Linking Risk Attitudes, Time Preferences, and Body Mass Index in Catalonia

Abstract

Obesity is projected to increase in the coming years, despite the various socioeconomic policies implemented by governments and policy makers. As a result, some studies have suggested that obesity should be looked at from a psychological point of view, that is, individuals' propensity to become addicted to the consumption of fat-rich foods. Although previous studies have supported this, the results have been inconclusive: methodologically and geographically. This study uses a robust approach to elicit the risk and time preferences of food consumers. It goes further to ascertain the correlations between these parameters and obesity. Despite the methodological and geographical differences, our results support a strong relationship between body mass index and risk aversion, but not for loss aversion. In addition, time discounting significantly influences individuals' propensity to increase body mass index.

Keywords: Prospect theory, Risk preferences, Time preferences; Body Mass Index, Catalonia

1. Introduction

The World Health Organization (WHO) considers obesity to be the most important cause of chronic illness and an epidemic in the 21st century, given its impact on morbidity, quality of life, and healthcare expenditure (WHO, 2016). People who are overweight or obese make up about 39% and 23% of the adult population in Spain (Gutiérrez-Fisac et al., 2012). People with obesity are at risk of heart attack and diabetes and show highly decreased levels of both productivity and life expectancy (Allison et al., 1999; Colditz, 1992). Economically, soaring obesity rates have led to a significant increase in both direct medical costs and the indirect costs resulting from lost productivity (McGinnis and Foege, 1993; Sturm, 2002; Wolf and Colditz, 1998).

Several socioeconomic factors have been found to play a major role in the high prevalence rate of obesity in Spain (Costa-Font and Gil, 2006). As a result, various socioeconomic policies have been targeted at obese people or people with a high risk of becoming obese. However, obesity is projected to increase in the coming years (OECD, 2017). As a result, some studies have suggested that obesity should be looked at from the context of individuals' propensity to become addicted to the consumption of certain foods (Cawley, 1999). Addiction to unhealthy behaviours, such as alcohol, drugs, and smoking, are usually explained by the rational addiction model of Becker and Murphy (1988). From the rational addiction context, obese individuals value the benefit from current consumption more than the present value of future health implications that result from overeating. The study of the interdependencies between the rate of time preferences, the coefficient of risk aversion, and an addiction to unhealthy behaviours, such as smoking, drinking, and unhealthy eating, has become popular (Ida and Goto, 2009).

Therefore, researchers have hypothesized that higher time discount rates could explain why some people are more likely to have unhealthy diets and respond unsuccessfully to interventions aimed at encouraging dietary change (Leitch et al., 2013; Rollins et al., 2010). Impatient people may disregard the long-term effects of fat and sugar consumption and invest in less healhty foods rather than in nutrient-rich foods. Previous studies have found that the extent of time discounting varies considerably among persons (Fishburn and Rubinstein, 1982; Frederick et al., 2002; Thaler and Shefrin, 1981), tending to be higher among younger persons (Reimers et al., 2009; Steinberg et al., 2009), individuals with lower socioeconomic status (Reimers et al., 2009), less-educated persons (Jaroni et al., 2004; Lee et al., 2013), and those with a higher risk of obesity (McLaren, 2007).

Aside from time discounting, people's risk preferences (risk aversion and loss aversion) have a predominant effect on their consumption decisions. Past literature has shown that individuals' struggles to maintain a healthy diet might be due to the existence of the phenomenon of loss aversion in consumption decision making. Loss aversion strongly influences the tendency for people to base decisions on movements away from a current state rather than on the final outcome and to regard losses from that state more than gains (Kahneman et al., 1991; Tversky and Kahneman, 1992).

Psychological factors, such as risk and time preferences, have a major influence on how individuals make food choices. In summary, the literature supports that obese and overweight persons are less risk averse or more loss averse (Anderson and Mellor, 2008; de Oliveira et al., 2016; Davis et al., 2010) and exhibit higher time preference rates (Borghans and Golsteyn, 2006; Komlos et al., 2004; Smith et al., 2005).

However, with the exception of de Oliveira et al. (2016), all studies mentioned above were partial, in the sense that they only consider the relationship between risk attitudes or time preferences of respondents with their body mass index. As in de Oliveira et al. (2016), the aim of this study is to jointly consider the role that risk and time preferences play in the tendency to become overweight and obese. Furthermore, this study tries to overcome some of the limitations of that study, namely: 1) as the focus was on people with low educational background, the visual multiple price list of Eckel and Grossman (2008) was used to elicit both risk and time preferences, which did not allow to account for subjects' attitudes toward losses, 2) their methodological framework was not flexible enough to estimate prospect theory parameters (risk aversion, loss aversion, and probability weighting), which has been proved to be very useful in behavioural economics, as we will show later, and 3) the method used to estimate the discount rate did not allow for differentiating whether subjects exhibit hyperbolic, quasi-hyperbolic or exponential time discounting behaviour.

To tackle these limitations, in this study we have adopted the incentivised double multiple price list (MPL) approach of Tanaka et al. (2010) as it allows estimating both prospect theory parameters (risk, loss aversion, and probability weighting) as well as time preference parameters (discount rate, present bias, and hyperbolicity) of consumers. This approach has been previously used in other domains to elicit both risk and time preferences such as Anderson and Mellor (2008) and Tanaka et al. (2010), to estimate risk and time preferences of the Danish adult population and Vietnamese rice farmers, respectively. However, this study constitutes, up to our knowledge, the first application on the consumers domain to investigate how risk and time preference parameters correlate with body mass index. To do that, two main tasks have been performed: 1) we have designed two lotteries to calculate risk and time preference parameters, 2) we have analyzed the impact of such parameters on participants' body mass index. In the latter, we have controlled for a variety of individual covariates, including marital status, education, age, and income, that have been shown in the literature to be common drivers of obesity.

The remainder of this article is structured as follows: section 2 provides a brief literature review on risk and time preferences. Section 3 discusses the sampling technique, experimental design, and the empirical methods used to derive our risk- and time-preference parameters. Section 4 presents and discusses the main results. The paper ends with some concluding remarks and limitations in section 5.

2. Conceptual framework and literature review

2.1 Risk preferences

The expected utility (EU) theory has long been the standard approach in behavioural economics modelling. Based on this framework, several methods have been developed to estimate the concavity of the utility function, such as the Balloon Analogue Risk Task (BART), the Eckel and Grossman method, the Domain-Specific Risk-Taking (DOSPERT) scale, or the Multiple Price Lists, among the most relevant.

The Balloon Analogue Risk Task (BART) (Lejuez et al., 2002) presents subjects with a sequence of choices of whether or not to gain additional money by pumping more air into a balloon, with each pump coming with the risk of losing the accumulated gains if the balloon pops. BART has been used to study risk attitudes across a variety of subfields, such as neuroscience (Fecteau et al., 2007), drug addiction (Bornovalova et al., 2005), and psychopathology (Hunt et al., 2005), However, it is not clear if this method, initially designed for analysing financial risk behaviour could be extended to other domains. In addition, BART requires a computer and multiple implementation trials, making it time consuming and inapplicable when there are no computers.

In the Eckel and Grossman method (Eckel and Grossman, 2008), participants are presented with a number of gambling games and are asked to choose one that they would like to play. This method has been used by Reynaud and Couture (2012) and Dave et al. (2010). Even though this method produces significantly less noisy estimates of risk preferences, compared to BART, it does not allow the researcher to differentiate between different degrees of risk-seeking behaviour.

