Matteo M. Galizzi and Marisa Miraldo

Are you what you eat? Healthy behaviour and risk preferences

Article (Published version) (Refereed)

Original citation:
Galizzi, Matteo M. and Miraldo, Marisa (2017) *Are you what you eat? Healthy behaviour and risk preferences.* The B.E. Journal of Economic Analysis & Policy, 17 (1). ISSN 2194-6108

DOI: http://dx.doi.org/10.1515/bejeap-2016-0081

Matteo M. Galizzi[1] / Marisa Miraldo[2]

Are You What You Eat? Healthy Behaviour and Risk Preferences

[1] Department of Social Policy, London School of Economics and Political Science, Old 2.35 Old Building Houghton Street, London WC2A 2AE, United Kingdom of Great Britain and Northern Ireland, E-mail: M.M.Galizzi@lse.ac.uk
[2] Imperial Business School, Imperial College London, SW72AZ London, United Kingdom of Great Britain and Northern Ireland, E-mail: m.miraldo@imperial.ac.uk

Abstract:
We elicit and estimate risk preferences for a pool of young adults in the UK, and explore their links with healthy eating and risky health behaviours. We construct the *Healthy Eating Index* (*HEI*) as an overall indicator of nutritional quality, and we use it to complement the body mass index *BMI*. While for females we find no significant association between the *BMI* and risk preferences, males with high *BMI* appear more risk-seeking. However, this association disappears when controlling for the quality of the diet. For males, the *HEI* is significantly associated with risk preferences. Males smoking status is not associated with risk preferences.

Keywords: risk aversion, healthy eating index, risky health behaviour, risk preferences
DOI: 10.1515/bejeap-2016-0081

1 Introduction

In OECD countries young adults are the segment of the population at higher risk of starting indulging in unhealthy behaviour with potential long-term consequences. The case of the UK is emblematic: most of the current 8.5 million of adult smokers started smoking at around college age and around 52 % of male and 43 % of female college students, respectively, drink alcohol above recommended levels (); the quality of diet over the lifetime reaches its poorest score between 15 and 29 years of age, especially among young men (Griffith et al., 2012a); nearly 55 % and 70 % of 20-years-old men and women, respectively, are predicted to be overweight or obese by 2050 (Stamatakis et al. 2010). Obesity in early adulthood, moreover, is strongly linked with excess weight and a range of diseases in later life, with associated long-term medical costs ().

Recent research has explored possible associations of risky health habits with experimental measures for risk preferences among both adults and children. The current evidence is mixed, though. For example, a recent review of the literature on risk preferences and smoking (Greiner 2004) shows that some papers find a correlation with proxies for risk aversion (Holt and Laury 2005), although the effect is often marginally significant, not robust to changes in the definition of 'smoker', and counterintuitive (i. e. smokers being more risk averse) (Johansson et al., 2009; Janssen, Katzmarzyk & Ross, 2004). An equal number of papers, however, fail to find significant association between risk preferences and smoking (Greiner, 2004; Guenther et al., 2006a; Hofstetter et al., 1986; Lahiri & Song, 2000; Lusk & Coble, 2005).

Besides obvious differences in estimation methods and subjects' pools, there are at least two reasons why results to date are not conclusive and hard to compare. First, most analyses do not systematically explore the links between directly estimated risk preferences and a broad range of risky behaviours considered together: this is of key importance given the growing evidence of interaction, compensatory, and 'spillover' effects from one health behaviour to another (Reynolds et al. 2004 ; Dolan and Galizzi (2014, 2015)). Secondly, the only indicator used for excess and unhealthy eating is typically the body mass index (*BMI*). Recently, however the validity of the *BMI* as a reliable nutritional and health indicator has been increasingly questioned, with many studies advocating the need for alternative measures (Ahima & Lazar, 2013; Bhattacharya, Currie & Haider, 2006; Harrison & Rutström, 2008).

While our work relates to these contributions, it builds on them in two innovative ways. First, we structurally estimate, using ML methods, the degree of risk aversion for a sample of young healthy adults and we explore its links with a broad range of risky behaviours considered together. Second, as indicator of the overall quality of diet, we complement, for the first time, the *BMI* with the Healthy Eating Index (*HEI*), and we relate both to estimated risk preferences.

Matteo M. Galizzi is the corresponding author.

Controlling simultaneously for the overall set of health habits is of key importance because there is evidence of interaction between diet quality, alcohol consumption, and smoking behaviour. Cigarette smoking, for instance, can directly impact obesity through biochemical and physical processes such as insulin homeostasis, activity of lipoprotein and sympathetic nervous system, physical activity, preferences in food consumption, and appetite reduction (Hakes & Viscusi, 2007; Kragelund & Omland, 2005). Also alcohol consumption is negatively related with diet quality (Bhattacharya, Currie, and Haider 2004). Finally, there is growing evidence of compensatory and '*licensing*' effects spilling over from a health behaviour to another (Blondel, Lohéac & Rinaudo, 2007; Reynolds et al., 2004 ; Dolan and Galizzi (2014, 2015)).

Secondly, the construction of the *HEI* index to complement the *BMI* is a major innovation with respect to the existing literature. Anderson and Mellor (2008) in fact, noticed that their results were sensitive to changes in the way risk behaviours were defined from the survey questions, and in particular to the definition of the 'cut-off' thresholds used to categorize a subject as '*obese*', '*smoker*', or '*heavy drinker*' for example. The authors further suggest that"*some caution is in order*" as their "*results are sensitive to how the behaviour is defined*", and observe that "*additional exploration of how risk behaviours are defined may be worthwhile in future studies*" (p. 1270). Contributing along this line, here we use a richer set of health indicators in the attempt to obtain estimates less sensitive to changes in the categorization of risky habits. In particular, we are interested in several specific hypotheses: i) whether the estimated risk preferences are significantly associated with the *BMI* for female and male young adults; ii) whether the estimated risk preferences are significantly associated with the *HEI* for female and male young adults; iii) whether the estimated risk preferences are significantly associated with smoking status for female and male young adults; iv) whether the estimated risk preferences are significantly associated with the alcohol drinking for female and male young adults; and v) whether the estimated risk preferences are significantly associated with the vigorous physical activity for female and male young adults.

Finally, focusing on young adults is of special interest for policy making. It is in these early phases of adult life when health behaviour is not yet affected by addiction or adaptation problems, and is typically associated with otherwise good health conditions, that prevention campaigns are most likely to be effective. Direct evidence on the links between estimated risk preferences and risky habits can thus provide insights on which attitudes to lever on when designing prevention policies to bring about behavioural change.

This study is organized as follows. Section 2 presents a self-contained literature review. Section 3 describes the methods, while Section 4 presents and discusses our results. Section 5 briefly concludes.

2 Literature Review

2.1 Risk Preferences in Health

The literature in this topic typically uses four main methods to assess risk preferences in the context of health: i) making use of *hypothetical gambles* to elicit preferences (e. g. Barsky et al. 1997); ii) making use of *actual health behaviour* as a proxy for risk preferences (Chiou et al., 2011; Gallagher, Visser & Sepulveda, 1996; Mitchell, 1999); iii) assessing *self-reported risk attitudes*, as in the German Socio-Economic Panel (SOEP) and in the *Understanding Society* (UK Longitudinal Household Survey, UKHLS) longitudinal surveys (Cawley 2004 ; Dolan and Galizzi (2014, 2015)); iv) making use of *domain-specific risk attitudes tests*, such as the Domain Specific Risk Test (DOSPERT) (Baum & Ford, 2004; Prentice & Jebb, 2001); and v) using *incentive-compatible tests*. Our paper relates in particular to the latter group of studies.[1]

Incentive-compatible tests have been originally proposed by the experimental economics literature. A number of experimental studies (see, for instance, Andersen et al., 2008; Griffith, O'Connell & Smith, 2012a; Harrison et al., 2005; Harrison et al., 2015) have highlighted that, in order to truthfully reveal their risk preferences, respondents should be rewarded with real monetary payments according to their stated choices. Harrison et al. (2005) , in particular, have proposed a paired-lotteries test that, following the "behavioural econometrics" maximum likelihood approach by Harrison (2008) and Andersen et al. (2008, 2010)), allows to structurally estimate the individual coefficient of risk aversion under a wide range of expected Utility Theory (EUT) and non-EUT models of risk preferences.[2]

Hey and Orme (1994), Blais and Weber (2006), Anderson and Mellor (2008), Guenther et al. (2006a), Lusk and Coble (2005), Lahiri and Song (2000), and Greiner (2004) are among the few studies that have combined incentive-compatible experimental measures of risk preferences with information on health behaviours.

Hey and Orme (1994) elicited risk preferences from 50 US undergraduate students using the Harrison et al. (2005) paired-lotteries test and related the observed preferences with survey data on the willingness to pay for genetically modified food. Subjects who, according to the experimental test were more risk averse, were found to be less willing to purchase and consume genetically modified food.

Blais and Weber (2006) elicited risk preferences making use of 14 binary risky choices with real monetary payments and compared them between 34 drug users in Paris taking methadone and a control group of 28 subjects with similar socio-demographic characteristics. Drug users were found to be significantly more risk-seeking.

