 of	€ 0,40	€ 2,60	-€ 1,14
11	3/10 of	€ 3,00	7/10 of	€ 0,80	€ 1,46	1/10 of	€ 29,80	9/10 of	€ 0,40	€ 3,34	-€ 1,88

SERIE 2

Question	Option A				EV(A)	Option B				EV(B)	Expected payoff difference (A-B)
1	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 4,10	3/10 of	€ 0,40	€ 2,99	-€ 0,06
2	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 4,20	3/10 of	€ 0,40	€ 3,06	-€ 0,13
3	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 4,40	3/10 of	€ 0,40	€ 3,20	-€ 0,27
4	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 4,50	3/10 of	€ 0,40	€ 3,27	-€ 0,34
5	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 4,70	3/10 of	€ 0,40	€ 3,41	-€ 0,48
6	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 4,90	3/10 of	€ 0,40	€ 3,55	-€ 0,62
7	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 5,10	3/10 of	€ 0,40	€ 3,69	-€ 0,76
8	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 5,40	3/10 of	€ 0,40	€ 3,90	-€ 0,97
9	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 5,80	3/10 of	€ 0,40	€ 4,18	-€ 1,25
10	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 6,20	3/10 of	€ 0,40	€ 4,46	-€ 1,53
11	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 6,70	3/10 of	€ 0,40	€ 4,81	-€ 1,88
12	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 7,50	3/10 of	€ 0,40	€ 5,37	-€ 2,44
13	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 8,20	3/10 of	€ 0,40	€ 5,86	-€ 2,93
14	9/10 of	€ 3,00	1/10 of	€ 2,30	€ 2,93	7/10 of	€ 9,70	3/10 of	€ 0,40	€ 6,91	-€ 3,98

SERIE 3

Question	Option A				EV(A)	Option B				EV(B)	Expected payoff difference (A-B)
1	5/10 of	€ 1,90	5/10 of	-€ 0,30	€ 0,80	5/10 of	€ 2,30	5/10 of	-€ 1,60	€ 0,35	€ 0,45
2	5/10 of	€ 0,30	5/10 of	-€ 0,30	-€ 0,15	5/10 of	€ 2,30	5/10 of	-€ 1,60	€ 0,35	-€ 0,50
3	5/10 of	€ 0,10	5/10 of	-€ 0,30	-€ 0,20	5/10 of	€ 2,30	5/10 of	-€ 1,60	€ 0,35	-€ 0,55
4	5/10 of	€ 0,10	5/10 of	-€ 0,30	-€ 0,20	5/10 of	€ 2,30	5/10 of	-€ 1,20	€ 0,55	-€ 0,75
5	5/10 of	€ 0,10	5/10 of	-€ 0,60	-€ 0,35	5/10 of	€ 2,30	5/10 of	-€ 1,20	€ 0,55	-€ 0,90
6	5/10 of	€ 0,10	5/10 of	-€ 0,60	-€ 0,35	5/10 of	€ 2,30	5/10 of	-€ 1,10	€ 0,60	-€ 0,95
7	5/10 of	€ 0,10	5/10 of	-€ 0,60	-€ 0,35	5/10 of	€ 2,30	5/10 of	-€ 0,90	€ 0,70	-€ 1,05

Screenshot I. Tables elicitation risk preference parameters

Appendix B.2. Mathematica script

Serie 1 and 2 jointly determined the values for σ (concavity of value function) and α (curvature of probability weighting function). The belonging inequalities were presented in Section 3.2. First, to calculate α, this participant switched in the seventh row in Serie 1 as well as in Serie 2. His/her alpha amounts to $0.66 < \alpha < 0.74$, or $\alpha = 0.7$. This was calculated by means of the following script in Mathematica 11.2:

```
f[wL_, wH_, p_] := wL^(1-σ) + Exp[-(-Log[p])^α] (wH^(1-σ) - wL^(1-σ))

probA = Evaluate[{α, f[8 / 10, 3, 3 / 10] > f[4 / 10, 94 / 10, 1 / 10],
   f[8 / 10, 3, 3 / 10] < f[4 / 10, 112 / 10, 1 / 10],
   f[23 / 10, 3, 9 / 10] > f[4 / 10, 49 / 10, 7 / 10],
   f[23 / 10, 3, 9 / 10] < f[4 / 10, 51 / 10, 7 / 10], 1 / 10 < α < 9 / 10,
   1 / 10 < σ < 9 / 10}]
```

$$\Big\{\alpha,$$
$$\left(\frac{4}{5}\right)^{1-\sigma} + \left(-\left(\frac{4}{5}\right)^{1-\sigma} + 3^{1-\sigma}\right) e^{-\mathrm{Log}\left[\frac{10}{3}\right]^{\alpha}} > \left(\frac{2}{5}\right)^{1-\sigma} + \left(-\left(\frac{2}{5}\right)^{1-\sigma} + \left(\frac{47}{5}\right)^{1-\sigma}\right) e^{-\mathrm{Log}[10]^{\alpha}},$$
$$\left(\frac{4}{5}\right)^{1-\sigma} + \left(-\left(\frac{4}{5}\right)^{1-\sigma} + 3^{1-\sigma}\right) e^{-\mathrm{Log}\left[\frac{10}{3}\right]^{\alpha}} < \left(\frac{2}{5}\right)^{1-\sigma} + \left(-\left(\frac{2}{5}\right)^{1-\sigma} + \left(\frac{56}{5}\right)^{1-\sigma}\right) e^{-\mathrm{Log}[10]^{\alpha}},$$
$$\left(\frac{23}{10}\right)^{1-\sigma} + \left(-\left(\frac{23}{10}\right)^{1-\sigma} + 3^{1-\sigma}\right) e^{-\mathrm{Log}\left[\frac{10}{9}\right]^{\alpha}} > \left(\frac{2}{5}\right)^{1-\sigma} + \left(-\left(\frac{2}{5}\right)^{1-\sigma} + \left(\frac{49}{10}\right)^{1-\sigma}\right) e^{-\mathrm{Log}\left[\frac{10}{7}\right]^{\alpha}},$$
$$\left(\frac{23}{10}\right)^{1-\sigma} + \left(-\left(\frac{23}{10}\right)^{1-\sigma} + 3^{1-\sigma}\right) e^{-\mathrm{Log}\left[\frac{10}{9}\right]^{\alpha}} < \left(\frac{2}{5}\right)^{1-\sigma} + \left(-\left(\frac{2}{5}\right)^{1-\sigma} + \left(\frac{51}{10}\right)^{1-\sigma}\right) e^{-\mathrm{Log}\left[\frac{10}{7}\right]^{\alpha}},$$
$$\frac{1}{10} < \alpha < \frac{9}{10}, \frac{1}{10} < \sigma < \frac{9}{10}\Big\}$$

```
FindMaximum[probA, {{α, .7}, {σ, .3}}]

{0.744622, {α → 0.744622, σ → 0.32083}}

probA /. {α → 0.7446218267372643`, σ → 0.3208301405513084`}

{0.744622, True, True, True, True, True, True}

FindMinimum[probA, {{α, .7}, {σ, .3}}]

{0.655117, {α → 0.655117, σ → 0.311652}}
```