The Domain-Specific Risk-Taking (DOSPERT) scale developed by Weber et al. (2002) elicitates risk parameters through a questionnaire. DOSPERT relies on the individual's self-reported propensity for risk. The scale contains 40 items: eight items in the domains of recreation, health, social, and ethical risks and four items in the domains of gambling and investment. DOSPERT has been applied by Hanoch et al. (2006) to elicit the domain-specific nature of risk preferences. Despite the simple nature of the DOSPERT method, Charness et al. (2013) argue that the elicited risk preferences may not reflect an individual's true attitudes toward risk in each domain since the technique is not incentivized.

Holt and Laury (2002) popularized the use of the Multiple Price List lottery to estimate the concavity of the individual's utility function. The MPL has become very popular and has been widely used by researchers to compare risk attitudes across a wide array of contexts and environments (Anderson and Mellor, 2008). However, as in the previous methods based on the expected utility framework, it only allows researchers to estimate the concavity of the utility function.

Prospect theory (PT) (Kahneman and Tversky,1979) and the mental accounting framework (Thaler, 1980) have become very relevant in recent literature on behavioural economics (Harrison et al., 2010; Liu and Huang, 2013; Tanaka et al., 2010). PT postulates that risk preferences are not solely based on the concavity of the utility function but also on probability weighting and individuals' aversion to losses. Integration of loss aversion and probability weighing into individual preferences has enabled the prospect theory to explain a wide variety of economic phenomena that were considered puzzles from the expected utility point of view (Nguyen and Leung, 2009). Tanaka et al. (2010), following the Holt and Laury's Multiple Price List lottery, proposed the double Multiple Price List (MPL) lottery to allow for the estimation of the three prospect theory parameters: risk aversion, loss aversion, and probability weighting. They applied it to elicit the risk preferences of Vietnamese farmers, assuming a constant absolute risk aversion (CARA) utility function that was separable and stationary across time.

The double MPL was initially criticized on the basis that respondents might not understand the lottery, which could reduce the reliability of the results. In addition, participants might make inconsistent decisions by switching more than once. However, Anderson and Galinsky (2006) and Tanaka et al. (2010) dealt with these limitations by imposing strict monotonicity on revealed preferences and enforced transitivity. Several studies in the past have tried to establish a relationship between obesity and risk attitudes, such as de Oliveira et al. (2016), Borghans and Golsteyn (2006), Komlos et al. (2004), and Smith et al. (2005). However, none of these studies used the double MPL lottery, which is one of the main novelties of this study.

2.2 Time Preferences

Delay discounting can be defined as the extent to which people discount rewards (e.g. money, food, weight loss, etc.) as a function of having to wait for it (Reynolds et al., 2004). A low time discount rate indicates that an individual is patient and has self-control; on the contrary, a high time discount rate indicates that the individual is impatient and puts more emphasis on current gains over future rewards. Policies, especially fiscal policies, addressing obesity-related problems and its determinants, are likely to be flawed if there is a strong relationship between the rate of time preference and the propensity to become obese. Interventions need to factor these behavioural patterns into policy development and implementation.

Measurement approaches to discount rates vary due to: i) how surveys are administered; ii) the technique by which the discount rate is to be estimated; and (iii) whether rewards are real or hypothetical monetary choices. Surveys are usually administered in two ways: i) by questionnaire or ii) by a computerized method. Discount rates and present bias parameters are usually estimated by fitting an exponential discounting model (Kirby and Maraković, 1995; Myerson and Green, 1995), a hyperbolic model (Kahneman and Tversky, 1979; Mazur, 1987; Thaler and Shefrin, 1981), or a quasi-hyperbolic discount method (Benhabib et al., 2010). Hyperbolic and exponential discount models only measure the discount rate of money, while the quasi-hyperbolic discount model measures both the discount rate and present bias. The literature supports that exponential discounting performs poorly in the presence of experimental data (Frederick et al., 2002). As such, Laibson (1997) proposed a quasi-hyperbolic discounting model that performs better with field data. Moreover, previous literature supports that individuals are present bias and have high affinity toward high discount rates.

Tanaka et al. (2010) suggested a general time-preference model based on Benhabib et al's. (2010) experimental approach that is able to estimate three time-preference parameters: discount rates, present bias, and hyperbolicity. Moreover, their model also allows for comparing its performance in relation to the exponential, hyperbolic, and quasi-hyperbolic models mentioned above.

The literature also provides a few studies that have tried to relate time preferences to unhealthy behaviours (Appelhans et al., 2012; Leitch et al., 2013; Rollins et al., 2010), all of them supporting the existence of a strong relationship using different functional forms to estimate the discount parameter. This study is the first attempt to analyse the relationship between BMI and time preferences by adopting a flexible functional form, allowing us to jointly consider discount rates, present bias, and hyperbolicity.

3. Methodological framework

3.1 The sample

Our sample comprised 180 respondents from the Metropolitan Area of Barcelona (Spain). The sample was stratified taking into account the 2012 distribution of the population by BMI and age from the National Health Survey. Survey participants signed a letter of confidentiality before the start of the experiment and were paid 30 euros for completing the survey. Each participant completed the entire questionnaire in an average of 60–75 minutes. Out of the 180 respondents who completed the questionnaire, seven submitted incomplete questionnaires and were, therefore, discarded. Each survey covered detailed information on individual characteristics and participants' choices for risk- and time-preferences games. Respondents were asked to state their body mass index, which was validated after the experiment. The weight and height of the respondents were validated by trained personnel using a calibrated digital scale and stadiometer, respectively. BMI was calculated using the standard formula: kg/m^2. Participants were categorized into three groups: underweight[1] and normal weight group (<24.9); overweight group (25–29.9); and obesity group (>30.0) based on WHO criteria.

3.2 Risk Preferences

Under the PT, the individual's utility function can be expressed as follows:

$$PT(x, y; p) = pv(x) + (1 - p)v(y) \tag{1}$$

$$\text{where } v(x) = \begin{cases} x^{\sigma} & for\ x \geq 0 \\ -\lambda(-x^{\sigma}) & for\ x < 0 \end{cases} \tag{2}$$

$$\text{and } w(p) = exp[-(-\ln p)^{\gamma}] \tag{3}$$

PT(x, y; p) is the expected prospect value over binary prospects consisting of the outcome (x, y) with the corresponding probability (p, $1 - p$). In our experiment, (x, y; p) was specified for plan A and plan B in all scenarios. Note that the value function $v(x)$ should be estimated with x^{σ} for $x > 0$ or $-\lambda(-x^{\sigma})$ for $x < 0$. The parameter σ represents the concavity of the value function (risk aversion)—high values indicate respondents are risk loving; λ represents the degree of loss aversion—high values indicating respondents are more loss averse; and γ is a proxy for the nonlinear probability weighting.

[1] The underweight and normal weight categories were combined due to the lower number of participants (2% of the sample) falling into the underweight category.

Experiment design

To elicit the three PT parameters (σ, λ, and γ), respondents were given three series of games that contained 35 pair-wise choices. Appendix A shows the three series of games. Series 1 consists of 14 games. Series 2 consists of 14 games, and Series 3 consists of seven games. In each game, the respondent is offered two plans: plan A and plan B. For instance, in series 1, the first game shows that plan A offers 30% chance of receiving 4 euros and 70% chance of receiving 1 euro, while plan B offers 10% chance of receiving 6.8 euros and 90% chance of receiving 0.5 euros. Since there are 14 games, each respondent has to decide whether he or she prefers plan A or plan B for each row[2].