Anderson and Mellor (2008) matched for the first time risk preferences elicited through the Harrison et al. (2005) method with several questions about risky health behaviour, such as seat belt use, smoking, heavy drinking, and being obese. Using a heterogeneous sample of 1,094 adults in Virginia, US, they found that risk aversion was negatively and sometimes significantly associated with cigarettes smoking, heavy drinking, and being overweight, although these associations were not robust to changes in the indexes for risky behaviours.[3]

Guenther et al. (2006a) elicited individual discount rates from a representative sample of the Danish population (252 subjects) and tested two hypotheses related to the time preferences of smokers and non-smokers subjects within their sample.[4] By doing so, they explicitly controlled for subjects' risk preferences, also elicited using the Harrison et al. (2005) method. They did not find any significant association of smoking with individual risk aversion among men, while, smoking women were found to be significantly *more* risk averse than non-smoking ones.

Lusk and Coble (2005) elicited risk preferences from a sample of 351 subjects taking part to a HIV test in a rural province in South Africa, using different experimental tests including the Harrison et al. (2005) method. The risk aversion measure based on the Harrison et al. (2005) test did not significantly predict any risky behaviour, including smoking, heavy drinking, and unprotected sex, and was only marginally correlated with alternative experimental measures.

Lahiri and Song (2000) elicited risk preferences from a sample of 661 children and adolescents aged 10–18 years in two schools in Tyrol, Austria, using a series of choices between playing a risky bet (on the colour of the ball to be drawn blindly from a bag), or taking a sure payoff. The point at which subjects switched from the gamble to the sure payoff was significantly associated with subjects' *BMI*: more risk-averse students had lower *BMI*. They found no significant association between the risk aversion indicator and smoking or drinking self-reported status.

Greiner (2004) elicited risk (and time) preferences from a sample of 175 undergraduate student smokers and non-smokers at the University of Cape Town, South Africa, using the Harrison et al. (2005) method. They found that smokers and non-smokers do not significantly differ in their estimated risk aversion, nor in their subjective perception of objective probabilities.[5]

While our work relates to these contributions, it builds on them in two innovative ways. First, we structurally estimate, using ML methods, the degree of risk aversion for a sample of young healthy adults and we explore its links with a broad range of risky behaviours considered together. Second, as indicator of the overall quality of diet, we complement, for the first time, the *BMI* with the Healthy Eating Index (*HEI*), and we relate both to estimated risk preferences.

Hey and Orme (1994) , in fact, only studied purchasing of genetically modified food. Blais and Weber (2006) considered drug-addicted subjects, while the sample in Lusk and Coble (2005) consisted of subjects undertaking HIV testing, half of which were HIV-positive. Lahiri and Song (2000) focused on children and adolescents. The key difference with Guenther et al. (2006a) and Greiner (2004) is that we extend their analysis on the differences between smokers and non-smokers to a broader set of health behaviours. Finally, our work builds on the analysis by Anderson and Mellor (2008) and Lahiri and Song (2000) in two ways. First, instead of categorizing the risk aversion based upon the observed switching points between two lotteries, we structurally estimate subjects' risk preferences. Second, instead of looking at how experimental measures of risk preferences predict each behaviour considered in isolation, we jointly consider the links between estimated risk preferences and a comprehensive range of health indicators, including the *HEI*.

Controlling simultaneously for the overall set of health habits is of key importance given the recent scientific evidence on the interaction between diet quality, alcohol consumption, and smoking behaviour. Cigarette smoking, for instance, can directly impact obesity through biochemical and physical processes such as insulin homeostasis, activity of lipoprotein and sympathetic nervous system, physical activity, preferences in food consumption, and appetite reduction (Nevill and Holder 1995). Also alcohol consumption is negatively related with diet quality (Breslow et al. 2006). Finally, there is growing evidence of compensatory and '*spillover*' effects spilling from a health behaviour to another (Werle et al. 2010; Wisdom et al. 2010; Dolan and Galizzi (2014, 2015)).

The construction of the *HEI* index to complement the *BMI*, together with the joint consideration of a comprehensive range of health behaviours, is major innovation with respect to the existing literature. Anderson and Mellor (2008) , in fact, noticed that their results were sensitive to changes in the way risk behaviours were defined from the survey questions, and in particular to the definition of the 'cut-off' thresholds used to categorize a subject as '*obese*', '*smoker*', or '*heavy drinker*' for example. The authors found that risk aversion was significantly associated with being overweight or obese when these health habits were captured by a dummy variable equal to 1 if subjects had a *BMI* above 25. This statistical significance, however, disappeared when being overweight or obese was defined by a dummy variable equal to 1 for *BMI* levels above 30. Similar results were obtained when changing the 'cut-off' thresholds to categorise smoking and heavy drinking behaviours. In their interpretation, the authors suggest that "*some caution is in order*" as their "*results are sensitive to how the behaviour is defined*", and observe that "*additional exploration of how risk behaviours are defined may be worthwhile in future studies*" (p. 1270). Contributing along this line, here we use a richer set of health indicators in the attempt to obtain estimates less sensitive to changes in the categorization of risky habits.

2.2 The *HEI*: Beyond *BMI*?

The construction of the *HEI* measure is discussed in detail in the Online Appendix C. In a nutshell, the *HEI* has been proposed in 1995 by nutrition experts within the US Department of Agriculture (*USDA*) (Kennedy et al. 1995), and its special attractiveness lies in the fact that it is a global measure of individual quality of diet and nutritional balance, adjusted by the total caloric intake of the subject. This feature makes the *HEI* particularly fit to complement the *BMI*.

The *HEI* has been recently used as an alternative to *BMI* in order to disentangle the complex effects of different aspects of healthy weight on socio-economic outcomes: for instance, Baum and Ford (2004) employ the *HEI* to assess the quality of the diet when exploring the link between food insecurity and poverty, while Bhattacharya et al. (2006) use it in an evaluation of the school breakfast program on the nutrition of children and their families. An increasing number of recent studies, moreover, employ the *HEI* as a global measure of the quality of diet, using surveys or scanning data for food purchases (Galizzi, Machado, and Miniaci 2016 and Feinberg 1977).

This recent tendency fits into a more general uprising interest in quality-of-diet measures as alternatives to the *BMI*. A growing number of studies in both the medical and the economics literature has, in fact, criticised the *BMI* as being, at best, an inaccurate measure of individual healthy weight, quality of diet, and overall nutritional balance, especially for subjects with not extreme health conditions, such as the young adults in our sample.

Paradoxical results, in fact, have been found on the relation between obesity, as defined on the *BMI*, and incidence and mortality for coronary heart diseases, or other cardiovascular diseases, (the so-called '*obesity-mortality paradox*', e. g. Ahima & Lazar, 2013; Croson & Gneezy, 2009; Harrison & Rutström, 2008). Numerous medical studies have also pointed out that the *BMI* cannot adequately distinguish between *body fat* (*BF*) and muscle, bone, and other *lean* body, or *fat-free mass* (*FFM*) (Dolan & Galizzi, 2014; Holt & Laury, 2002); conveys misleading information about *BF* levels and healthy weight in several sub-groups of the population, such as, the elderly, the children and many ethnic groups (Dohmen et al., 2011; Information Center for Health and Social Care, 2008); and is only an indirect and partial indicator of the overall nutritional balance, failing to account for the role of different nutritional intakes in a diet (Fischbacher 2007).

In economics research, the fact that *BMI* is an inaccurate indicator of individual body composition and nutritional balance can contribute to explain some of the puzzling findings concerning, for instance, the effects of overweight and obesity on the labour market outcomes. Indeed, while there is a general consensus on a negative association between obesity and wages for white females (Barsky et al., 1997; Bhattacharya, Currie & Haider, 2006; Harrison, Lau & Rutström, 2010), no clear evidence is available for males and non-white female groups (Bhattacharya, Currie, and Haider 2006).

Not by coincidence a comment in *The Lancet* significantly entitled "*A Farewell to Body-Mass Index?*" concluded that *BMI* is an "*obsolete*" measure of overweight and can result in significant "*underestimation of the grave consequences of the obesity epidemic*" (Harrison and Rutström 2008 , 1589–90). Somehow in parallel, economists concluded that "*social scientists should avoid uncritically using BMI as a measure of fatness*" and "*should acknowledge that, because of its failure to distinguish body composition, BMI is a deeply flawed measure*" (Bhattacharya, Currie, and Haider 2006 , 520 and 527). This has recently culminated in a perspective article in *Science* advocating the urgent need for "*better metrics*" for obesity (Ahima and Lazar 2013). [6]

These considerations have led an increasing number of researchers to emphasize the need for the development of alternative measures of healthy weight and quality-of-diet (Bhattacharya, Currie & Haider, 2006; Dohmen et al., 2011; Ohmura, Takahashi & Kitamura, 2005). In this context the *HEI* is currently the most comprehensive state-of-the-art measure for the overall nutritional balance and quality of diet (Baum and Ford 2004 , 2006; Galizzi, Machado, and Miniaci 2016 and Feinberg 1977 ; Griffith et al. Fischbacher; Filippin & Crosetto; Flegal et al.).