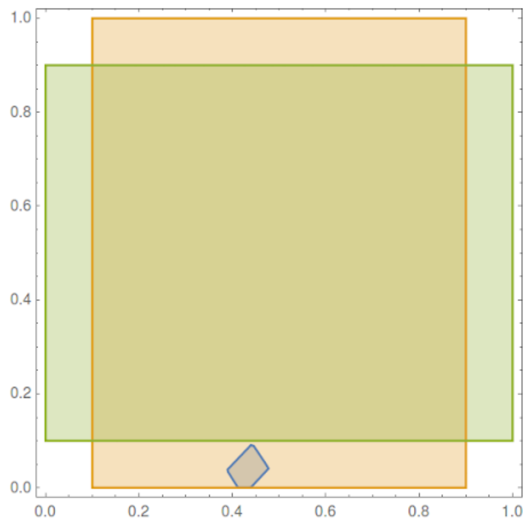
Screenshot II. Calculation of α for participant who switched in seventh row in Serie 1 and 2.

Second, to calculate σ, as indicated, this participant switched in the seventh row in Serie 1 as well as in Serie 2. His/her sigma amounts to $0.0.27 < \sigma < 0.36$, or $\sigma = 0.31$. This was calculated by means of the following script in Mathematica 11.2:

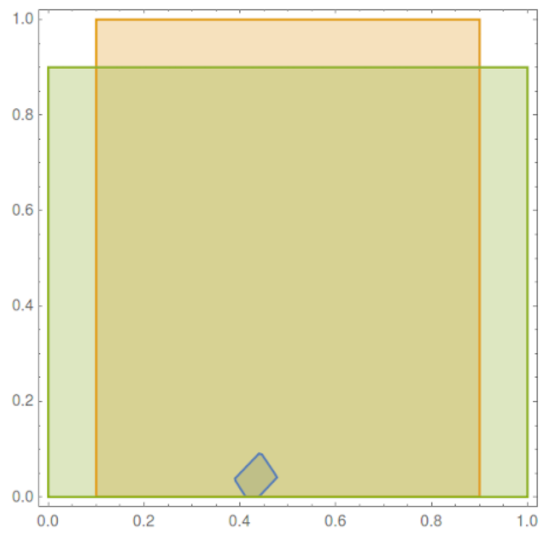
```
probS = Evaluate[{σ, f[8 / 10, 3, 3 / 10] > f[4 / 10, 94 / 10, 1 / 10],
    f[8 / 10, 3, 3 / 10] < f[4 / 10, 112 / 10, 1 / 10],
    f[23 / 10, 3, 9 / 10] > f[4 / 10, 49 / 10, 7 / 10],
    f[23 / 10, 3, 9 / 10] < f[4 / 10, 51 / 10, 7 / 10], 1 / 10 < α < 9 / 10,
    1 / 10 < σ < 9 / 10}];

FindMaximum[probS, {{α, .7}, {σ, .3}}]

{0.363273, {α → 0.706425, σ → 0.363273}}

FindMinimum[probS, {{α, .7}, {σ, .3}}]

{0.267296, {α → 0.692737, σ → 0.267296}}
```

Screenshot III. Calculation of σ for participant who switched in seventh row in Serie 1 and 2.

The example above is also demonstrated in Liu (2013), validating the script in Mathematica 11.2. For all participants, the combination of (α, σ) is determined. The imposed restrictions for α as well as for σ, $(1/10 < \alpha < 9/10,\ 1/10 < \sigma < 9/10)$ are introduced for numerical stability. However, for some participants, the constraint was too restrictive. Therefore, the restrictions were also relaxed to $1/10 < \alpha < 11/10$ and $0 < \sigma < 9/10$.



Regionplot 1: Constraint for σ is too restrictive



Regionplot 2: Constraint for σ is relaxed

The small blue area is defined by the first four inequalities, the yellow area is the restriction imposed by the second to last inequality, while the green area portrays the last inequality. In regionplot 1, the blue area does not intersect with the green one because the constraint for σ is too restrictive. Yet, if the constraint is relaxed, as in regionplot 2, the blue area intersects with the green as well as the yellow area, and values can be calculated.

The following tables were derived:

Curvature probability weighting function (alpha)	Switching question in series 1											
Switching question in series 2	1	2	3	4	5	6	7	8	9	10	11	Never (12)
1	0.67	0.72	0.77	0.83	0.88	0.93	1.00	1.03	1.08	1.13	1.18	1.23
2	0.62	0.67	0.72	0.00	0.83	0.88	0.93	1.00	1.03	1.08	1.14	1.18
3	0.57	0.62	0.67	0.71	0.75	0.82	0.87	0.93	1.00	1.03	1.08	1.13
4	0.52	0.57	0.62	0.68	0.71	0.77	0.83	0.87	0.93	1.00	1.03	1.08
5	0.47	0.52	0.57	0.62	0.67	0.72	0.77	0.83	0.87	0.93	1.00	1.03
6	0.44	0.47	0.53	0.58	0.63	0.68	0.74	0.80	0.83	0.88	0.95	1.00
7	0.39	0.44	0.49	0.54	0.59	0.65	0.70	0.74	0.80	0.83	0.88	0.95
8	0.35	0.39	0.45	0.50	0.55	0.61	0.65	0.71	0.75	0.78	0.85	0.88
9	0.30	0.35	0.40	0.45	0.50	0.56	0.61	0.66	0.71	0.74	0.80	0.85
10	0.26	0.30	0.35	0.40	0.46	0.51	0.56	0.61	0.66	0.70	0.75	0.80
11	0.21	0.26	0.31	0.35	0.41	0.46	0.51	0.56	0.60	0.65	0.70	0.75
12	0.17	0.21	0.26	0.31	0.36	0.41	0.46	0.51	0.55	0.60	0.64	0.70
13	0.12	0.17	0.22	0.26	0.31	0.36	0.41	0.46	0.50	0.55	0.59	0.64
14	0.07	0.12	0.17	0.22	0.26	0.31	0.36	0.41	0.45	0.49	0.54	0.59
Never (15)	0.02	0.07	0.12	0.17	0.22	0.26	0.31	0.36	0.41	0.45	0.49	0.54