Following Tanaka et al. (2010), monotonicity was imposed on the respondents' choice decisions, indicating that if respondent *i* switches at row q for series 1, we conclude that he/she prefers plan A over plan B at row q-1 and prefers plan B over plan A at row q. Thus, each respondent had three options: a) choose plan A throughout all games; b) choose plan B throughout all games; and c) choose plan A for a certain number of games and then switch to plan B for the rest. Individuals who are more averse to loss would choose plan A a greater number of times over plan B. Series 2 followed the same procedure as in series 1. The loss-aversion parameter is calculated using series 3. Contrary to the previous two series, payoffs in this series were either positive or negative.

After the respondent completed the experiment, two bingo cages were used to determine the money that each respondent took home. The first bingo cage contained 35 numbered balls (indicating which row/question to play), while the second contained 10 numbered balls (indicating the probability). If ball number 10 was randomly selected from the first bingo cage, this meant that the subject would play row/question 10 out of the 35 questions. Once the question has been determined, a ball would be drawn from the 10 numbered balls in the second bingo and the selected question was played according to the subject's plan. For instance, if the subject drew the ball number 2 from the second bingo and had previously chosen plan A, he or she would have earned 4 Euro (or 0.5 Euro if the respondent had chosen plan B).

Calculating risk parameters

The switching points from series 1 and series 2 are used to estimate the curvature of the utility function (risk aversion) and the nonlinear probability-weighting parameter of each

[2] The maximum amount offered in Plan B was 170€, equivalent to the regulated minimum salary for one week.

participant. Calculated parameter estimates[3] of risk aversion and probability weighting for different combinations of the switching points in series 1 and series 2 are shown in Table 1 and Table 2, respectively. For instance, from Table 1, if the respondent switched at game 5 in series 1 and game 3 in series 2, then the corresponding risk aversion parameter is 1.0, indicating risk neutral. Also, for the probability-weighting parameter, if the respondent switched at game 5 in series 1 and game 3 in series 2, then the corresponding risk aversion parameter is 0.8, indicating overweighting of low probabilities.

Paste Table 1 here

Paste Table 2 here

After obtaining the risk-aversion and probability-weighting parameters from both series 1 and series 2, we can estimate the loss-aversion parameter using the switching points in series 3. This was achieved by writing out an inequality for the switching points of series 3 and introducing the risk parameter into the equation 1 (see Liu and Huang, 2013).

3.3 Time preferences

Following Benhabib et al. (2004) and Tanaka et al. (2010), we have estimated a general time-preference model that nested other models that have been traditionally used in the literature to elicit time preferences: exponential, hyperbolic, and quasi-hyperbolic discounting. Under the general framework, the present value of income, y, at time t>0 adopts the following expression:

$$y\beta(1-(1-\theta)rt)^{1/(1-\theta)} \tag{4}$$

where r, β, and θ are the time discounting, present bias, and hyperbolicity parameters of the time preference function. If $\beta = 1$, as θ approaches 1, then the discounted value of y reduces to exponential discounting (e^{-rt}) in the limit. However, if $\beta = 1$, when $\theta = 2$, the discounted value reduces to a hyperbolic discounting model (1/(1+rt)). In the same way, if $\theta = 1$ (in the limit) and β is free, the discounted value reduces to a quasi-hyperbolic

[3] Example when a respondent switch from plan A to B at the fifth question in series 1 and at the third question in series 2, the following inequalities should hold. Average estimates are shown in Table 1 and Table 2.
$4^{\sigma}\exp[-(-\ln .3)^{\alpha}]+1^{\sigma}\exp[-(-\ln .7)^{\alpha}]>9.3^{\sigma}\exp[-(-\ln .1)^{\alpha}]+0.5^{\sigma}\exp[-(-\ln .9)^{\alpha}]$,
$4^{\sigma}\exp[-(-\ln .3)^{\alpha}]+1^{\sigma}\exp[-(-\ln .7)^{\alpha}]<10.6^{\sigma}\exp[-(-\ln .1)^{\alpha}]+0.5^{\sigma}\exp[-(-\ln .9)^{\alpha}]$,
$4^{\sigma}\exp[-(-\ln .9)^{\alpha}]+3^{\sigma}\exp[-(-\ln .1)^{\alpha}]>5.6^{\sigma}\exp[-(-\ln .7)^{\alpha}]+0.5^{\sigma}\exp[-(-\ln .3)^{\alpha}]$,
$4^{\sigma}\exp[-(-\ln .9)^{\alpha}]+3^{\sigma}\exp[-(-\ln .1)^{\alpha}]<5.8^{\sigma}\exp[-(-\ln .7)^{\alpha}]+0.5^{\sigma}\exp[-(-\ln .3)^{\alpha}]$.

discounting model (βe^{-rt}). These restrictions imposed on the general model allow us to estimate and compare four time discounting models.

Experiment Design

The basic experimental design for eliciting individual discount rates and present bias follows the approach of Tanaka et al. (2010). The experiment started by reading the following instruction to participants: "In this game, you will receive money either today or sometime in the future, depending on the choices you make. There are 75 games (Appendix B). In each game, we will offer you two plans: plan A or plan B. We would like you to choose either plan A or plan B for each question." The experiment lasted about 35 minutes. A trusted agent[4] was chosen who would keep the money until the delayed delivery date to ensure subjects believed the money would be delivered. The agents were instructed to deliver the money to the respondent, which tried to equalize the pure transaction costs of receiving money immediately (i.e. at the end of the experiment) or in the future. In the latter case, the participant placed the money into an envelope, sealed it, and wrote his (her) name and the date of delivery on the envelope. All envelopes were given to the trusted agency.

After the instruction, each respondent in our experiment was given payoff tables as shown in appendix B to elicit their discount rates for money and present bias. Each payoff matrix gives the respondent the choice to choose between plan A, corresponding to an amount *y* euro over a period of 3 days to 3 months, and plan B to earn an amount *x* today. Whilst the amount earned in option A remains constant, the amount earned increases in option B as the respondent moves down the five games in each of the 15 series considered. As in the previous experiment, to determine the amount of money the respondent took home and when, a bingo cage containing 75 numbered balls was used. At the end of the experiment, each respondent was asked to draw one ball to determine which game would be played for real money. The amount earned varied between 0.5 euros and 30 euros. As an example, from appendix B, suppose that the i-th respondent drew ball 21. If he or she had chosen plan A, then he/she would be paid 30 euros in 1 month (the money was placed in an envelope, was closed and signed by the respondent, and delivered to the trusted agent). However, if he/she had chosen plan B, then he/she received 5 euros on the same day of the experiment.

[4] In this study, the trusted agent was the recruitment company, as normally citizens participating in our experiment are recruited between 8 to 12 times during the year, by this company, to participate in other experiments.

The probability that respondent *i* will choose an immediate reward *x* over the delayed reward *y* in *t* days by P(x>(y,t)) was described by the logistic function:

$$P(x > (y,t)) \frac{1}{1+\exp(-\mu(x-y)\beta(1-(1-\theta)rt)^{1/1-\theta}))} \quad (5)$$

The time-preference parameters r, β, and θ are recovered from the logistic regression function, where μ is the noise coefficient.

4. Results

4.1 Some preliminary results

The main household characteristics of the sample used in this paper are shown in Table 3. About 69% of the respondents in our dataset were married, the remaining being single, divorced, or widowed. More than 90% of the respondents had more than a basic education: trained professionals or secondary school or university graduates. About 32% of the respondents earned the average salary in the Metropolitan Area of Barcelona (Spain) with the rest earning more than the average salary. The average weight and height in our sample were 69.88 kg and 1.66 meters, respectively, leading to an average BMI of 25.36 kg/m^2.