3 Design and Methods

The experimental sessions took place at the EXEC laboratory, York.[7] Subjects were recruited using the ORSEE online system (Dolan and Galizzi 2015) among the volunteers in the EXEC mailing list. There was no eligibility or exclusion criterion to select participants. In the email invitation, subjects were not informed about the exact nature of the experiment, and were only told that they would receive £10 for their participation, and would have the chance to get an extra payment related to their tasks. Subjects could sign up to any of six sessions taking place in different days of the week. A total of 120 students participated in the experimental sessions, 54 of which were female. Most subjects were undergraduate students, while 31 were graduate students. Only 7 subjects were economics students. The majority of subjects reported to be white British, 11 Chinese, 13 from other Asian origins, 11 non-white British, and 8 from other ethnic origins. Experimental sessions lasted approximately one hour and half, and subjects received an average payment of £22.7, taking into account the payment for the paired-lotteries tests described below.

Subjects were given aloud and written instructions and were told that the experimental session consisted of two different parts. In the first part, subjects were administered a computerised questionnaire on individual life habits. The second part of the experiment consisted of the paired-lotteries experimental test to elicit individual risk preferences.[8] The experiment was run with z-Tree 3.2.11 (Cox and Sadiraj 2005).

The questionnaire contained detailed questions on health habits, eating, drinking and smoking behaviour, and physical exercise. We followed closely the wording of existing surveys on health and nutrition: the British Household Panel Survey, the Health in England survey, the National Diet and Nutrition Survey and the English version of SHARE.

The resulting survey had questions on socio-demographic characteristics (age, gender, university degree, height, weight, nationality, ethnicity, religion, weekly budget, nationality, job and highest level of education of the parents); weekly intakes and portions of different categories of food (e. g. cereals, vegetables, fruits, meat, fish, milk and cheese, sweets); weekly intakes of drinks and alcohol; smoking habits; time spent in sports and physical activity; weekly use of take-away, prepared or frozen food; time spent on cooking and eating; composition of meals out and at home.

3.1 Elicitation of Risk Preferences

Alike Guenther et al. (2006a) and Anderson and Mellor (2008) we elicited individual risk preferences through incentive-compatible tests used in experimental economics (Anderson & Mellor, 2008; Griffith, O'Connell & Smith, 2012a; Harrison et al., 2005). In particular, we applied the multiple price list (MPL) design by (Andersen et al., 2006; Harrison et al., 2005).

Briefly, the Harrison et al. (2005) MPL test consists in presenting the subjects a series of questions, each reproducing a choice between two lotteries. Lotteries are binary and give a low payoff with some probability, and a high payoff with the complementary probability. One of the proposed lotteries (say lottery A) is characterized by a lower variance, in terms of smaller difference between monetary payoffs, than the other lottery (say B). The series of proposed pairs of lotteries only differ with respect to the probabilities of occurrence for the high payoff. Thus, for low probabilities, lottery A typically has the higher expected payment, while lottery B gives the higher expected returns for high probabilities. In Table 1 in the Online Appendix A, we provide a representation of some of the pairs of lotteries presented to subjects in our experimental test.[9]

The first row of the matrix shows that lottery A gave a 10 % chance to win £20 and a 90 % chance to win £16 (with an expected value, not shown to subjects, of £16.4), while lottery B gave a 10 % chance to win £38.5 and a 90 % chance to win £1 (with an expected value of £4.75, again not shown to the subjects). In the experimental test, for each row, subjects had to choose which lottery, among A and B, they preferred.[10] The idea behind this test is that risk-neutral subjects, aiming at maximizing their expected monetary payments, should switch from the "safe" option (lottery A) to the "risky" option (lottery B) only when the expected monetary payment is greater in lottery B than in A. Looking at Table 1, a risk neutral subject should choose A in the choices corresponding to rows 1–4, before switching to lottery B in the choice corresponding to row 5, and selecting that lottery in all the remaining choices. A strongly risk averse subject would instead prefer lottery A also in choices after the one corresponding to row 5, while a strongly risk lover should switch before that.[11] Thus, by observing all the choices made by a subject and the lotteries in correspondence of which a switch has occurred, it is possible to measure the individual attitude towards risk.

In particular, we consider all the binary choices made by each subject to estimate the parameter of a latent utility function that can explain such choices. As discussed more in detail below, following Andersen et al. (2008) , under the assumption that subjects in our experiment are characterized by a constant relative risk aversion

(CRRA) specification of the utility function, for a candidate value of the parameter in that function, it is possible to calculate the expected utility of each lottery, and then infer the likelihood of the observed choice.

In our questionnaire, we presented subjects a total of 40 pair-wise choices. In each of the 40 subjects were asked to choose between two presented lotteries of the type discussed above. The four experimental tasks differed with respect to the stakes of the lotteries, which spanned the range of monetary amounts over which the risk preferences are estimated. The four sets of stakes were the following, with the first two numbers referring to lottery A and the last two to lottery B: i) (A1: £20, £16) (B1: £38.5, £1); ii) (A2: £6, £4.80) (B2: £11.55, £0.30); iii) (A3: £200, £160) (B3: £385, £10); iv) (A4; £40, £32); (B4: £77, £2). This was done to capture possible cases of risk preferences depending on the absolute value of the monetary stakes (for instance, being risk averse for relatively low amounts, but risk loving for relatively high amounts, or the other way around).[12] Given that our sample was composed by college students and young adults, the range of monetary stakes in our tests is fairly comparable to the one considered for more heterogeneous samples of the population (e. g. Guenther et al. 2006a). Payoff matrix representations of the 40 pair-wise lottery choices presented to subjects in our experiment can be found in Table 2 in Online Appendix A, while the instructions for the experimental test can be found in Online Appendix B.

In order to guarantee a truthful elicitation of preferences, at the end of the questionnaire, one of the 40 pair-wise choices was randomly selected for the payment. The two lotteries within the selected choice were then played for real in the experiment, and subjects were thus paid cash according to the realized outcome of their preferred lottery.[13]

3.2 *HEI*, Health Indexes, and Control Variables

Using weight and height we have constructed a continuous variable for BMI and further BMI-based health indicators. In particular, we have considered two dummy variables: the first (*ObeseD*) assumes value 1 if the *BMI* is above 30 (e. g. subjects are considered obese), while the second (*OverwD*) assumes value 1 if the *BMI* is above 25 (e. g. subjects are considered overweight). Furthermore, based on standard clinical definitions of healthy weight, we have also built an ordered categorical variable (*BMIcat*) that is equal to: 1 for *BMI* lower than 18 (underweight); 2 for a *BMI* between 18 and 25 (normal weight); 3 for a *BMI* higher than 25 but lower than 30 (overweight); and 4 for a *BMI* above 30 (obese).

Importantly, we complement the *BMI* index with an indicator that captures the quality of diet and nutrition behaviour – *HEI* – proposed by the *US* Department of Agriculture (Fischbacher, 2007; Filippin & Crosetto, 2014; Flegal et al., 2005). The *HEI* is currently considered the most advanced and complete measure of nutritional balance and quality of diet. In particular, the updated version of the index – *HEI-2005*, is a global measure of individual nutritional balance adjusted by the total caloric intake of the subject. It measures the overall nutritional balance and is constructed as a weighted sum of twelve sub-indexes. By construction, *HEI* is a 0–100 score, increasing with the nutritional balance, assuming value 100 for subjects taking the maximum score in each of the sub-indexes. Full details can be found in Online Appendix C.

It is important to emphasize that since all quantities are expressed per 1,000 kcal, the nutritional intakes are considered in relative, rather than absolute terms, and are therefore adjusted at an individual level. This renders the *HEI* a global measure of how far away from an "individually optimal" nutritional balance the actual diet is (Fischbacher, 2007; Filippin & Crosetto, 2014).

We have also computed several other indicators of health habits and life style. In particular, we constructed *SmokeD*, as a dummy equal to 1 for the current smokers. In order to differentiate the former smokers from the ones who never smoked, we also constructed *QuitSmokeD* as taking value 1 for the subjects who have smoked in the past but have then quitted. Moreover, in some specifications and robustness checks, we have used some other control variables: *Alcohol* captures the number of alcohol units drunk per week; *SportUnits* are the reported hours of vigorous physical activities, including sport, per week.

We also control for a number of standard socio-demographic variables, such as the age (*Age*); the disposable weekly budget in British pounds (*Budget*); the highest level of education of the parents as a proxy of family background (*ParentEduc*, an ordered variable taking values between 1 and 5, increasing with the highest qualification completed by either parent, with 1 being "*have completed the primary school*" and 5 "*have completed post-graduate degree*"); the ethnicity (the dummy variable *NotWBritD* takes value 1 for ethnic background other than white British).

3.3 Estimation of Risk Preferences

Following the literature on structural estimation of risk preferences (Andersen et al., 2008; Guenther et al., 2006b), we assume that the utility function of our subjects is of a CRRA specification:

$$U\left(M\right)=\frac{M^{1-r}}{1-r} \tag{1}$$

where M is a monetary payoff of the lottery, and r is the CRRA coefficient, with $r\neq 1$. Depending on the estimated value of r subjects show different risk attitudes, that can be grouped in three general types of preferences: risk neutral ($r=0$), risk averse ($r>0$) and risk seeker ($r<0$).