Concavity of value function (sigma)	Switching question in series 1											
Switching question in series 2	1	2	3	4	5	6	7	8	9	10	11	Never (12)
1	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.11	0.17	0.23	0.29
2	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.11	0.17	0.23	0.29	0.34
3	0.00	0.00	0.00	0.00	0.03	0.06	0.11	0.17	0.22	0.28	0.34	0.39
4	0.00	0.00	0.00	0.00	0.05	0.12	0.17	0.22	0.28	0.33	0.39	0.43
5	0.00	0.00	0.02	0.05	0.13	0.17	0.21	0.28	0.32	0.38	0.43	0.48
6	0.00	0.02	0.05	0.13	0.17	0.20	0.27	0.32	0.38	0.43	0.48	0.51
7	0.02	0.05	0.10	0.17	0.20	0.28	0.32	0.37	0.42	0.48	0.51	0.56
8	0.05	0.10	0.16	0.26	0.28	0.33	0.37	0.42	0.48	0.51	0.56	0.61
9	0.10	0.17	0.22	0.30	0.34	0.37	0.42	0.48	0.52	0.57	0.61	0.65
10	0.17	0.24	0.30	0.35	0.38	0.43	0.48	0.53	0.57	0.61	0.65	0.69
11	0.24	0.30	0.36	0.40	0.43	0.48	0.53	0.58	0.61	0.66	0.69	0.74
12	0.30	0.36	0.41	0.45	0.50	0.55	0.58	0.62	0.66	0.69	0.74	0.78
13	0.36	0.42	0.47	0.51	0.54	0.60	0.63	0.67	0.70	0.74	0.78	0.82
14	0.42	0.48	0.52	0.56	0.60	0.64	0.68	0.72	0.75	0.78	0.82	0.86
Never (15)	0.48	0.52	0.56	0.60	0.64	0.68	0.72	0.75	0.78	0.82	0.86	0.90

Screenshot IV: Tables with values for (α, σ) derived from the switching points

Lastly, Serie 3 determined λ (the degree of loss aversion). This was calculated by means of the following script in Mathematica 11.2:

```
PTutility[x_, λ_, σ_] := Piecewise[{{-λ (-x)^(1-σ), x < 0}, {x^(1-σ), x ≥ 0}}]

PTutility[w, λ, σ]

 - (-w)^(1-σ) λ   w < 0
 w^(1-σ)          w ≥ 0
 0                True
```

```
fWithLambda[wL_, wH_, p_, λ_] :=
 PTutility[wL, λ, .02] +
  Exp[-(-Log[p])^1] (PTutility[wH, λ, .02] - PTutility[wL, λ, .02])


Lambda =
 Evaluate[
  {λ, fWithLambda[-3 / 10, 19 / 10, .5, λ] >
     fWithLambda[-16 / 10, 23 / 10, .5, λ],
    fWithLambda[-3 / 10, 3 / 10, .5, λ] <
     fWithLambda[-16 / 10, 23 / 10, .5, λ], 5 / 10 < λ < 5.0}]

{λ, 0.5 (1.87577 + 0.307312 λ) - 0.307312 λ >
  -1.58503 λ + 0.5 (2.262 + 1.58503 λ),
 0.5 (0.307312 + 0.307312 λ) - 0.307312 λ <
  -1.58503 λ + 0.5 (2.262 + 1.58503 λ), 1/2 < λ < 5.}


FindMaximum[Lambda, {{λ, 1}}]

{1.52983, {λ → 1.52983}}

FindMinimum[Lambda, {{λ, 1}}]

{0.5, {λ → 0.5}}
```

Screenshot V: Calculation of λ for participant who switches in second row in Serie 3

This participant, with $\alpha = 1$ and $\sigma = 0.02$, switched in the second row in Serie 3. Thus, he/she preferred Option A to Option B in Row 1, but preferred Option B to Option A in Row 2, and his/her lambda amounts to $0.5 < \lambda < 1.53$, or $\lambda = 1$.

Appendix C. Eliciting Discounting Parameters

Here, Serie 1 and 2 to elicit the time discounting parameters are presented. If a subject switched from Option A to Option B at the sixth row in Serie 1, his or her δ_1 lies in between 15% and 17.50%, yielding the midpoint 16.75%. If the same subject switched from Option A to Option B at the sixth row in Serie 2 as well, his or her δ_2 lies in between 15% and 17.50%. This could have been evidence for discounted utility, or constant discounting, because δ_1 and δ_2 are equal. Another example is the following: If a subject switched in the seventh row in Serie 1, his or her discount rate (δ_1) lies in the interval 17.50% - 20.00%, yielding the midpoint 18.75%. Then, if the same subject switched in the sixth row in Serie 2, his or her discount rate (δ_2) lies in the interval 15,00% - 17.50%, yielding the midpoint 16.25%. This might have been evidence for hyperbolic discounting, because $\delta_1 > \delta_2$, and, if preferences are hyperbolic, elicited discount rates decline as the time horizon is increased.

For the calculation of the IDRs, Mazur's specification for exponential discounting, $V_i = A_i e^{-kD_i}$, was employed and the fitted parameters were calculated for all participants. The k indicates how much someone values future outcomes relative to present outcomes. Screenshot I and II present Serie 1 and 2 included in the online experiment. Notice that the values for Mazur's K were not presented to participants of the online survey.

SERIE 1						
Question	**Option A** (amount to be paid in 0.5 month)	**Option B** (amount to be paid in 2.5 months)	**AR**	**AER**	**Mazur's K** Hyperbolic Function	**Mazur's K** Exponential Function
1	€10	€ 10.08	5.00%	5.09%	0.05	0.05
2	€10	€ 10.12	7.50%	7.71%	0.06	0.06
3	€10	€ 10.17	10.00%	10.38%	0.09	0.09
4	€10	€ 10.21	12.50%	13.1%	0.11	0.11
5	€10	€ 10.25	15.00%	15.87%	0.13	0.13
6	€10	€ 10.28	17.50%	18.68%	0.16	0.16
7	€10	€ 10.33	20.00%	21.55%	0.18	0.18
8	€10	€ 10.37	22.50%	24.47%	0.21	0.21
9	€10	€ 10.41	25.00%	27.44%	0.23	0.23
10	€10	€ 10.45	27.50%	30.47%	0.25	0.25
11	€10	€ 10.49	30.00%	33.55%	0.28	0.28
12	€10	€ 10.53	32.50%	36.68%	0.3	0.3
13	€10	€ 10.58	35.00%	39.87%	0.32	0.32
14	€10	€ 10.62	37.50%	43.11%	0.35	0.35
15	€10	€ 10.66	40.00%	46.41%	0.37	0.37
16	€10	€ 10.70	42.50%	49.77%	0.39	0.39
17	€10	€ 10.74	45.00%	53.18%	0.42	0.42
18	€10	€ 10.77	47.50%	55.95%	0.44	0.44
19	€10	€ 10.82	50.00%	60.19%	0.46	0.46
					0.47	0.47