Paste Table 3 here

The BMI distribution among the sample is shown in Figures 1 and 2. The distribution was skewed to the right, indicating that the majority of the respondents had a BMI greater than the 25 kg/m^2. Only one respondent had a BMI greater than 40 kg/m^2. Overweight and obese people represented 37.8 and 10.9 percent of the sample, respectively. These figures are close to those estimated for the Barcelona population in 2012 by the Public Health Department[5] (35.2% of the populace were overweight and 13.8% were obese).

Paste Figure 1 here

Paste Figure 2 here

In relation to risk attitudes, Table 4 shows the average number of choices made by respondents in series 1 and 2 (see Appendix A). The numbers in the first column and row correspond to the switching points in series 1 and 2. The frequency numbers in the table represent the number of subjects who switched at that particular combination of switching points in series 1 and 2. The bolded figures correspond to the number of respondents whose choices would correspond to those predicted by the expected utility. As can be observed, for

[5] https://www.diba.cat/es/web/entorn-urba-i-salut/sobrepes-i-obesitat

this particular experiment, the results indicate that the majority of the respondents made their choices outside the expected utility (EU) theory.

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The calculated prospect theory (PT) parameters are shown in Table 5. The average risk-aversion parameter was 0.588, indicating that, on average, respondents are risk averse. The average loss-aversion parameter is 3.67, which also indicates that, globally, respondents are loss averse. The average of the nonlinear probability-weighting parameter is 0.69 (less than 1), meaning that the majority of the respondents have a tendency to overweigh low probabilities. According to Tanaka et al. (2010), if γ =1 and $\lambda = 1$, then the utility function reduces to the EU function. We strongly reject this hypothesis in our experiment, indicating that PT is the adequate framework to analyse risk preferences within our sample. In addition to the calculated sample averages, Figure 3 and Figure 4 show the normal distribution of the risk-aversion and loss-aversion coefficients among participants, respectively. The distribution of the risk-aversion coefficient shows an affinity toward lower risk since the majority of the respondents are found on the left side of the normal distribution. In relation to loss aversion, Figure 4 does not support the absence of loss aversion since the coefficient is above 0. Most respondents have a loss-aversion coefficient between 0.06 and 11.79; larger loss-aversion coefficients indicate a higher aversion to losses.

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4.2 Risk Preferences and Body Mass Index

To analyse the relationship between risk preferences and BMI, we estimated, by ordinary least squares, three regressions of the curvature of the utility function (σ), the loss aversion parameter (λ), and probability-weighting parameter (γ) against BMI, while controlling for socioeconomic characteristics. Robust standard errors are reported for all three equations in Table 6. As can be observed, we have found a significant positive relationship between risk aversion and BMI indicating that less risk averse persons have a higher propensity to develop higher BMI. This result is consistent with previous studies by Anderson and Mellor (2008) and de Oliveira et al. (2016). This results also confirms the rational addiction theory, which postulate that less risk averse individuals are willing to take the risk of eating unhealthy foods despite the negative health consequences. No significant relationship was found between loss aversion and probability weighting and BMI. This means that even though obese people are less risk averse, the propensity to become obese is independent of subjects' aversion to loss.

Some control covariates had significant relationships with the curvature of the utility function (σ), the loss-aversion parameter (λ), and the probability-weighting parameter (γ). The strongest effects suggest older subjects were more risk averse, while lower income subjects were less risk-averse. These results confirm hypothetical studies that found older adults to be more risk averse (Botwinick and Thompson, 1966; Kogan and Wallach, 1961). The relationship between income and risk tend to contradict previous studies that found that risk aversion reduces some as income increases (Barsky et al., 1997; Donkers et al., 2001). Studies like Levin et al. (1988) found that women are more risk averse than men. However, we did not find any significant results.

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4.3 Time Preferences and Body Mass Index

A significant share of previous literature that tried to elicit individual time preferences was based on the estimation of an exponential discounting model. However, this model has often been rejected by experimental and field data (Frederick et al., 2002). The results in Table 7 show that we have estimated four time-preference models, with equations 1–3 being nested in equation 4 based on restrictions imposed on beta *(β)* and/or theta *(θ)*. The statistical performance, in terms of the R^2, improves from equation 1 to equation 3. This suggests that the quasi-hyperbolic and the general model with unrestricted beta and theta are superior to the exponential and hyperbolic models. The advantage of the quasi-hyperbolic model over both the exponential and hyperbolic model is that, with beta being unrestricted, the quasi-hyperbolic model allows the estimation of both present bias and discount rate. Similarly, the general model goes further to estimate hyperbolicity *(θ)* of the preference model (see Tanaka et al., 2010). From the general model, the parameters for discount rate, present bias, and hyperbolicity are 0.006, 0.82, and 3.513, respectively. This implies that our respondents should trade 78.99 euros today for 100 euros in a week and 71.27 today for 100 euros in one month. However, estimating the general model with unrestricted θ does not improve R^2 compared with the estimation of the quasi-hyperbolic model, so we only focused our attention on the quasi-hyperbolic discounting.

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To identify the relationship between the time preference and subjects' demographic covariates, we introduced BMI and control covariates into the quasi-hyperbolic time-preference model. The quasi-hyperbolic time-preference parameters were derived using the logistic model described below:

$$(x > (y,t)) \frac{1}{1+\exp(-\mu(x-y\beta exp[\,rt]))} \qquad (6)$$

where $\beta = \beta_0 + \sum \beta_i X_i$, $r = r_0 + \sum r_i X_i$, X_i are demographic variables described above. β_i and r_i are the estimated coefficients associated with the X_i.

Estimated parameters from both equations are shown in Table 8. As can be observed, BMI is positively correlated with impatience (higher discount rates). The implication is that people who are impatient have a tendency to develop higher BMI. This result is consistent with that from Borghans and Golsteyn (2006); Scharff (2009); Smith et al. (2005); Weller et al. (2008); and Zhang and Rashad (2008) who showed that impatience positively correlates with a higher BMI.

Among the socioeconomic covariates, people with only a primary education are more impatient as compared to people with a secondary and university education. Fuchs (1982), Huffman et al. (2017) and Tanaka et al. (2010) also found lower discount rates among highly educated people. This is plausible as people who drop out of school usually prefer to work and earn an income as soon as possible seeing the benefit of higher education as delaying the gratification from today's income. Finally, we have found that females are more impatient than males in the study area, while Dittrich and Leipold (2014) showed the contrary.

Present bias is significant at the 1% level, suggesting the existence of present bias among respondents. Tanaka et al. (2010) also found the existence of present bias among farmers in Vietnam. While Courtemanche et al. (2015) predicted that present bias increases with BMI, this study shows that present bias increases with BMI only among women.

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5. Conclusions

Obesity in Spain is on the rise despite the numerous sociopolitical and socioeconomic policies that have been implemented during the past decades. The framework of rational addiction models the behaviour of individuals from the context of risk and time preferences.

Therefore, many hypothetical studies have suggested a strong correlation between risk, time preferences, and obesity rates. However, no such empirical study has been carried out in Spain to ascertain whether such a relationship exists.

The aim of this study was to investigate and ascertain the relationship between risk attitudes, time preferences, and BMI in Spain. We used the experimental approach of Tanaka et al. based on the prospect theory framework to estimate three risk preference parameters: risk aversion, loss aversion, and probability weighting. Similarly, based on the experimental approach of Tanaka et al. and the empirical framework of Benhabib et al. 2007, we estimated four time-preference models (exponential, hyperbolic, quasi-hyperbolic, and the general model); in the quasi-hyperbolic model, we tested for the relationships between present bias and time discounting and obesity.