The CRRA specification is commonly used in the literature on risk preferences (Andersen et al., 2008; Guenther et al., 2006a; Harrison et al., 2005) allowing for comparability of results. There is evidence from both the lab (Harrison et al. 2005) and the field (Griffith, O'Connell, and Smith 2012a) that the CRRA specification of the utility function performs well in fitting the individual choices for our range of monetary stakes.

While the full details of the ML "behavioural econometrics" approach can be found in Andersen et al. (2008) and in Appendix F of Guenther et al. (2006b) , here we briefly report the main steps of the estimation of risk preferences. Each subject in the experiment was asked to choose between two lotteries, A and B, each having two possible monetary outcomes, say, 1 and 2. In the 40 pairs of lotteries proposed to subjects in the experiment, we varied both the probabilities p_{jk} and the monetary payoff M_{jk} associated to each outcome of the two lotteries, with $j=A,B$ and $k=1,2$. Under *EUT*, the expected utility of subject i of a given lottery $j=A,B$ is just the utility of each outcome in that lottery $U\left(M_{jk}\right)$, weighted by the probability of the outcome p_{jk}:

$$EU_j=\sum_{k=1,2}p_{jk}U\left(M_{jk}\right)=\sum_{k=1,2}p_{jk}\frac{\left(M_{jk}\right)^{1-r}}{1-r} \tag{2}$$

Clearly the expected utility of the lottery depends on the degree of risk aversion r, the parameter that we want to estimate. Based on a candidate value of r, an index Δ(EU) can be constructed as the difference between the expected utilities from the two lotteries A and B:

$$\Delta\left(EU\right)=EU_A-EU_B \tag{3}$$

Such an index depends on the latent risk preferences and takes positive values when the expected utility from lottery A is higher than the utility from B, and vice versa. This latent index is then linked to the observed binary choices, by using a standard cumulative density function (*CDF*). In particular, assume that the latent index $\Delta(EU)$ is distributed according to a normal distribution. Therefore, as in a probit, a normal CDF $\Phi(\Delta(EU))$ takes any argument $\Delta\left(EU\right)$ and transforms it into a number between 0 and 1:

$$\text{Probability}\left(\text{choosinglottery}A\right)=\Phi\left(\Delta\left(EU\right)\right) \tag{4}$$

This probit-type of function thus links the latent individual risk preferences with the choices observed in the experiment: whenever $\Phi(\Delta(EU))>1-\Phi(\Delta(EU))$, the subject chooses lottery A. Therefore, under the assumptions that subjects in our experiment behave according to EUT, and are characterised by a *CRRA* utility functions, the likelihood of observing a specific choice depends on the estimated risk aversion parameter r, given the normal *CDF* linking the latent index to the observed choices. Since indifference responses were explicitly ruled out in our experiment, the log-likelihood conditional to the observed choices y_i is given by:

$$LnL\left(r;y,X\right)=\sum_i\left[\left(\left(ln\Phi(\Delta\left(EU\right)\right)I(y_i=1)\right)+\left(\left(ln\Phi(1-\Delta\left(EU\right)\right)I(y_i=0)\right)\right] \tag{5}$$

where $I\left(y_i=.\right)$ is the indicator function, $y_i=1$ (0) denotes the choice of lottery A (B) in the proposed pair of lotteries, and X is a vector of individual observed characteristics, including a set of socio-demographic controls, such as age, ethnicity, parental education, weekly budget, and the set of health habits variables *HEI, BMI, SmokeD, QuitSmokeD*, for instance. In fact, following (32,33) and in a way similar to what (11) did for the smoking status, we allow the *CRRA* coefficient in (5) to vary with the individual observed characteristics, as a function $r=r_0+\sum_k\gamma_k X_k$, where X contains a number k of different socio-demographic characteristics and individual health habits.

In particular, we pooled all the observations together: as our questionnaire collected 40 responses on risk preferences per subject, the resulting dataset comprised 4,800 observations that eventually reduced to 4,570 once the missing responses were dropped. We corrected for heteroskedasticity and autocorrelation of observations, by treating the residuals from the same subject as potentially correlated, and by computing cluster-robust standard errors of the estimates. Using Stata, we computed the expected utilities by the subjects and the latent index Δ (*EU*) and to construct the above log-likelihood function.[14] The computing program passed into the log-likelihood function the data on the probabilities and monetary payoffs of the experimental lotteries and the observations on the preferred choices by the subjects. The log-likelihood function was then read and evaluated by Stata maximum likelihood routine and maximized using Newton-Raphson optimization technique.

4 Results and Discussion

Table 3 shows the descriptive statistics, together with the computed scores for the global *HEI* index and for its 0–20 sub-index for the discretionary calories, derived from Solid Fat, Alcohol and Added Sugars (so-called *SoFAAS*, see the Appendix for more detail), for females and males. Although all subjects in our pool are undergraduate and graduate students, the data shows sufficient heterogeneity in health habits and individual characteristics (e. g. age). The exception is active smoking: only 11 subjects in our pool reported to be current smokers, 9 males and 2 females. In our sample, however, there are 21 more subjects that used to smoke and then quitted (10 females and 11 males), so that heterogeneity in smoking behaviour is also fairly represented. The share of smokers is in line with the latest figures available on the diffusion of smoking among the young in England, and in particular university students (Harrison, Lau, and Rutström 2007).

The average *BMI* within our sample is 22.384 with a standard deviation of 4.55. Females have higher *BMI* with a mean of 22.9 compared to a mean of 21.8 for males but also exhibit higher standard variation (5.6 vs 3.37 for males): a *t*-test indicates that the difference in the *BMI* of females and males is only marginally significantly different ($p = 0.0973$). On average, the *BMI* in our sample is substantially in line with the national figures for this age group: in England individuals aged 16–24 have an average *BMI* of 24.4 for males, and 24.2 for females (Andersen et al., 2008; Harrison et al., 2005).

Most young adults in our sample do not have extreme *BMI*: 93 subjects (77.5 %) have *BMI* values within normal limits (*BMI* included between 18 and 25); 20 subjects (16.7 % of the sample) are overweight but not obese (*BMI* included between 25 and 30); while three subjects (2.5 % of the sample) are only marginally underweight (*BMI* included between 15 and 18). There is, however, a small number of subjects with extremely high values of *BMI*: four above 30 of which three above 40. As it will be posited below, the presence of these ‘outliers’ can play a role in the robustness of results when *BMI*-based indicators are introduced in the analysis.

On the other hand, the average *HEI* score in our sample is 53.18, with a standard deviation of 11.33. This suggests that, even when young adults are characterised by normal weight and health conditions according to the *BMI* measure, diets and nutritional balance may be rather unsatisfactory when evaluated using the *HEI*. This is particularly evident for young men. Despite having, on average, a marginally higher *BMI*, females have, overall, a better nutritional balance, with an average *HEI* of 54.6 compared to 51.9 for males: the difference in the *HEI* of females and males is only marginally significantly different ($p = 0.0964$).[15] Actually, about half the young men in our pool have a score for the *HEI* index of 35 or below, three out of four of 53 or less, and 90 % not higher than 65, with the highest score at around 72.

National estimates for the *HEI* have not been published for the UK. Compared to other available figures, however, our sample seems to have an equally poor nutritional balance. For the US, for example Baum and Ford (2004) find that the average *HEI* for the 18–64 year olds to range between 56.9 and 63.2 and for the 12–17 year olds between 54 and 64. For the UK, Griffith, O’Connell, Smith (2012a) using the LCFS and the Kantar scanner data for 2008 and 2009, find mean scores for the *HEI* at a household level equal to 57.08 and 56.56, respectively. They also find similar gender differences in diet quality: for 19–29 years old, the *HEI* score was 53.21 for females, compared to 49.60 for males.

Table 4 shows the pair-wise correlations. There are a few variables that show strong significant correlations. For example, the relatively strong correlations between *Age* and *Budget* (0.3191, $p < 0.001$), and *Age* and *QuitSmokeD* (0.1337, $p < 0.001$) reflect the facts that, compared to younger peers, older university students tend to have higher budgets and are more likely to have smoked in the past. The positive correlations between *Budget* and *ParentEduc* (0.1283, $p < 0.001$), and *Budget* and *SportUnits* (0.2225, $p < 0.001$) are also similarly intuitive. Several health variables show significant, although often weak, correlations. We find a weak positive, but significant, correlation between *BMI* and *HEI* (0.0585, $p < 0.001$), which suggests that the two measures seem to capture rather different aspects associated with healthy weight and diet quality. A prominent exception is alcohol consumption. While alcohol consumption is very weakly (negatively) correlated with *BMI* (–0.0299, $p < 0.001$), it shows a strongly significant and negative correlation with the global *HEI* index (–0.4531, $p < 0.001$). Whereas this seems to provide evidence in support of the ability of *HEI* to encompass a broad set of nutritional aspects, it should be noticed that the strong negative correlation can be due to the contribution of the alcohol consumption to the *HEI* sub-index of the “discretionary” calories from Solid Fat, Alcohol and Added Sugars

(*SoFAAS*). Alcohol consumption is also positively and significantly correlated with smoking (0.1352, $p < 0.001$). Smoking, in turn, is also negatively and significantly correlated with the *HEI* (–0.2413, $p < 0.001$). Smokers, therefore, also drink more and have poorer diets than non-smokers. These correlations reinstate the importance of looking at the associations between the different risky health behaviours in conjunction rather than in isolation.