Screenshot I: Tables with values for δ_1 and *IDR1* derived from the switching points

SERIE 2					
Question	Option A (amount to be paid in 0.5 month)	Option B (amount to be paid in 4.5 months)		AR	AER
1	€10	€ 10.17		5.00%	5.09%
2	€10	€ 10.25		7.50%	7.71%
3	€10	€ 10.33		10.00%	10.38%
4	€10	€ 10.42		12.50%	13.1%
5	€10	€ 10.50		15.00%	15.87%
6	€10	€ 10.59		17.50%	18.68%
7	€10	€ 10.67		20.00%	21.55%
8	€10	€ 10.76		22.50%	24.47%
9	€10	€ 10.84		25.00%	27.44%
10	€10	€ 10.93		27.50%	30.47%
11	€10	€ 11.01		30.00%	33.55%
12	€10	€ 11.10		32.50%	36.68%
13	€10	€ 11.18		35.00%	39.87%
14	€10	€ 11.27		37.50%	43.11%
15	€10	€ 11.36		40.00%	46.41%
16	€10	€ 11.44		42.50%	49.77%
17	€10	€ 11.53		45.00%	53.18%
18	€10	€ 11.60		47.50%	55.95%
19	€10	€ 11.70		50.00%	60.19%

Screenshot II: Tables with values for δ_2 derived from the switching points

Appendix D. Overview of variables

An overview of the transformed and untransformed variables is given[52].

Name	Description	Values
Risk1	Option A and Option B are lottery choices in the positive domain. This variable indicates the switching point (Option A to Option B) in Serie 1.	1 - 12
Risk2	Option A and Option B are lottery choices in the positive domain. This variable indicates the switching point (Option A to Option B) in Serie 2.	1 - 15
Risk3	Option A and Option B are lottery choices in the positive, as well as in the negative domain. This variable indicates the switching point (Option A to Option B) in Serie 3.	1 - 7
Alpha	This variable is the probability weighting function parameter. The value is elicited from Serie 1 and 2 in Part II.	0.02 - 1.18
Sigma	This variable is the curvature value function parameter. The value is elicited from Serie 1 and 2 in Part II.	0.00 - 0.86
Lambda	This variable is the loss aversion parameter. The value is elicited from Serie 3 in Part II.	0 - 6.18
Optimistic	This dummy variable indicates whether a subject is optimistic (=1) or not. If a subject is optimistic, it is described by an inverted S Shaped probability weighting function and an alpha smaller than 1.	0 - 0.99
Pessimistic	This dummy variable indicates whether a subject is pessimistic (=1) or not. If a subject is pessimistic, it is described by an S Shaped probability weighting function and an alpha larger than 1.	> 1
Discount1	Option A (amount to be paid in 0,5 month) or Option B (amount to be paid in 2,5 month) are choices in the positive domain. This variable indicates the switching point (Option A to Option B) in Serie 1.	0 - 50
Discount2	Option A (amount to be paid in 0,5 month) or Option B (amount to be paid in 4,5 month) are choices in the positive domain. This variable indicates the switching point (Option A to Option B) in Serie 2.	0 - 50
Discount change_cat	This variable indicates a subject's time preference.	1: Increasing 2: Exponential 3: Hyperbolic
IDR1	Mazur's fitted parameter k is derived from the value of Discount1. The value is elicited from Serie 1 in Part I.	0.05 - 0.47
IDR2	Mazur's fitted parameter k is derived from the value of Discount2. The value is elicited from Serie 2 in Part I.	0.05 - 0.47
HighPatience (HP)	This dummy variable indicates whether a participant is a high patience (low IDR, high alpha) or a low patience (high IDR, low alpha) type. The data regarding the variables IDR and alpha is employed to partition observations into two clusters.	0: Yes 1: No

Table I. Variables Part I and Part II

[52] In the online survey, almost everywhere, except from the email-address, answers are forced. On forehand, I figured that people might want to stay anonymous. However, the no-response bias with respect to the email-address is low.

Name	Description	Values
Belief1[53]	Recently you may have noticed that global warming has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think? Do you think global warming is happening?	1: Extremely sure global warming is not happening 2: Very sure global warming is not happening 3: Somewhat sure global warming is not happening 4: Not at all sure global warming is not happening 5: Don't know 6: Not at all sure global warming is happening 7: Somewhat sure global warming is happening 8: Very sure global warming is happening 9: Extremely sure global warming is happening.
Belief2	Assuming global warming is happening, do you think it is…	1: Caused mostly by human activities 2: Caused mostly by natural changes in the environment 3: Other 4: None of the above because global warming isn't happening
Belief3	How much do you think global warming will harm you personally?	0: Don't know 1: Not at all 2: Only a little 3: A moderate amount 4: A great deal
Belief4	How much do you think global warming will harm future generations?	0: Don't know 1: Not at all 2: Only a little 3: A moderate amount 4: A great deal
Belief5	When do you think global warming will start to harm people in the region that you live in?	1: Never 2: 100 years 3: 50 years 4: 25 years 5: 10 years 6: They are being harmed now
Belief6	Which of the following statements comes closest to your view?	1: Global warming isn't happening 2: Humans can't reduce global warming, even if it is happening 3: Humans could reduce global warming, but people aren't willing to change their behavior, so we're not going to 4: Humans could reduce global warming, but it's unclear at this point whether we will do what's needed 5: Humans can reduce global warming, and we are going to do so successfully
Inv1	How worried are you about global warming?	1: Not at all worried 2: Not very worried 3: Somewhat worried 4: Very worried
Inv2	How much had you thought about global warming before today?	1. Not at all 2. A little 3. Some 4. A lot

[53] Belief=Belief, INV=Issue Involvement, Behaviour=Behaviour, and PSR=Preferred Societal Response.