The experimental data shows the existence of risk aversion, aversion toward losses, and impatience among our respondents. BMI was significant and positively associated with risk aversion. In addition, impatience was found to be highly associated with people with a high BMI. Our results also confirm that risk and time preferences are independent of the methodological framework. No significant relationship exists between probability weighting, loss aversion, and present bias and BMI among our subjects.

Considering the importance of risk and time preferences on the development of obesity, economic policies should begin to factor such individual heterogeneity into economic policy instruments. For instance, policy recommendations that suggest taxes or fiscal policies can influence consumer behaviour leading to a reduction in obesity should consider psychological differences in demand modelling. In addition, the government should develop policies targeted at specific segments of the society instead of a one-for-all policy goal that yields little or no results.

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Table 1 Switching point (question) in Series 1 and 2, and approximations of σ (parameter for the curvature of power value function/risk parameter)

σ	**Switching point for series 1**													
Series 2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Never
1	1.50	1.40	1.35	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.65	0.55	0.50
2	1.40	1.30	1.25	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.60	0.55	0.50
3	1.30	1.20	1.15	1.10	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45
4	1.20	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45	0.40
5	1.15	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.55	0.50	0.45	0.40	0.35
6	1.05	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35
7	1.00	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30
8	0.95	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25
9	0.90	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20
10	0.85	0.80	0.75	0.70	0.65	0.60	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20
11	0.80	0.70	0.65	0.60	0.65	0.55	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15
12	0.75	0.65	0.60	0.55	0.50	0.50	0.45	0.40	0.35	0.30	0.25	0.20	0.20	0.15	0.10
13	0.65	0.60	0.55	0.50	0.45	0.45	0.40	0.35	0.30	0.25	0.20	0.15	0.15	0.10	0.10
14	0.60	0.55	0.50	0.45	0.40	0.35	0.35	0.30	0.25	0.20	0.15	0.10	0.10	0.10	0.05
Never	0.50	0.45	0.40	0.40	0.35	0.30	0.30	0.25	0.20	0.15	0.10	0.10	0.05	0.05	0.05

Table 2 Switching point (question) in Series 1 and 2, and α (probability sensitivity parameter in Prelec's weighting function)

α	**Switching question in series 1**														
Series 2	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Never
1	0.60	0.75	0.75	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30	1.40	1.45
2	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.35	1.40
3	0.55	0.60	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25	1.30
4	0.50	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20	1.25
5	0.45	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15	1.20
6	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10	1.15
7	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05	1.10
8	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00	1.05
9	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00
10	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
11	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
12	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85
13	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80
14	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75
Never	0.05	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.45	0.55	0.55	0.65	0.60

Table 3 Household characteristic (%)

Variables	Mean	Std. Error	[95% Conf.	Interval]
Probability Weighting	0.64	0.03	0.59	0.69
Risk Aversion Coefficient	0.58	0.03	0.52	0.63
Loss Aversion Coefficient	3.67	0.30	3.09	4.26
Married	0.69	0.04	0.62	0.76
Age	46.38	1.11	44.20	48.57
Basic Education	0.08	0.02	0.04	0.12
Income Less 1500	0.32	0.04	0.25	0.39
Income Between 1500 And 2500	0.42	0.04	0.34	0.49
Income Between 2500 And 4000	0.19	0.03	0.13	0.25
BMI	25.36	0.32	24.53	25.80
Body Weight	69.88	1.12	67.67	72.09
Body Height	1.66	0.01	1.65	1.68