4.1 Risk Preferences, Healthy Eating, and Health Behaviours

The results of the estimation of the individual degree of risk aversion r for the 120 subjects in our sample based upon the log-likelihood function (5) are presented in Table 5. The ML estimate returned a value for the parameter of risk aversion of, $\hat{r} = 0.679$, indicating that subjects in our pool were risk averse (e. g. Andersen et al., 2008; Harrison et al., 2005).

Following the literature (Andersen et al., 2008; Guenther et al., 2006a; Guenther et al., 2006b), we have then estimated the log-likelihood function in (5) where the coefficient of individual degree of risk aversion is estimated as a function $r = r_0 + \sum_k \gamma_k X_k$, where X contains a number k of different socio-demographic characteristics and individual health habits. In order to jointly assess the links between estimated risk preferences and a comprehensive range of health indicators, in our specifications we include besides the *HEI* and the indexes based on the *BMI* also the *SmokeD* and *QuitSmokeD* dummies, and the *Alcohol* and *SportUnits* variables.

The experimental evidence by Guenther et al. (2006a) points to the existence of potential interaction between smoking behaviour and gender in relation to risk attitudes. Furthermore, the health economics literature suggests that the role of the *BMI* strongly depends on gender: for instance, while found for females, there is no clear association between wages and *BMI* for males (Baum 2004; Bhattacharya, Currie, and Haider 2006). Therefore, to fully disentangle the links between health variables and risk preferences we present two distinct sets of estimations for young men (Table 6 and Table 7) and women (Table 8 and Table 9) in our sample. As we pool all experimental responses together, results are based on a minimum of 2,490 and 1,910 observations, respectively.

The gender-specific structural estimations suggest that females in our sample are slightly more risk averse, having an estimated CRRA coefficient $\hat{r} = 0.692$compared to $\hat{r} = 0.668$for males.[16]

For *young men* risk preferences do not appear to significantly vary across different ethnicity and socio-economic background, as reflected by the income variable *Budget* (*Model I-XIV* in Table 6 and Table 7). Nevertheless in most specifications the parent education level is significant with a negative sign. If one interprets parents' education as a proxy of the household's income and background (and given that students *Budget* is a very crude proxy for income) this result is in line with what usually found by the literature.

Concerning health habits, *ObeseD* (dummy equal to 1 if the *BMI* is above 30) appears significantly associated with the degree of risk aversion among young men in our sample (*Models II and III*, Table 6): male subjects with a *BMI* above 30 appear to be more risk-seeking. In our sample, however, only one man can be defined as obese, having, in particular, a value of *BMI* above 40. It thus seems worth to check to which extent this association between risk seeking attitude and *BMI* could be driven by such an extreme value.

We have thus considered a categorical variable for the *BMI*, (i. e. *BMIcat*), which classifies subjects in four weight classes, allowing for a finer categorisation of the *BMI*. With *BMIcat*, although still with a negative sign, *BMI* is no longer significantly associated with risk preferences (*Models IV–V*, Table 6). Similar results hold when we use a different cut-off dichotomous variable, such as *OverwD*, a dummy equal to 1 when the *BMI* takes values above 25 (*Models VII–VIII*, Table 6): the association between risk preferences and being overweight as measured is not statistically significant. To further confirm this, we have run numerous alternative specifications and robustness checks. We have, for instance, directly included the *BMI* as a continuous variable in the regressions, and found that its negative association with risk preferences is only marginally significant when all male subjects are included in the sample (*Models IX* and *XI*, Table 7). When, however, the analysis excludes the young men with a *BMI* outlier value, its association with risk preferences is not at all significant (*Models XII* and *XIV*, Table 7).

This first set of results is in line with the evidence by Andersen et al. (2008) who, using a sample of 1,094 US adults, found that the (negative) association between *BMI* and the individual risk aversion was very sensitive to the type of BMI based indicators used.

The second set of results relates to the *HEI* index. The overall evidence suggests, first, that, when used in alternative to *BMI*-based measures, the *HEI* is always significantly associated with the risk attitudes of the male subjects in our pool (*Models I* and *VI*, Table 6; *Models X* and *XIII*, Table 7): healthier nutritional habits, reflected by higher *HEI* values, tend to be associated with higher risk aversion. Moreover, its sign, size, and statistical association appear robust across alternative specifications also when used in combination with the *BMI* (*Models XI* and *XIV* in Table 7) or other *BMI*-based variables (*Models III*, *V* and *VIII*, Table 6). Virtually every time is compared head-to-head with the *BMI*, the *HEI* is the only indicator to show a significant association with risk preferences, especially when outliers are excluded. Furthermore, in all models *HEI* reaches statistical significance without substantially altering the size, or the lack of significance, of the variable *BMIcat*, *OverwD* or *BMI*.

This direct comparison between *HEI* and *BMI* suggests that the two variables indeed capture different aspects of young men's behaviour and should be used as an alternative to the *BMI* (Bhattacharya, Currie, and Haider 2006). In absence of other, more direct and accurate, indicators for fatness – such as the *BF* and the *FFM* measures (Ahima & Lazar, 2013; Bhattacharya, Currie & Haider, 2006; Harrison & Rutström, 2008) – *BMI* may allow to detect extreme health conditions related to severe obesity. Being ultimately explained by the ratio between weight and height, however, the *BMI* likely fails to effectively account for the heterogeneity in the overall diet quality of subjects who are of normal weight, or only marginally overweight, as in our case of healthy young adults. As an alternative, the *HEI* is rather sensitive to changes in any nutritional component of a diet, and therefore shows larger variations than *BMI* even across relatively healthy subjects with non-extreme health conditions. As such, it is more likely to vary with underlying preferences or behavioural attitudes, at least across young men.

The last set of results for males refers to the finding that, across all specifications, there seems to be no significant association between individual attitude for risk and alcohol consumption, or smoking, in line with Lusk and Coble (2005) and Lahiri and Song (2000) . Moreover, males doing more vigorous exercise in most specifications appeared more risk averse, although the effect is only marginally significant.

Turning now to *female subjects*, older females tend to be more risk averse (*Models XXVI–XXVIII* in Table 9).Compared to men, for young women the association between parents' qualifications and risk aversion tends to be weaker.

On what concerns health habits, estimates show, first, that the *BMI* index is never significantly associated with the degree of risk aversion for the female subjects in our sample. This finding is robust across different alternative indicators based on the *BMI* and also in terms of socio-demographic characteristics included as determinants and controls. In Table 9, for instance, we replicate the analysis we did for the males, by excluding the three subjects with *BMI* outlier values, and we find virtually no difference (*Models XXVI–XXVIII*). This result is partly in contrast with (Anderson and Mellor 2008): in their sample, individual risk aversion was negatively correlated with being overweight as measured by scores of the *BMI* above 25, although the relation with *BMI* was not statistically significant when measured by scores of the *BMI* above 30. Our results also differ from (Sutter et al. 2012) who found a significant association between experimental measures for risk aversion and BMI.

Several factors may explain these differences. For instance, it may be the case that our pool of UK young subjects shows different associations between *BMI* and risk attitudes than the sample of US adults considered by (Anderson and Mellor 2008) or the sample of Austrian children and adolescents in Lahiri and Song (2000) . Another explanation may be found in the different tests and empirical methods employed. Lahiri and Song (2000) used a series of choices between gambles and safe options instead of the Harrison et al. (2005) test and looked at whether the switching points in those choices associate to each behaviour considered in isolation. Although they also used the same test, Anderson and Mellor (2008) did not distinguish between men and women, and categorised the degree of risk aversion based upon the observed switching points between lotteries, instead of structurally estimating the parameters.

Furthermore, unlike what found for male subjects, when introduced in the analysis, the *HEI* index is never significantly associated with the estimated risk attitudes for young women. Alike for the case of *BMI*, the lack of association appears consistently robust across all specifications, and holds both when the *HEI* variable is introduced on its own, or together with *BMI*-based indexes. Together with the above results for men, this suggests that the association between risk attitudes and the *HEI* appears to be gender-specific, and that the introduction of measures for healthy weight alternative to the *BMI* seems particularly promising for male subjects, in line with the literature (Bhattacharya, Currie, and Haider 2006) for the *FFM* and *BF* measures.

A further set of results for females is that, whilst for males *Alcohol* and *Exercise* are rarely significantly associated with the estimated risk preferences, for females these associations hold in almost all specifications: young women who report to consume more units of alcohol per week (or to spend fewer hours in vigorous physical exercise) tend to be more risk averse. The finding of a significant relation between risk aversion and alcohol consumption is in line with the experimental evidence by Anderson and Mellor (2008) and Barsky et al. (1997) using hypothetical gambles measures from HRS and PSID surveys in the US.