Inv3	How important is the issue of global warming to you personally?	1. Not at all important 2. Not too important 3. Somewhat important 4. Very important 5. Extremely important
Inv4	How many of your friends share your views on global warming?	1. None 2. A few 3. Some 4. Most 5. All
Behaviour1	Over the past 12 months, how often have you punished companies that are opposing steps to reduce global warming by NOT buying their products?	0. Don't know 1. Never 2. Once 3. A few times (2-3) 4. Several times (4- 5) 5. Many times (6+)
Behaviour2	How many days a week do you eat meat or fish at the main meal?	1. 7 times 2. 5 or 6 times 3. 3 or 4 times 4. 1 or 2 times 5. I am vegetarian; I don't eat meat and fish 6. I am vegan; I don't eat meat and fish, or other animal products
PSR1	Do you think global warming should be a low, medium, high, or very high priority of the European Union (if you live in the EU) or United States (if you live in the US)?	1. Low 2. Medium 3. High 4. Very high
PSR2	Do you think citizens themselves should be doing more or less to address global warming?	1. Much less 2. Less 3. Currently doing the right amount 4. More 5. Much more
PSR3	People disagree whether the European Union (if you live in the EU) or United States (if you live in the US) should reduce greenhouse gas emissions on its own, or make reductions only if other countries do too. Which of the following statements comes closest to your own point of view? The European Union (or United States) should reduce its greenhouse gas emissions ...	0. Don't know 1. The EU (if you live in the EU) or US (if you live in the US) should not reduce its emissions 2. Only if other industrialised countries and developing countries reduce their emissions 3. Only if other industrialised countries reduce their emissions 4. Regardless of what other countries do
Attitudes6	The latter 15-items are constructed together into the six attitude types.	1: Alarmed 2: Concerned 3: Cautious 4: Disengaged 5: Doubtful 6: Dismissive
Attitudes3	The latter 15-items are constructed together into the six attitude types.	1: Alarmed & Concerned 2: Cautious & Disengaged 3: Doubtful & Dismissive

Table II. Variables Part III

Name	Description	Values
Female	What is your gender?	0: Male 1: Female
Age	What is your age?	12 - 100
Schooling	What is the highest degree or level of school you have completed? If currently enrolled, highest degree received.	1: Less than high school 2: High school graduate 3: Some college (MBO if you're Dutch) 4: University of applied sciences (HBO if you're Dutch) or Bachelor's degree 5: Bachelor's degree (WO if you're Dutch) 6: Master's degree (WO) 7: PhD or higher
Student	Are you currently a student?	0: No If no is selected, skip to question about nationality 1: Yes 2: Graduated (less than 6 months ago)
Study	What is your field of study?	1: My highest level of school completed is high school or less than high school 2: Biological/Agricultural Sciences 3: Physical/Earth Sciences 4: Mathematics/Computer Science 5: Engineering 6: Health 7: Arts/Humanities 8: Behavioural/Social Sciences 9: Education 10: Economics/Business 11: Public Administration 12: Law
Nationality	What is your nationality?	1: Dutch 2: Other European nationality 3: American 4: South American 5: Other ...
Living	Where do you currently live?	1: The Netherlands 2: Another European country 3: United States 4: Other
Linksurvey	How did you find the link to this Survey	Facebook/Reddit
Emailaddres s	Please leave your email address to be included in the drawing.	Email-address

Table III. Variables part III

Appendix E. Experimental Design

In this part, the payout-method (E.1.), the explanation given to subjects in the introduction, the examples, and Parts I, II, and III (E.2.), and the emails sent to participants of the survey (E.3), are presented.

Appendix E.1. Payment to subjects

Participant #86 and #91 were randomly selected and paid out. The following illustrates the complete payout-method:

> On 28/09, more than one hundred subjects had participated. Randomly (through random.org), two participants (#86 and #91) were chosen whose choices in Part I or II were paid out. The payoff of €10.80 for #86 was calculated as follows: first, the show up fee of 10 euros was assigned to him or her. Then, random.org determined that a choice in Part II was paid out and another throw determined that Row 2 in Serie 1 was paid out. Here, participant #86 switched at question 7, and thus, preferred Lottery A (0.3, €3.00 ; 0.7, €0.80) to Lottery B (0.1, €5.60 ; 0.9, €0.40) in this row. Then, random.org was used to determine the payoff of Lottery A. Since the random number 9 came out, participant #86 earned €0.80[54] in addition to his or her €10.00 show up fee. On 28/09, participant #86 received an email concerning the total payoff of €10.80. The email was answered and the money was immediately transferred.

Appendix E.2. Explanation given to subjects

> **<u>Introduction</u>**
>
> Thank you for participating in this survey. It concerns the economics of decision making.
>
> Recall that you have the opportunity to earn up to approximately 40 euros with this experiment (or equivalent of 40 euros, approximately 48 USD, in case you live in the US). What you earn depends partly on your decisions and partly on chance. Remember to choose according to your true preferences, since your decision might be paid out for real.
>
> After the experimental period ends, on 27/09, two participants are chosen at random. If you are chosen, you receive a payoff that consists of a fixed amount (10 euros) +/- money related to your decision. The money will be transferred to your bank account or Pay Pal account (in case you live in the US).
>
> All information provided will be kept confidential. Information in the study will be used for research purposes only. Remember that there are no right or wrong answers. The only right answer is what you would really choose.

[54] The numbers 1,2,3 would have indicated a payout of €3.00, while the numbers 4-10 point out to €0.80.

Explanation

The experiment consists of three parts: I, II, and III.

Part I is a decision problem: you have to make a series of choices between two options. Part II is a different decision problem. Again, you have to make a series of choices between two options. Part III consists of some questions about you.

In the decision problems, you are asked to indicate your choice for Option A or Option B. You can only switch (go from A to B) once, but you do not need to switch.

Examples

Part I considers questions about money amounts and different time horizons.

Part II considers questions about lotteries. This is illustrated by an example:

Question	Option A			
1	9/10 of	€ 3,00	1/10 of	€ 2,30

Question	Option B			
1	7/10 of	€ 4,10	3/10 of	€ 0,40

If you choose Lottery A (left), you have a 90% chance to win € 3.00, and a 10% chance to win € 2.30

If you choose Lottery B (right), you have a 70% chance to win € 4.10, and a 30% chance to win € 0.40

To illustrate, when there are 11 questions (comparing Option A and Option B), you have three possibilities how to answer:

Possibility 1: *You* ***switch*** *at question (type a number):*

(In this example, you switch at Question 7. This implies that you prefer Option A to Option B for the first six questions, but you prefer Option B to Option A for the questions 7-11.)