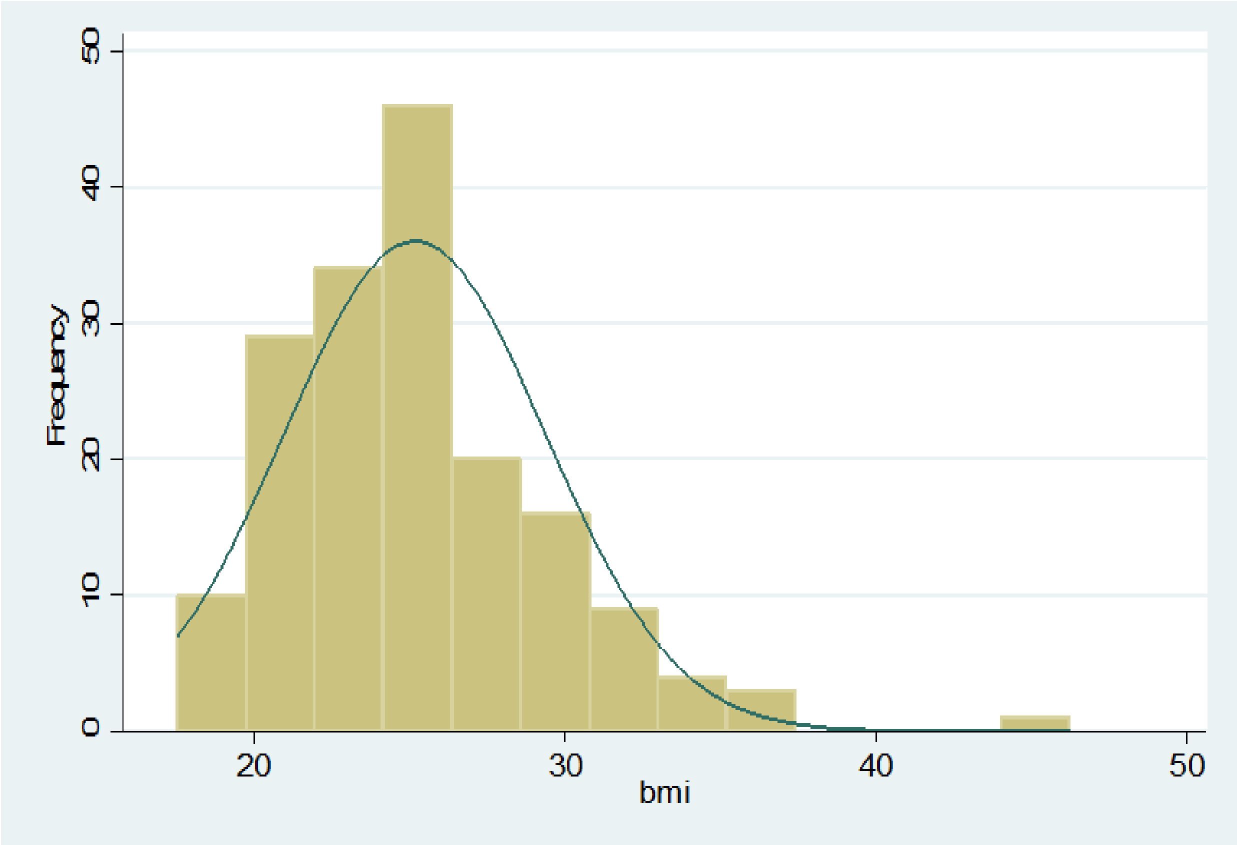

Figure 1 Normal and frequency distribution by BMI

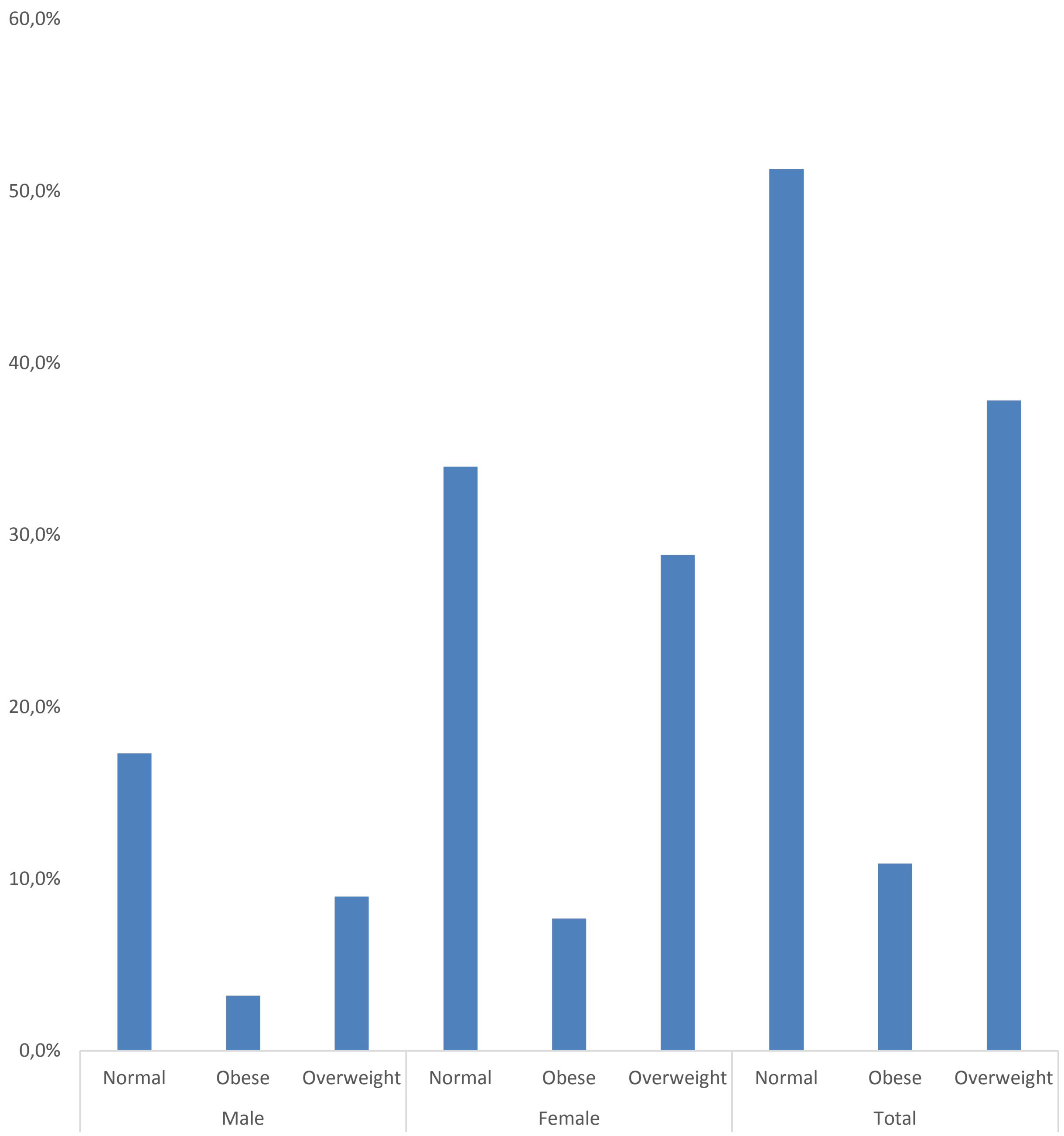

Figure 2 Distribution of respondents by BMI

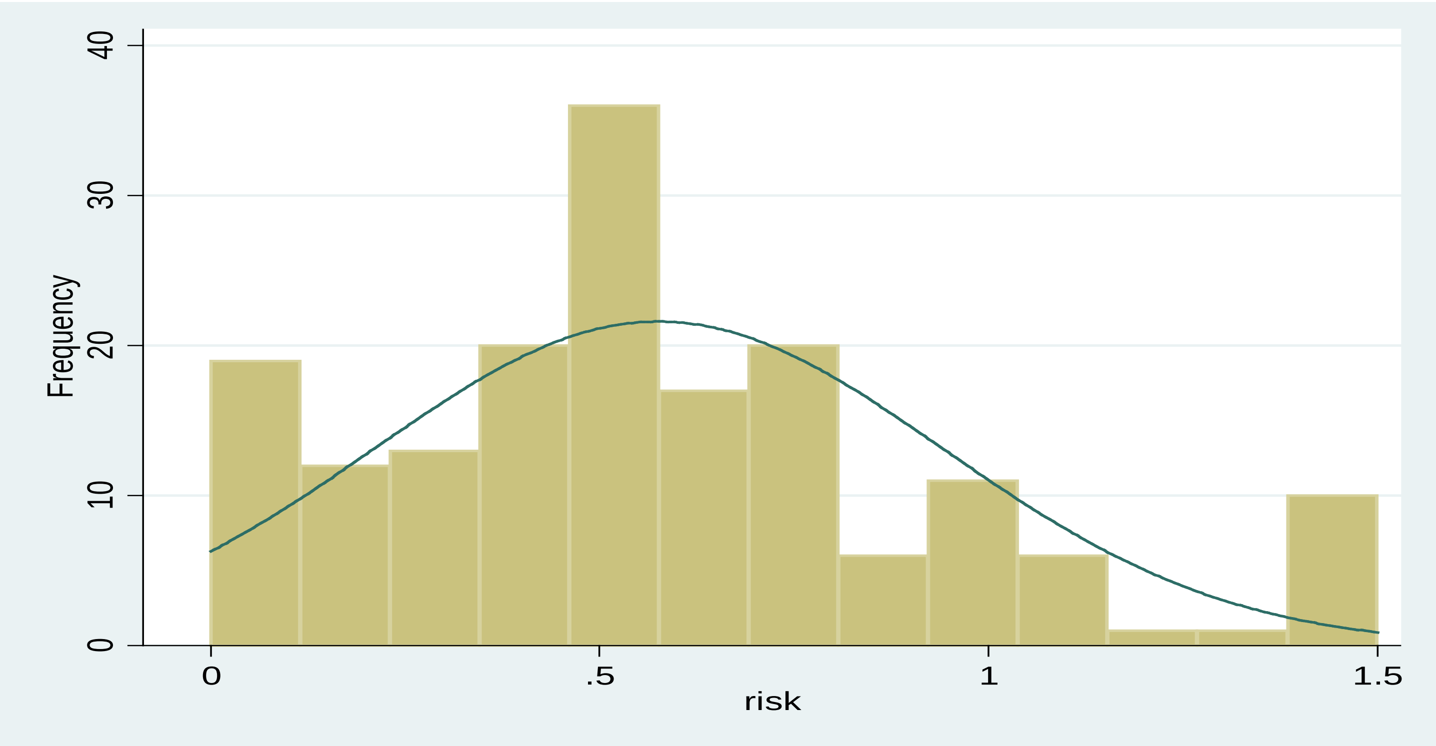

Figure 3 Normal and frequency distribution by risk aversion coefficient

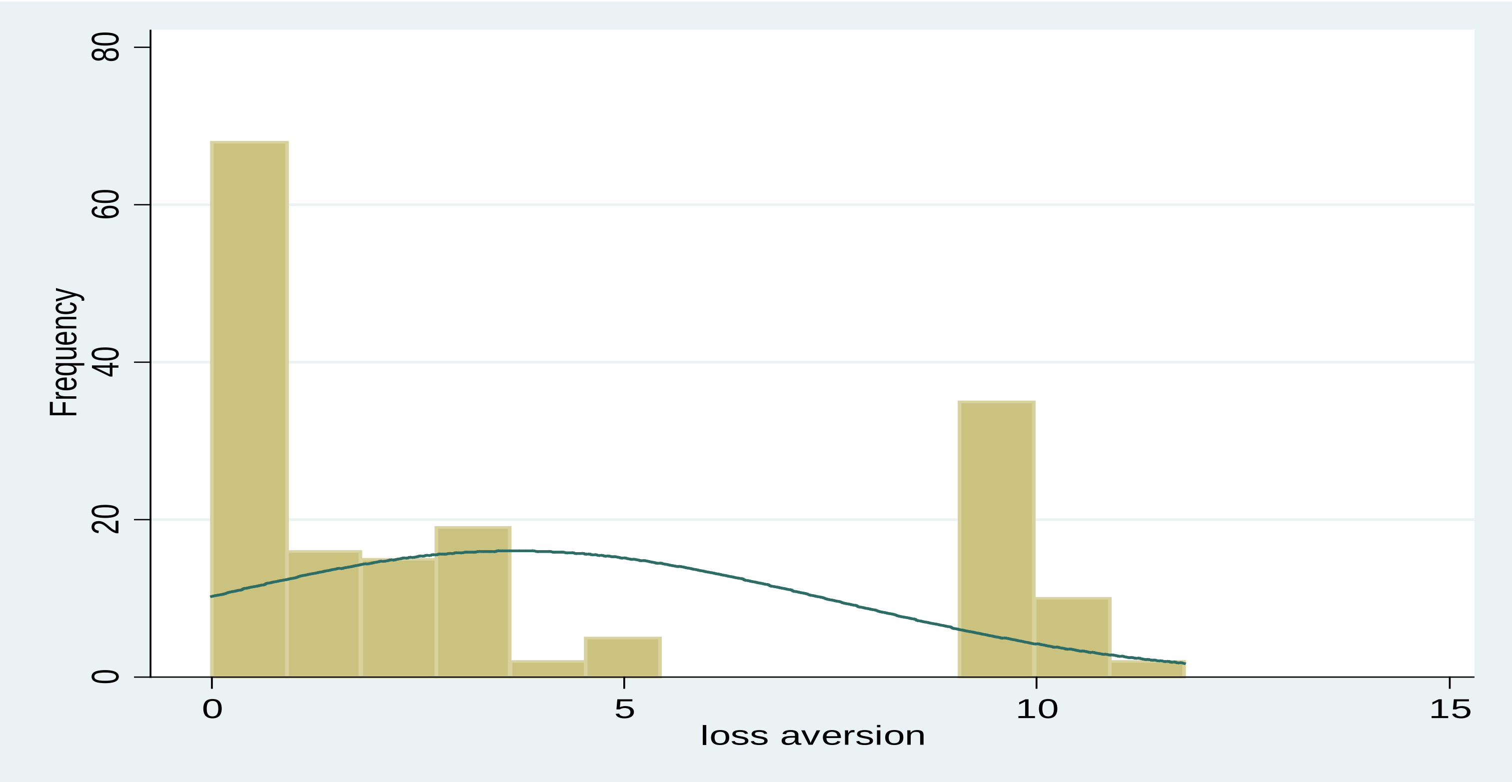

Figure 4 Normal and frequency distribution of loss aversion

Table 4 Distribution of Switching Points in Series 1 and Series 2

		Series 1											
	Switching Points	**Never**	**1**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
	Never	6	10		2	2	3	4	3	3	3	1	1
	1	6	10		1	3	**2**	3	2	2	3	2	1
	3		1	1								1	
	4	1	1	**1**	1				1	2			
	5		1			1							
	6					2		1					
	7				1	1		2		1	1		
Series 2	**8**	1	3	1		3	2		4				1
	9		1		1	1	4	2	1		1		
	10	1			1	2		3	4				
	11						1	1	1				
	12	1	1		3	1	1	3	1		1	1	1
	13				1							2	
	14						1				1	2	1

Table 5 Risk preference parameters

Variables	Mean	Std. Error	[95% Conf.	Interval]
Probability Weighting	0.64	0.03	0.59	0.69
Risk Aversion Coefficient	0.58	0.03	0.52	0.63
Loss Aversion Coefficient	3.67	0.30	3.09	4.26

Table 6 —Correlations with determinants of Risk aversion, Loss aversion and probability sensitivity parameter in Prelec's weighting function

Explanatory Variables	**Risk aversion**	**Loss aversion**	**Probability weighting**
Body Mass Index	0.014 (-0.008)*	0.000 (0.082)	0.002 (0.007)
Age	-0.003 (-0.002)**	0.057 (0.017)***	0.000 (0.002)
Married =1	0.023 (-0.063)	0.995 (0.711)	0.023 (0.066)
Gender (Female=1)	-0.103 (-0.065)	-0.660 (0.717)	-0.087 (0.060)
Education(Basic =1)	0.110 (-0.119)	0.574 (1.237)	-0.189 (0.098)*
Income (Less 1500 =1)	0.111 (-0.056)**	0.409 (0.713)	0.078 (0.064)
Constant	0.399 (-0.207)*	0.562 (2.108)	0.622 (0.194)***

*,**,*** respresent significant at 10%, 5%, 1%, respectively.

Table 7 Comparison of Exponential, Hyperbolic, and Quasi-Hyperbolic Discounting Models

choice	Exponential	Hyperbolic	Quasi-hyperbolic	Equation (1)
Meu	0.093***	0.093***	0.119***	0.119***
Rate	0.009***	0.009***	0.004***	0.006***
Beta			0.800***	0.816***
Theta				3.513***
Adjusted R-Squared	0.5217	0.5231	0.5278	0.5278

*** represent 1% significant. p-values derived from robust standard errors

Table 8 —Correlations with Present Bias and Discount Rates (OLS)

	Present Bias	Discount Rate
µ	0.130***	
Beta/Rate	1.064***	-0.007
Gender*BMI	0.011*	-0.033
Married	0.010	-0.167
Gender	-0.296*	0.967*
Age	-0.004	-0.0002
BMI	-0.006	0.038**
Primary	0.024	0.704**
Age square	0.00002**	0.00006

*Coefficients of discount rate are multiplied by 100. *,**,*** respresent significant at 10%, 5%, 1%, respectively.*

Appendix A

Series 1	Plan A	Plan B
1	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	6,8€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
2	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	7,5€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
3	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	8,3€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
4	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	9,3€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
5	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	10,6€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
6	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	12,5€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
7	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	15,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
8	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	18,5€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
9	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	22,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
10	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	30,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
11	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	40,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
12	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	60,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
13	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	100,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
14	4€ Yes ①②③ 1€ Yes ④⑤⑥⑦⑧⑨⑩	170,0€ Yes ① 0,5€ Yes ②③④⑤⑥⑦⑧⑨⑩
	I choose Plan A for Questions 1-____	I choose Plan B for Questions___ -14
Series 2	Plan A	Plan B
15	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	5,4€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
16	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	5,6€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
17	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	5,8€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
18	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	6,0€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
19	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	6,2€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
20	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	6,5€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
21	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	6,8€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
22	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	7,2€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩

23	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	7,7€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
24	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	8,3€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
25	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	9,0€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
26	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	10,0€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
27	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	11,0€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
28	4€ Yes ①②③④⑤⑥⑦⑧⑨ 3€ Yes ⑩	13,0€ Yes ①②③④⑤⑥⑦ 0,5€ Yes ⑧⑨⑩
	I choose Plan A for Questions 15 - ____	I choose Plan B for Questions___ - 28
Series 3	Plan A	Plan B
29	Gain 2,5€ Yes ①②③④⑤ Loss 0,4€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 2,1€ Yes ⑥⑦⑧⑨⑩
30	Gain 0,4€ Yes ①②③④⑤ Loss 0,4€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 2,1€ Yes ⑥⑦⑧⑨⑩
31	Gain 0,1€ Yes ①②③④⑤ Loss 0,4€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 2,1€ Yes ⑥⑦⑧⑨⑩
32	Gain 0,1€ Yes ①②③④⑤ Loss 0,4€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 1,6€ Yes ⑥⑦⑧⑨⑩
33	Gain 0,1€ Yes ①②③④⑤ Loss 0,8€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 1,6€ Yes ⑥⑦⑧⑨⑩
34	Gain 0,1€ Yes ①②③④⑤ Loss 0,8€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 1,4€ Yes ⑥⑦⑧⑨⑩
35	Gain 0,1€ Yes ①②③④⑤ Loss 0,8€ Yes ⑥⑦⑧⑨⑩	Gain 3,0€ Yes ①②③④⑤ Loss 1,1€ Yes ⑥⑦⑧⑨⑩
	I choose Plan A for Questions 29 - ____	I choose Plan B for Questions___ - 35

Appendix B

	Plan A	Plan B
1	Receive 12€ in a week	Receive 2€ today
2	Receive 12€ in a week	Receive 4€ today
3	Receive 12€ in a week	Receive 6€ today
4	Receive 12€ in a week	Receive 8€ today
5	Receive 12€ in a week	Receive 10€ today
I choose Plan A for Questions1 until ___		I choose Plan B for Questions___ until 5
	Plan A	**Plan B**
6	Receive 12€ in a month	Receive 2€ today
7	Receive 12€ in a month	Receive 4€ today
8	Receive 12€ in a month	Receive 6€ today
9	Receive 12€ in a month	Receive 8€ today
10	Receive 12€ in a month	Receive 10€ today
I choose Plan A for Questions 6 until ___		I choose Plan B for Questions___ until 10
	Plan A	**Plan B**
11	Receive 12€ in 3 months	Receive 2€ today
12	Receive 12€ in 3 months	Receive 4€ today
13	Receive 12€ in 3 months	Receive 6€ today
14	Receive 12€ in 3 months	Receive 8€ today
15	Receive 12€ in 3 months	Receive 10€ today
I choose Plan A for Questions11 until___		I choose Plan B for Questions___ until 15
	Plan A	**Plan B**
16	Receive 30€ in a week	Receive 5€ today
17	Receive 30€ in a week	Receive 10€ today
18	Receive 30€ in a week	Receive 15€ today
19	Receive 30€ in a week	Receive 20€ today
20	Receive 30€ in a week	Receive 25€ today
I choose Plan A for Questions16 until___		I choose Plan B for Questions___ until 20
	Plan A	**Plan B**
21	Receive 30€ in a month	Receive 5€ today
22	Receive 30€ in a month	Receive 10€ today
23	Receive 30€ in a month	Receive 15€ today
24	Receive 30€ in a month	Receive 20€ today
25	Receive 30€ in a month	Receive 25€ today
I choose Plan A for Questions 21 until___		I choose Plan B for Questions___ until 25
	Plan A	**Plan B**
26	Receive 30€ in 3 months	Receive 5€ today
27	Receive 30€ in 3 months	Receive 10€ today
28	Receive 30€ in 3 months	Receive 15€ today
29	Receive 30€ in 3 months	Receive 20€ today
30	Receive 30€ in 3 months	Receive 25€ today
I choose Plan A for Questions 26 until ___		I choose Plan B for Questions___ until 30

	Plan A	Plan B
31	Receive 3€ in a week	Receive 0,5 today
32	Receive 3€ in a week	Receive 1€ today
33	Receive 3€ in a week	Receive 1,5€ today
34	Receive 3€ in a week	Receive 2€ today
35	Receive 3€ in a week	Receive 2,5€ today
I choose Plan A for Questions 31 until___		I choose Plan B for Questions___ until 35
	Plan A	**Plan B**
36	Receive 3€ in a month	Receive 0,5 today
37	Receive 3€ in a month	Receive 1€ today
38	Receive 3€ in a month	Receive 1,5€ today
39	Receive 3€ in a month	Receive 2€ today
40	Receive 3€ in a month	Receive 2,5€ today
I choose Plan A for Questions 36 until___		I choose Plan B for Questions___ until 40
	Plan A	**Plan B**
41	Receive 3€ in 3 months	Receive 0,5 today
42	Receive 3€ in 3 months	Receive 1€ today
43	Receive 3€ in 3 months	Receive 1,5€ today
44	Receive 3€ in 3 months	Receive 2€ today
45	Receive 3€ in 3 months	Receive 2,5€ today
I choose Plan A for Questions 41 until___		I choose Plan B for Questions___ until 45
	Plan A	**Plan B**
46	Receive 24€ in 3 days	Receive 4€ today
47	Receive 24€ in 3 days	Receive 8€ today
48	Receive 24€ in 3 days	Receive 12€ today
49	Receive 24€ in 3 days	Receive 16€ today
50	Receive 24€ in 3 days	Receive 20€ today
I choose Plan A for Questions 46 until___		I choose Plan B for Questions___ until 50
	Plan A	**Plan B**
51	Receive 24€ in 2 weeks	Receive 4€ today
52	Receive 24€ in 2 weeks	Receive 8€ today
53	Receive 24€ in 2 weeks	Receive 12€ today
54	Receive 24€ in 2 weeks	Receive 16€ today
55	Receive 24€ in 2 weeks	Receive 20€ today
I choose Plan A for Questions 51 until___		I choose Plan B for Questions___ until 55
	Plan A	**Plan B**
56	Receive 24€ in 2 months	Receive 4€ today
57	Receive 24€ in 2 months	Receive 8€ today
58	Receive 24€ in 2 months	Receive 12€ today
59	Receive 24€ in 2 months	Receive 16€ today
60	Receive 24€ in 2 months	Receive 20€ today
I choose Plan A for Questions 56 until___		I choose Plan B for Questions___ until 60

	Plan A	Plan B
61	Receive 6€ in 3 days	Receive 1€ today
62	Receive 6€ in 3 days	Receive 2€ today
63	Receive 6€ in 3 days	Receive 3€ today
64	Receive 6€ in 3 days	Receive 4€ today
65	Receive 6€ in 3 days	Receive 5€ today
I choose Plan A for Questions 61 until___		I choose Plan B for Questions___ until 65

	Plan A	Plan B
66	Receive 6€ in 2 weeks	Receive 1€ today
67	Receive 6€ in 2 weeks	Receive 2€ today
68	Receive 6€ in 2 weeks	Receive 3€ today
69	Receive 6€ in 2 weeks	Receive 4€ today
70	Receive 6€ in 2 weeks	Receive 5€ today
I choose Plan A for Questions 66 until___		I choose Plan B for Questions___ until 70

	Plan A	Plan B
71	Receive 6€ in 2 months	Receive 1€ today
72	Receive 6€ in 2 months	Receive 2€ today
73	Receive 6€ in 2 months	Receive 3€ today
74	Receive 6€ in 2 months	Receive 4€ today
75	Receive 6€ in 2 months	Receive 5€ today
I choose Plan A for Questions 71 until___		I choose Plan B for Questions___ until 75

1