4.2 Further Robustness Checks

A total of 12 subjects in our sample are older than 24 years, with 6 subjects being older than 30 years (the oldest subject in the sample is 43 years old). One may wonder whether the results reported above are robust by considering a more homogeneous set of young adult respondents, for example by considering only the subjects who are less than 24 years old.

We have thus replicated all the structural estimations described above considering only the 108 subjects who are less than 24 years old in our sample. The results of this extra set of robustness checks estimations are reported in Table 11, Table 12, Table 13, Table 14 in Appendix E. As it can be seen from those tables, the results are substantially identical to the ones described above for the whole sample: in a nutshell, young women do not show any significant robust associations between risk preferences and *BMI*, while for young men the *HEI* index is significantly and consistently associated with risk preferences: healthier nutritional habits are robustly associated with higher risk aversion. We have further replicated the same estimations using alternative subsamples (for example, in terms of age threshold) and found again substantially identical results (all available on request).

4.3 Risk Preferences and Smoking Status

The link between risk preferences and smoking status is worth a brief final digression. It first should be recalled that, in our sample, we have a limited number of active smokers, so that the results should be interpreted cautiously. Nonetheless, since the literature discussed above is mixed and not conclusive to date, a comparison of our results with the other existing studies is of interest.

We estimated the risk preferences for four sub-groups differing with respect to gender and smoking status: i) current smokers, ii) subjects who never smoked; iii) non-smokers who smoked in the past (ex-smokers); and iv) a group pooling together all subjects who either smoke or have smoked in the past (Table 10).

Comparing never-smokers with current smokers, we find that the never-smokers were more risk averse (the estimated CRRA coefficient is $\hat{r} = 0.66$for never-smokers compared to the $\hat{r} = 0.565$of currently smoker subjects), and that the difference in the average risk aversion between never-smokers and current smokers is larger among females than males (the CRRA coefficient is $\hat{r} = 0.666$for male never-smokers compared to the $\hat{r} = 0.581$of their smoking counterparts, while, for females, these figures are $\hat{r} = 0.653$ and is $\hat{r} = 0.48$respectively).

Actually, looking in greater detail at Table 6 and Table 7, for male subjects in our sample, the dummy variable *SmokeD* for current smokers is never significantly associated with the individual degree of risk aversion, even when jointly controlling for the dummy *QuitSmokeD*, accounting for whether the subjects used to smoke and then quitted. This result is closely in line with Guenther et al. (2006a), Lusk and Coble (2005), Lahiri and Song (2000), and Hofstetter et al. (1986) and with what recently documented with a larger sample of young smokers and non-smokers in South Africa by Greiner (2004) .

On what concerns females, looking at the smoking status dummies, it turns out that the dummy for the current smoking status is highly significantly associated with the estimated CRRA parameter for risk preferences, pointing in particular to female smokers being significantly more risk-seeking than never-smokers (Table 8 and Table 9). This is in line with evidence by Anderson and Mellor (2008) who found that smokers in their sample were significantly less risk averse than non-smokers, but differs from Guenther et al. (2006a) , who found that smoking women were *more* risk averse than their non-smoking peers in their sample.

Some considerations, however, are in order while interpreting these sets of results. First, the pools of subjects in Austria, Denmark, South Africa, UK, and US may have different associations between risk attitudes and smoking behaviour. Secondly, unlike in our analysis as well as in Guenther et al. (2006a) and in Greiner (2004) , the contributions by Lusk and Coble (2005), Lahiri and Song (2000), and Anderson and Mellor (2008) did not allow an interaction between gender and smoking status, and categorised the degree of risk aversion based upon the observed switching point between lotteries (or risky and safe options) rather than based on structural estimates.

One should consider the latter finding on females together with the substantial lack of any association for male subjects. Taken together, the above results add more evidence on the weak association between risk attitudes and smoking status found by Guenther et al. (2006a) who suggested "*caution against the use of smoking status*" as "*a proxy for risk attitudes*" (p. 713), by Greiner (2004) who found "*no statistically significant relationship between risk preferences and smoking status*", and by Cawley (2004) who concluded that "*smoking can only be considered a very imperfect substitute for more direct measures of risk attitudes*" (p. 22). This result is in contrast with the correlation between risk tolerance and smoking typically found in studies that use hypothetical measures to control for risk attitudes (Barsky et al., 1997; Harrison & Lau, 2014), or that implicitly assume that smokers are risk-seeking (Kennedy, Carlson, and Fleming 1995).

5 Conclusions

Despite the central role that risk preferences can play in the assessment of health risky behaviour, the current evidence is mixed and not conclusive, as epitomised by the case of smoking (Anderson & Mellor, 2008; Greiner, 2004; Guenther et al., 2006a; Hofstetter et al., 1986; Johansson et al., 2009; Janssen, Katzmarzyk & Ross, 2004; Lahiri & Song, 2000; Lusk & Coble, 2005). One reason is that most analyses do not systematically explore the links between directly estimated risk preferences and a broad range of risky behaviours considered together. Another is that the only indicator used for unhealthy eating is typically the *BMI*.

We present the results of a lab experiment where we elicit risk preferences for a sample of 120 young adults in the UK using real monetary payments. We then jointly estimate their links with a comprehensive range of risky health behaviours. Among other measures, we innovatively include the *HEI* as a global indicator of nutritional quality, to complement the *BMI*. To the best of our knowledge, our study is the first that relates the *HEI* to behavioural attitudes, and, in particular, to directly estimated risk preferences.

Our results show that risk preferences significantly differ across young adults with different, not extreme, health conditions. In particular, they reinstate the importance of conducting analyses that look separately at the two sub-samples of female and male subjects (Burkhauser & Cawley, 2008; Guenther et al., 2006a). This allows disentangling the links and interactions between preferences and key health variables such as smoking, and also to fully account for the gender-specific effects of the *BMI* and of alternative indicators of healthy weight (Bhattacharya, Currie & Haider, 2006; Bhattacharya, Currie & Haider, 2006; Guenther et al., 2006a).

Second, in our sample young women do not show any significant robust associations between risk preferences and *BMI*. Third, for young men – but not women – the *HEI* index appears to be significantly and consistently associated with risk preferences: across all specifications, healthier nutritional habits, tend to be robustly associated with higher risk aversion. This, together with the lack of significance of *BMI*-based indexes, suggests that, for subjects with not extreme health conditions, there is a wide scope to use measures alternative (or complementary) to the *BMI*, as indicators of the overall quality of diet. Similarly to what documented in the literature (Bhattacharya, Currie, and Haider 2006) for the *BF* and *FFM* measures, the scope for alternative measures is greater for men for which the *BMI* seems to work particularly poorly.

By showing, for the first time, that the *HEI* is more likely than the *BMI* to vary with key behavioural attitudes such as the risk preferences, our work contributes in the direction suggested by an increasing number of studies questioning the reliability of the *BMI*, and advocating the need for alternative measures for the health and nutrition quality of diet (e. g. Ahima & Lazar, 2013; Bhattacharya, Currie & Haider, 2006; Harrison & Rutström, 2008)

The experimental design of the present study limits the nature of the research questions that can be addressed, while it also motivates future work. For instance, the fact that the experimental tests were administered just at one point does not allow dealing with the causality and endogeneity issues between individual risk preferences and risky health behaviours on the other. It is possible to think of alternative experimental designs that would allow to directly deal with the potential endogeneity issue. For example, using a between-subjects design like in Reynolds et al. (2004) , Wisdom et al. (2010), Blondel, Lohéac, and Rinaudo (2007) , Dolan and Galizzi (2014, 2015), Dolan and Galizzi (2014, 2015), it would be possible to randomly allocate subjects to an intervention where risk taking is directly induced by an experimental manipulation and then to directly observe how this affects their health behaviour later on. Alternatively, risk preferences could be measured at two or more points in time using longitudinal field experiments such as Harrison and Lau (2014) and Dolan and Galizzi (2014, 2015) where direct health information could be accessed through linked administrative records or biomarkers. While our data does not allow such analysis, we aim at exploring these promising alternative experimental designs in future research.

Another possible limitation that should be acknowledged is that the lack of significant association between risk preferences and health behaviours could be potentially due to the relative small number of subjects in our experiment. Although the number of experimental subjects was informed by formal sample size calculations (Breslow 2005) and our sample size is large compared to other similar studies with specific samples of subjects (e. g. Blais & Weber, 2006; Hey & Orme, 1994), there is no doubt our sample size is smaller than the number of respondents in similar studies with general or representative samples of the population (Anderson & Mellor, 2008; Guenther et al., 2006a). Although we are currently extending our approach to representative samples of the UK population, the significant associations found in the present study could be tentatively regarded as lower bounds of the associations between risk preferences and health behaviours (and in particular the *HEI*) that would emerge considering larger and more general samples of the population.

Relatedly, we have focused on young adults who are at high risk of start indulging in risky behaviour and therefore our results might not generalize to more diversified samples of the population. On the other hand, if experimentally elicited risk preferences significantly differ across subjects with similar health socio-demographic characteristics like in our pool, one can plausibly conjecture that risk preferences can vary to an even larger extent across more heterogeneous subjects from the general population.