Question	Option A				Option B			
1	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 5,10	8/10 of	€ 0,40
2	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 5,60	8/10 of	€ 0,40
3	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 6,20	8/10 of	€ 0,40
4	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 7,00	8/10 of	€ 0,40
5	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 7,90	8/10 of	€ 0,40
6	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 9,40	8/10 of	€ 0,40
7	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 11,20	8/10 of	€ 0,40
8	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 13,80	8/10 of	€ 0,40
9	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 16,40	8/10 of	€ 0,40
10	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 22,40	8/10 of	€ 0,40
11	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 29,80	8/10 of	€ 0,40

You indicate this choice by this button:

I switch at Question (type a number, 2-11)

7

I choose Option A for all questions (I never switch)

I choose Option B for all questions (I switch at question 1)

***Possibility 2**: You choose Option A for all questions*

Question	Option A					Option B			
1	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 5,10	8/10 of	€ 0,40
2	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 5,60	8/10 of	€ 0,40
3	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 6,20	8/10 of	€ 0,40
4	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 7,00	8/10 of	€ 0,40
5	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 7,90	8/10 of	€ 0,40
6	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 9,40	8/10 of	€ 0,40
7	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 11,20	8/10 of	€ 0,40
8	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 13,80	8/10 of	€ 0,40
9	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 16,40	8/10 of	€ 0,40
10	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 22,40	8/10 of	€ 0,40
11	4/10 of	€ 3,10	6/10 of	€ 0,90		2/10 of	€ 29,80	8/10 of	€ 0,40

You indicate this choice by this button:

I switch at Question (type a number, 2-11)

I choose Option A for all questions (I never switch)

I choose Option B for all questions (I switch at question 1)

***Possibility 3**: You choose Option B for all questions*

Question	Option A				Option B			
1	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 5,10	8/10 of	€ 0,40
2	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 5,60	8/10 of	€ 0,40
3	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 6,20	8/10 of	€ 0,40
4	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 7,00	8/10 of	€ 0,40
5	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 7,90	8/10 of	€ 0,40
6	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 9,40	8/10 of	€ 0,40
7	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 11,20	8/10 of	€ 0,40
8	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 13,80	8/10 of	€ 0,40
9	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 16,40	8/10 of	€ 0,40
10	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 22,40	8/10 of	€ 0,40
11	4/10 of	€ 3,10	6/10 of	€ 0,90	2/10 of	€ 29,80	8/10 of	€ 0,40

You indicate this choice by this button:

I switch at Question (type a number, 2-11)

I choose Option A for all questions (I never switch)

I choose Option B for all questions (I switch at question 1)

Part I.

For 2 series of questions, you are asked to indicate your choice for Option A or Option B. The questions consider money amounts and different time horizons.

You will receive money either in 0.5 month from today or sometime in the future (2.5 months or 4.5 months from today).

In each question, you are given information on the Annual Interest Rate (AR) and Annual Effective Interest Rate (AER). The AR is the nominal interest rate stated on a financial product. The AER is calculated by taking the AR and adjusting it for the number of compounding periods the financial product will experience.

Thus, the AR is expressed as a per-year percentage and does not account for compounding that occurs throughout the year. The AER, on the other hand, accounts for the compounding that takes place on a quarterly basis.

If you have a rough understanding of what an interest rate is, you already understand enough to make good decisions. It is not necessary to completely understand the concepts of AR and AER.

Remember: you can only switch (go from A to B) once, but you do not need to switch.

Serie 1 of Part **I** is already presented in this paper.

Serie 2

Please choose between the following options:

SERIE 2				
Question	**Option A** (amount to be paid in 0.5 month)	**Option B** (amount to be paid in 4.5 months)	**AR**	**AER**
1	€10	€ 10.17	5.00%	5.09%
2	€10	€ 10.25	7.50%	7.71%
3	€10	€ 10.33	10.00%	10.38%
4	€10	€ 10.42	12.50%	13.1%
5	€10	€ 10.50	15.00%	15.87%
6	€10	€ 10.59	17.50%	18.68%
7	€10	€ 10.67	20.00%	21.55%
8	€10	€ 10.76	22.50%	24.47%
9	€10	€ 10.84	25.00%	27.44%
10	€10	€ 10.93	27.50%	30.47%
11	€10	€ 11.01	30.00%	33.55%
12	€10	€ 11.10	32.50%	36.68%
13	€10	€ 11.18	35.00%	39.87%
14	€10	€ 11.27	37.50%	43.11%
15	€10	€ 11.36	40.00%	46.41%
16	€10	€ 11.44	42.50%	49.77%
17	€10	€ 11.53	45.00%	53.18%
18	€10	€ 11.60	47.50%	55.95%
19	€10	€ 11.70	50.00%	60.19%

AR is Annual Interest Rate and AER is Annual Effective Interest Rate

Serie 1 of Part **II** is already presented in this paper.

Serie 2

Please choose between the following options:

SERIE 2

Question	Option A				Question	Option B			
1	9/10 of	€ 3.00	1/10 of	€ 2.30	1	7/10 of	€ 4.10	3/10 of	€ 0.40
2	9/10 of	€ 3.00	1/10 of	€ 2.30	2	7/10 of	€ 4.20	3/10 of	€ 0.40
3	9/10 of	€ 3.00	1/10 of	€ 2.30	3	7/10 of	€ 4.40	3/10 of	€ 0.40
4	9/10 of	€ 3.00	1/10 of	€ 2.30	4	7/10 of	€ 4.50	3/10 of	€ 0.40
5	9/10 of	€ 3.00	1/10 of	€ 2.30	5	7/10 of	€ 4.70	3/10 of	€ 0.40
6	9/10 of	€ 3.00	1/10 of	€ 2.30	6	7/10 of	€ 4.90	3/10 of	€ 0.40
7	9/10 of	€ 3.00	1/10 of	€ 2.30	7	7/10 of	€ 5.10	3/10 of	€ 0.40
8	9/10 of	€ 3.00	1/10 of	€ 2.30	8	7/10 of	€ 5.40	3/10 of	€ 0.40
9	9/10 of	€ 3.00	1/10 of	€ 2.30	9	7/10 of	€ 5.80	3/10 of	€ 0.40
10	9/10 of	€ 3.00	1/10 of	€ 2.30	10	7/10 of	€ 6.20	3/10 of	€ 0.40
11	9/10 of	€ 3.00	1/10 of	€ 2.30	11	7/10 of	€ 6.70	3/10 of	€ 0.40
12	9/10 of	€ 3.00	1/10 of	€ 2.30	12	7/10 of	€ 7.50	3/10 of	€ 0.40
13	9/10 of	€ 3.00	1/10 of	€ 2.30	13	7/10 of	€ 8.20	3/10 of	€ 0.40
14	9/10 of	€ 3.00	1/10 of	€ 2.30	14	7/10 of	€ 9.70	3/10 of	€ 0.40

In Serie 3, you might lose some money. However, remember that, when you are randomly chosen to be paid out for real, you receive the fixed amount of 10 euros as a buffer. Whatever you might earn from this question, is added to or subtracted from the 10 euros, so that you always end up with a positive amount of money.

Serie 3

Please choose between the following options:

SERIE 3

Question	Option A				Question	Option B			
1	5/10 of	€ 1.90	5/10 of	-€ 0.30	1	5/10 of	€ 2.30	5/10 of	-€ 1.60
2	5/10 of	€ 0.30	5/10 of	-€ 0.30	2	5/10 of	€ 2.30	5/10 of	-€ 1.60
3	5/10 of	€ 0.10	5/10 of	-€ 0.30	3	5/10 of	€ 2.30	5/10 of	-€ 1.60
4	5/10 of	€ 0.10	5/10 of	-€ 0.30	4	5/10 of	€ 2.30	5/10 of	-€ 1.20
5	5/10 of	€ 0.10	5/10 of	-€ 0.60	5	5/10 of	€ 2.30	5/10 of	-€ 1.20
6	5/10 of	€ 0.10	5/10 of	-€ 0.60	6	5/10 of	€ 2.30	5/10 of	-€ 1.10
7	5/10 of	€ 0.10	5/10 of	-€ 0.60	7	5/10 of	€ 2.30	5/10 of	-€ 0.90

Appendix E.3. Emails sent to participants

Dear participant,

You participated in my online survey. Congratulations, you are selected to be paid out for real! As mentioned in the online survey, your payoff consists of the fixed amount (10 euros) +/- money related to your decision.

A drawing has taken place and randomly, it is decided that Part II, Question 2 (#86) OR Part II, Question 28 (#91) is paid out. The randomly selected decision situation for you is:

#86: Part II, Question 2 (Serie 1)	#91: Part II, Question 28 (Serie 3, Question 3)
Option A: 3/10 of €3,00 7/10 of €0,80 Option B: 1/10 of €5,60 9/10 of €0,40	Option A: 5/10 of €0,10 5/10 of -€0,30 Option B: 5/10 of €2,30 5/10 of -€1,60

For #86:
In Serie 1, you decided to switch at Question 7, and thus, have chosen Option A for Question 2.

The random number drawn is: 9. Therefore, the money related to your decision is: €0,80.
Therefore, your total payoff comes down to: 10 euros +/- 0,80 euros = 10,80 euros.

For #91:
In Serie 3, you decided to switch at Question 2, and thus, have chosen Option B for Question 3.

The random number drawn is: 3. Therefore, the money related to your decision is: €2,30.
Therefore, your total payoff comes down to: 10 euros +/- 2,30 euros = 12,30 euros.

Please send me your bank account details, so that I can transfer you the money immediately.

To ensure credibility that this payment is real, in the attachment, you find a print screen of the prepared bank transfer. I just need your bank account details to transfer you the money.

Thank you again for participating in this survey.

If you would like to receive the results when I finish the master's thesis, just send me a request via email, and I will keep you posted.

Best,

Joni Reijven

Email 1. The email sent to the two participants that were selected to be paid out

Dear participant,

You participated in my online survey. Unfortunately, you are not selected to be paid out for real.

Either way, thank you again for participating in this survey.

If you would like to receive the results when I finish the master's thesis, just send me a request via e-mail, and I will keep you posted.

Best,

Joni Reijven

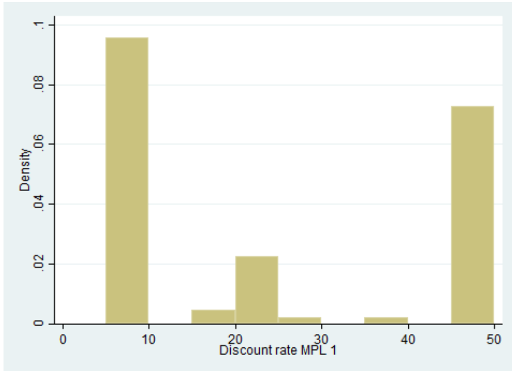
Email 2. The email sent to all participants that were not selected to be paid out

Appendix F. Data Analysis

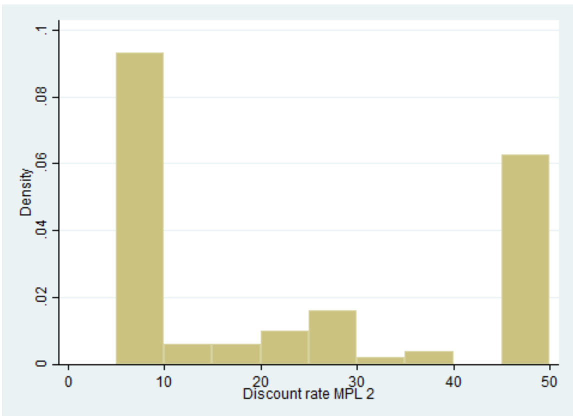
Appendix F.1. Summary statistics of key variables of interest

The following variables were not discussed in detail in the paper, but are of interest, and thus, are discussed in this section.

Discount1: This discount rate was measured with Serie 1 of the time preference experiment. Histogram A shows that, for N=88, the average was 24.47. The standard deviation was 20.59[55]. The minimum was 5 and the maximum was 50. Having a high (low) discount rate means that you value present outcomes as much more (less) important than the future. The higher the discount rate, the more impatient the subject is.



Histogram A. *Discount1*

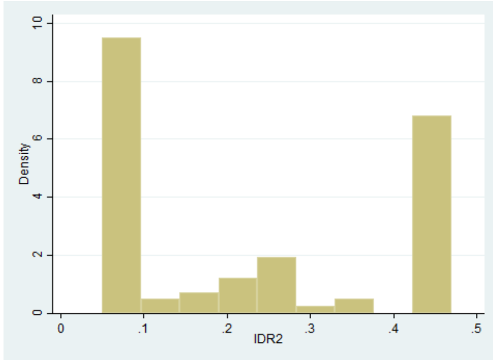


Histogram B. *Discount2*

Discount2: This discount rate was measured with Serie 2 of the time preference experiment. Histogram B shows that, for N=88, the average was 24.26. The standard deviation was 19.72[56]. The minimum was 5 and the maximum was 50. Having a high (low) discount rate means that you value present outcomes as much more (less) important than the future. The higher the discount rate, the more impatient the subject is.

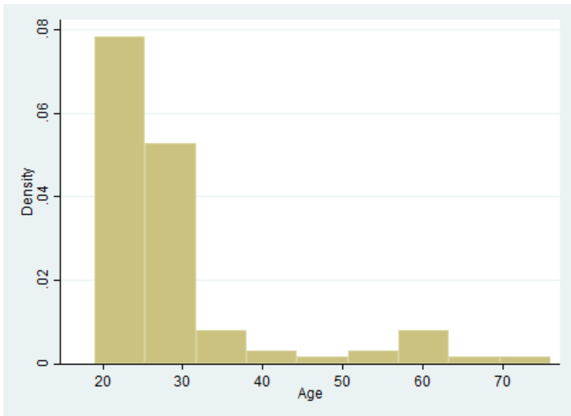
[55] For N=99, the average was 23.70. The standard deviation was 20.63.
[56] For N=99, the average was 23.57. The standard deviation was 19.82.