Another caveat of the present experimental design is that, in order to guarantee incentive-compatible elicitation through real payments, we could only elicit risk preferences in a monetary domain, rather than in health-related framings. While the existing literature in psychology and economics question whether risk preferences are indeed stable across different domains and contexts (Kennedy, Carlson, and Fleming 1995), an explicit investigation of the relations between risk preferences in the monetary and health domains would require a different experimental design (Dolan and Galizzi (2014, 2015)).

Notwithstanding these limitations, our results suggest that looking at the interaction between experimental tests and a comprehensive range of health behaviours can be a promising area of investigation. If confirmed by further evidence, the finding that unhealthy eating or excessive alcohol consumption among young adults are associated to risk preferences, opens up the possibility to use such individual attitudes as levers to trigger envisaged behavioural change. From a health policy perspective, our study suggests that in young adults who have not yet developed chronic or extreme health conditions, looking at a comprehensive nutritional indicator such as the *HEI* could provide more direct insights to the deeply rooted behavioural mechanisms that drive health behaviours than considering an indirect and increasingly questioned measure such as the *BMI* (Ahima & Lazar, 2013; Bhattacharya, Currie & Haider, 2006; Harrison & Rutström, 2008).

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

[1]For a detailed review of the advantages and disadvantages of these methods in the context of health see (Dolan and Galizzi (2014, 2015)).

[2]A limitation of this method in the context of health is that, in order to guarantee truthful revelation of individual preferences through real payments, risk preferences are typically elicited within a monetary, rather than a health, domain. See also (Dolan and Galizzi (2014, 2015)) for a detailed discussion on this point.

[3]See also below for a discussion on this point.

[4]The two hypotheses are whether i) smokers have higher individual discount rates than non-smokers; and ii) smokers are more likely to exhibit hyperbolic discounting than non-smokers. Concerning the first, Guenther et al. (2006a) found that there is a significant correlation between individual discount rates and smoking only among men in their sample: male smokers have significantly higher discount rates than non-smokers, while individual discount rates for smokers and non-smokers women are not significantly different. Concerning the second hypothesis, Guenther et al. (2006a) found that smokers and non-smokers have the same propensity to exhibit hyperbolic discounting.

[5]Concerning time preferences, Greiner (2004) also found that smokers and non-smokers differed in their baseline discount rates, but did not significantly differ in their present bias.

[6]These increasing concerns over the limitations of the *BMI* measure have also been shared by policy-makers: in a consensus report, the World Health Organization warns that researchers should interpret carefully the measure of *BMI*, and avoid to confound the effects due to muscularity with obesity (WHO, 2003).

[7]The project was funded from the Center for Health Economics at the University of York, and received ethical approval from the Research Ethics Board of the Center for Experimental Economics (EXEC) at the University of York.

[8]In the pilot we experimented both orders of administration of the two parts of the study, with either the questionnaire first, or the experimental test first, and we found no significantly different patterns of responses. We finally opted for administering the questionnaire first because we wanted to avoid possible "priming" effects of having been exposed to risk preferences tests when responding to questions about risky health behaviours. Potential "carryover" effects from the questionnaire to the risk preferences tests were of a lesser concern given that the risk preferences questions were incentivized.

[9]Notice that the columns of the table showing the expected values of the two lotteries, their difference, and the implied intervals for the risk aversion parameter r of a CRRA utility function, were not shown to subjects in the experiment, and are reported for illustration purposes only.

[10]In the experimental test subjects had to choose either lottery A or B. Expressing indifference between the two lotteries was not possible in our experiment. This feature of our experimental design does not alter our findings, since in alternative settings where subjects could also express indifference, usually very few subjects used that option, as reported in (Andersen et al. 2008).

[11]As in (Guenther et al. 2006a), the choice in the last row can be simply seen as a test that subjects understood the logic behind the task.

[12]See, for example, Guenther et al. (2007), Garn, Leonard, and Hawthorne (1986), Harrison et al. (2015), and Breslow, Guenther, and Smothers (2010) .

[13]At the end of each experimental session, we selected randomly one subject in the lab and asked her to draw a ball from an urn that had been prepared for any of the lotteries presented in the selected choice. One out of ten subjects, selected randomly, was then paid cash the amount corresponding to the realized outcome of their preferred lottery in that choice. This random selection procedure is standard and well-established in the experimental elicitation of time and risk preferences using real monetary rewards, as it allows using large incentives even with a limited research budget. See (Griffith, O'Connell & Smith, 2012a; Guenther et al., 2006b) for a discussion of the experimental evidence that paying subjects by randomly selecting a task does not distort individual choices.

[14]The Stata syntax we have used is similar to the one provided by Glenn Harrison (http://cear.gsu.edu./gwh/) and is available upon request, together with the whole source code.
[15]Formal tests also indicate that compared to female subjects, male subjects are marginally older ($p = 0.0668$), are significantly more likely to smoke ($p = 0.0307$), drink significantly more alcohol units per week ($p = 0.0020$), and have significantly higher weekly budgets ($p = 0.0445$). There are no other statistically significant differences.
[16]However, a formal test of significance of the dummy variable for gender in the structurally estimated coefficient of risk aversion when pooling all subjects together indicates that the difference in risk preferences across genders is not statistically significant ($p = 0.626$). This is in contrast with some experimental evidence that risk taking can be different across genders (Burkhauser & Cawley, 2008; Cawley, 2004), but is in line with the recent review by Cohen (1969) of the studies using the Harrison et al. (2005) method to measure risk preferences, which also finds no significant difference in structurally estimated risk aversion across male and female subjects.

References

Ahima, R. S., and M. A. Lazar. 2013 (Aug) 23. "The Health Risk of Obesity—Better Metrics Imperative." *Science* 341 (6148): 856–858.

Andersen, S., G. Harrison, M. Lau, and E. E. Rutström. 2006 (Dec) 1. "Elicitation Using Multiple Price List Formats." *Experiments Economics* 9 (4): 383–405.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström. 2008 (May). "Eliciting Risk and Time Preferences." *Econometrica* 76 (3): 583–618.

Anderson, L. R., and J. M. Mellor. 2008 (Sep). "Predicting Health Behaviors with an Experimental Measure of Risk Preference." *Journal of Health Economics* 27 (5):. 1260–1274.

Andersen, S., G. W. Harrison, M. Lau, and E. E. Rutström. 2010. "Behavioral econometrics for psychologists." *Journal of Economic Psychology* 31 : 553–576.

Barsky, R. B., F. T. Juster, M. S. Kimball, and M. D. Shapiro. 1997 (May) 1. "Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study." *The Quarterly Journal of Economics* 112 (2): 537–579.

Baum, C. L., and W. F. Ford. 2004 (Sep) 1. "The Wage Effects of Obesity: A Longitudinal Study." *Health Economics* 13 (9): 885–899.

Baum, CL, and WF Ford. 2004. "The Wage Effects of Obesity: a Longitudinal Study." *Health Economics* 13 (9): 885–899.

Blais, A. R., and E. U. Weber. 2006. "A Domain-Specific Risk Taking (DOSPERT) Scale for Adult Populations." *Judgment and Decision Making* 1 (1): 33–47.

Bhattacharya, J., J. Currie, and S. Haider. 2004 (Jul). "Poverty, Food Insecurity, and Nutritional Outcomes in Children and Adults." *Journal of Health Economics* 23 (4): 839–862.

Bhattacharya, J, J Currie, and SJ Haider. 2006. "Poverty, Food Insecurity, and Nutritional Outcomes in Children and Adults." *Journal of Health Economics* 23 : 839–862.

Bhattacharya, J, J Currie, and SJ Haider. 2006. "Breakfast of Champions? The School Breakfast Program and the Nutrition of Children and Families." *Journal of Human Resources* 41 (3): 445–466.

Blondel, S., Y. Lohéac, and S. Rinaudo. 2007. "Rational Decision of Drug Users: An Experimental Approach." *Journal of Health Economics* 26 (3): 643–658.

Breslow, R. A. 2005 (Dec) 22. "Alcohol Drinking Patterns and Diet Quality: The 1999-2000 National Health and Nutrition Examination Survey." *American Journal of Epidemiology* 163 (4): 359–366.

Breslow, RA., PM. Guenther, and BA Smothers. 2010. "Alcohol Drinking Patterns and Diet Quality: The 1999-2000 National Health and Nutrition Examination Survey." *American Journal of Epidemiology* 163 : 359–366.

Burkhauser, R. V., and J. Cawley. 2008 (Mar). "Beyond BMI: The Value of More Accurate Measures of Fatness and Obesity in Social Science Research." *Journal of Health Economics* 27 (2): 519–529.

Cawley, J. 2004. "The Impact of Obesity on Wages." *The Journal of Human Resources* 39 (2): 451.

Chiou, W. B., C. S. Wan, W. Wu, and K. T. Lee. 2011. "A Randomized Experiment to Examine Unintended Consequences of Dietary Supplement Use among Daily Smokers: Taking Supplements Reduces Self-Regulation of Smoking." *Addiction* 106 (12): 2221–2228.

Cohen, J. 1969. *Statistical Power Analysis for the Behavioral Sciences*. New York: Academic Press.

Cox, J., and V. Sadiraj. 2005. "Small- and Large-Stakes Risk Aversion: Implications of Concavity Calibration for Decision Theory." *Games and Economic Behavior* 56 (1): 45–60.