IDR2: This discount rate was measured with Serie 2 of the time preference experiment. These k-values were calculated through Mazur's exponential discounting formula. Histogram C shows that, for N=88, the average was 0.23. The standard deviation was 0.18[57]. The minimum was 0.05 and the maximum was 0.47. Having a high (low) discount rate means that you value present outcomes as much more (less) important than the future. The higher the discount rate, the more impatient the subject is.



Histogram C. *IDR2*

Age: Histogram D shows that, for N=99, the average was 29.26 years of age. The standard deviation was 11.18 years of age. The minimum was 19 and the maximum was 76. The median age was 26 and the IQR (Q3 - Q1) boiled down to 5 years.



Histogram D. *Age*

Schooling	Frequency	Percentage	Cumulative
High school graduate	9	9.09%	9.09%
Some college (MBO if you're Dutch)	4	4.04%	13.13%
University of applied sciences (HBO if you're Dutch)	44	44.44%	57.58%
Bachelor's degree (WO if you're Dutch)	34	34.34%	91.92%
Master's degree (WO)	7	7.07%	98.99%
PhD or higher	1	1.01%	100.00%
Total	99	100.00%	

Table A. Descriptive statistics *schooling*

[57] For N=99, the average was 0.22. The standard deviation was 0.19.

Student	Frequency	Percentage	Cumulative
Yes	45	45.45%	45.45%
Graduated (less than 6 months ago)	44	44.44%	89.90%
No	10	10.10%	100.00%
Total	99	100.00%	

Table B. Descriptive statistics *student*

Field of Study	Frequency	Percentage	Cumulative
My highest level of school completed is high school	1	1.85%	1.85%
Physical/Earth Sciences	3	5.56%	7.41%
Mathematics/ Computer Science	1	1.85%	9.26%
Engineering	5	9.26%	18.52%
Health	2	3.70%	22.22%
Arts/Humanities	4	7.41%	29.63%
Behavioural/Social Sciences	17	31.48%	61.11%
Education	1	1.85%	62.96%
Economics/Business	16	29.63%	92.59%
Public Administration	3	5.56%	98.15%
Law	1	1.85%	100.00%
Total	99	100.00%	

Table C. Descriptive statistics *field study*

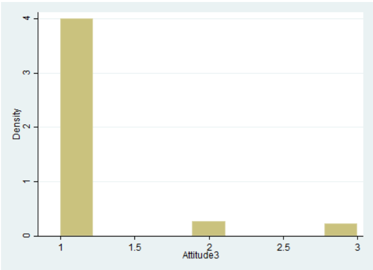
Nationality	Frequency	Percentage	Cumulative
Dutch	65	65.66%	65.66%
Other European nationality	21	21.21%	86.87%
American	10	10.10%	96.97%
South American	2	2.02%	98.99%
Other	1	1.01%	100.00%
Total	99	100.00%	

Table D. Descriptive statistics *field study*

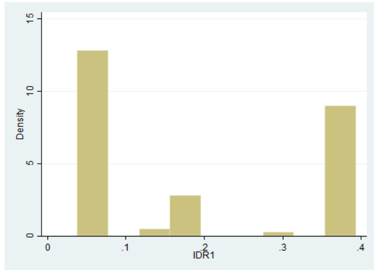
Geographic living	Frequency	Percentage	Cumulative
The Netherlands	79	80.61%	80.61%
Another European Country	9	9.18%	89.80%
United States	9	9.18%	98.98%

Other: Australia	1	1.02%	100.00%
Total	99	100.00%	

Table E. Descriptive statistics *living*



Histogram E. *Attitude3* (p-value: 0.000)



Histogram F. *IDR1* (p-value: 0.08498)

Appendix F.2. Pairwise correlation matrices

	Alpha	Sigma	Lambda	IDR1	Attitude3
Alpha	1.0000				
Sigma	-0.4500 (0.0000)	1.0000			
Lambda	-0.0945 (0.3813)	-0.0714 (0.5088)	1.0000		
IDR1	-0.0952 (0.3775)	-0.0272 (0.8012)	0.2484 (0.0196)	1.0000	
Attitude3	0.1280 (0.2348)	-0.1309 (0.2241)	0.1790 (0.0951)	0.1044 (0.3331)	1.0000

Table F. Pairwise correlation matrix key variables of interest (N=88)

	Age	Age2	Schooling	Field study	Student	Living	LivingNL	Econ student	Nationality	Female
Age	1.0000									
Age2	0.9870 (0.0000)	1.0000								
Schooling	0.3120 (0.0031)	0.2525 (0.0176)	1.0000							
Field study	0.4028 (0.0055)	0.3712 (0.0111)	0.3783 (0.0095)	1.0000						
Student	-0.4355 (0.0000)	-0.3801 (0.0003)	-0.2166 (0.0426)	0.1511 (0.3160)	1.0000					
Living	0.2557 (0.0168)	0.2801 (0.0086)	0.0658 (0.5446)	-0.2668 (0.0731)	-0.1216 (0.2618)	1.0000				
LivingNL	-0.2288 (0.0320)	-0.2333 (0.0287)	-0.1087 (0.3135)	0.1814 (0.2275)	0.1971 (0.0657)	-0.9181 (0.0000)	1.0000			

Econ student	-0.1418 (0.1874)	-0.1334 (0.2152)	0.0452 (0.6756)	0.5763 (0.0000)	0.3318 (0.0016)	-0.1658 (0.1248)	0.1849 (0.0845)	1.0000		
Nationality	0.1923 (0.0726)	0.1934 (0.0710)	0.0355 (0.7426)	-0.1582 (0.2938)	-0.1336 (0.2146)	0.7376 (0.0000)	-0.6068 (0.0000)	-0.0563 (0.6024)	1.0000	
Female	0.1257 (0.2433)	0.1484 (0.1677)	0.0018 (0.9864)	0.0173 (0.9090)	0.0076 (0.9437)	-0.0390 (0.7196)	0.0369 (0.7330)	0.0274 (0.7999)	-0.1201 (0.2649)	1.0000

Table G. Pairwise correlation matrix control variables (N=88)

Appendix F.3. Robustness checks

Optimistic $(\alpha < 1)$	**Frequency**	**Percentage**
No (EU maximisers)	16	17.98%
Yes	73	82.02%
Total	89	100.00%

Table H. *Optimistic* and *EU* subjects (subjects with alphas of 0.93 or 1.03 treated as EU)

Patience Type	**Alpha**	**IDR1**
High Patience (N=28)	Mean value: 0.9117857	Mean value: 0.1353571
Low Patience (N=61)	Mean value: 0.4163934	Mean value: 0.2732787
Total (N=89)		

Table I. Categorisation patience types on basis of *Alpha* and *IDR1*