Croson, R., and U. Gneezy. 2009 (May). "Gender Differences in Preferences." *Journal of Economic Literature* 47 (2): 448–474.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner. 2011 (Mar) 31. "Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences." *Journal of the European Economic Association* 9 (3): 522–550.

Dolan, P., and M.M Galizzi. (2014).LSE CEP Discussion Paper CEPDP1286 Because I'm Worth It. A Lab-Field Experiment on Spillover Effects of Incentives in Health.

Dolan, P., and M.M Galizzi. (2015).Journal of Economic Psychology 1–16 Like Ripples on a Pond: Behavioural Spillovers and Their Consequences for Research and Policy201547.

Galizzi, M.M, S.R Machado, and R. Miniaci. 2016. "Temporal stability, cross-validity, and external validity of risk preferences measures: experimental evidence from a UK representative survey." *LSE Research Online Working Paper 67554*. Department of Social Policy, London School of Economics.

Feinberg, R. 1977. "Risk Aversion, Risk and the Duration of Unemployment." *Review of Economics and Statistics* 59 (3): 264–271.

Filippin, A., and P. Crosetto. "A Reconsideration of Gender Differences in Risk Attitudes. *IZA Discussion Paper 8184* 2014.

Fischbacher, U. 2007 (Feb) 7. "Z-Tree: Zurich Toolbox for Ready-Made Economic Experiments." *Experiments Economics* 10 (2): 171–178.

Flegal, K. M., B. I. Graubard, D. F. Williamson, and M. H. Gail. 2005. "Excess Deaths Associated with Underweight, Overweight, and Obesity." *Jama* 293 : 1861–1867.

Gallagher, D., M. Visser, D. Sepulveda, et al.. 1996. "How Useful Is the Body Mass Index for Comparison of Body Fatness across Age, Sex, and Ethnic Groups?" *American Journal of Epidemiology* 143 (3): 228–239.

Garn, S. M., W. R. Leonard, and V. M. Hawthorne. 1986. "Three Limitations of the Body Mass Index." *American Journal of Clinical Nutrition* 44 : 996–997.
Greiner, B.. "The Online Recruitment System ORSEE 2.0: A Guide for the Organization of Experiments in Economics. *Working Paper Series in Economics 10* University of Cologne, 2004.
Griffith, R., M. O'Connell, and K. Smith. 2012a. ""Measuring the Quality of People's Diets: A Comparison of Intake and Purchase Data.". ANR-ESRC Workshop on Econometrics and I.O. of Nutrition, Toulouse, School of Economics.
Guenther, P. M., J. Reedy, S. M. Krebs-Smith, B. B. Reeve, and P. P. Basiotis. 2006a (Aug). "The Revised Healthy Eating Index: A Tool for Measuring Change in Diet Quality." *Journal of the American Dietetic Association* 106 (8): 68. A.
Guenther, P. M., S. M. Krebs-Smith, J. Reedy, P. Britten, W. Juan, M. Lino, et al.. "Healthy Eating Index-2005. *(CNPP Fact Sheet No. 1)* Center for Nutrition Policy and Promotion, U.S. Department of Agriculture, 2006b.
Guenther, P. M., J. Reedy, S. M. Krebs-Smith, B. B. Reeve, and P. P. Basiotis. (2007).Development and Evaluation of the Healthy Eating Index: Technical ReportCenter for Nutrition Policy and Promotion, US Department of Agriculture.
Hakes, J. K., and W. K. Viscusi. 2007. "Automobile Seatbelt Usage and the Value of a Statistical Life." *Southern Economic Journal* 73 : 659–676.
Harrison, G. W., E. Johnson, M. M. McInnes, and E. E. Rutstrom. 2005. "Risk Aversion and Incentive Effects: Comment." *The American Economic Review* 95 (3): 897–901.
Harrison, G. W., A. Hofmeyr, D. Ross, and J. T. Swarthout. Risk Preferences, Time Preferences, and Smoking Behaviour. *CEAR Working Paper 2015-11* Georgia State University, 2015.
Harrison, G. W., M. I. Lau, and E. E. Rutström. 2007 (Jun). "Estimating Risk Attitudes in Denmark: A Field Experiment." *The Scandinavian Journal of Economics* 109 (2): 341–368.
Harrison, G. W., and E. E. Rutström. 2008. *Risk Aversion in Experiments*, edited by J.C. Cox, and G.W. Harrison. Bingley, UK: Emerald Research in Experimental Economics Risk aversion in the laboratoryVolume 12.
Harrison, G. W., M. I. Lau, and E. E. Rutström. 2010 (Sep). "Individual Discount Rates and Smoking: Evidence from a Field Experiment in Denmark." *Journal of Health Economics* 29 (5): 708–717.
Harrison, G. W., and E. E. Rutström. 2008 (Jun) 13. "Expected Utility Theory and Prospect Theory: One Wedding and a Decent Funeral." *Experiments Economics* 12 (2): 133–158.
Harrison, G.W, and M.I Lau. 2014. "Risk attitudes, sample selection, and attrition in a longitudinal field experiment." *CEAR Working Paper 2014-04*. Robinson College of Business. Georgia State University.
Hey, J. D., and C. Orme. 1994. "Investigating Generalizations of Expected Utility Theory Using Experimental Data." *Econometrica* 62 (6): 1291–1326.
Hofstetter, A., Y. Schutz, E. Jéquier, and J. Wahren. 1986 (Jan) 9. "Increased 24-Hour Energy Expenditure in Cigarette Smokers." *The New England Journal of Medicine* 314 (2): 79–82.
Holt, C. A., and S. K. Laury. 2002 (Dec). "Risk Aversion and Incentive Effects." *The American Economic Review* 92 (5): 1644–1655.
Holt, C. A., and S. K. Laury. 2005. "Risk Aversion and Incentive Effects: New Data without Order Effects." *The American Economic Review* 95 (3): 902–912.
Information Center for Health and Social Care. 2008. *Smoking, Drinking and Drug Use Among Young People in England in 2008* London, National Health Service.
Janssen, I., P. T. Katzmarzyk, and R. Ross. 2004. "Waist Circumference and Not Body Mass Index Explains Obesity-Related Health Risk." *American Journal of Clinical Nutrition* 79 : 379–784.
Johansson, E., P. Bockerman, U. Kilskinen, and M. Heliovaara. 2009. "Obesity and Labour Market Success in Finland: The Difference between Having a High BMI and Being Fat." *Economics and Human Biology* 7 : 36–45.
Kennedy, E, S Carlson, and K Fleming. 1995. "The Healthy Eating Index: Design and Applications. Journal of the American Dietetic Association." *Journal of the American Dietetic Association* 95 (10): 1103–1108.
Kragelund, C., and T. Omland. 2005 (Nov). "A Farewell to Body-Mass Index?" *The Lancet* 366 (9497): 1589–1591.
Lahiri, K., and J. G. Song. 2000. "The Effect of Smoking on Health Using a Sequential Self-Selection Model." *Health Economics* 9 (6): 491–511.
Lusk, J. L., and K. H. Coble. 2005. "Risk Perceptions, Risk Preference and Acceptance of Risky Food." *Americal Journal of Agricultural Economics* 87 (2): 393–405.
Mitchell, S. 1999. "Measures of Impulsivity in Cigarette Smokers and Nonsmokers." *PsychopharmacologyBerl*) 146 : 455–464.
Nevill, A. M., and R. L. Holder. 1995. "Body Mass Index: A Measure of Fatness or Leanness?" *British Journal of Nutrition* 73 : 507–516.
Ohmura, Y., T. Takahashi, and N. Kitamura. 2005. "Discounting Delayed and Probabilistic Monetary Gains and Losses by Smokers of Cigarettes." *PsychopharmacologyBerl*) 182 : 508–515.
Prentice, A. M., and S. A. Jebb. 2001. "Beyond Body Mass Index." *Obesity Reviews* 2 (3): 141–147.
Reynolds, B., J. Richards, K. Horn, and K. Karraker. 2004. "Delay Discounting and Probability Discounting as Related to Cigarette Smoking Status in Adults." *Behavioural Processes* 65 : 35–42.
Reynolds, B. 2006. "The Experiential Discounting Task is Sensitive to Cigarette-Smoking Status and Correlates with a Measure of Delay Discounting." *Behavioural Pharmacology* 17 : 133–142.
Slovic, P. 1972. "Procession Situation, Information, and the Generality of Risk-Taking Behavior." *Journal of Personality and Social Psychology* 22 : 128–134.
Stamford, B. A., S. Matter, R. D. Fell, and P. Papanek. 1986 (Apr). "Effects of Smoking Cessation on Weight Gain, Metabolic Rate, Caloric Consumption, and Blood Lipids." *The American Journal of Clinical Nutrition* 43 (4): 486–494.
Sutter, M., M. Kocher, D. Glatzle-Rutzler, and S. Trautmann. 2013. "Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior." *The American Economic Review* 103 (1): 510–531.
Sutter, M, MG Kocher, D Glatzle-Rutzler, and ST Trautmann. 2013. "Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior." *American Economic Review* 103 (1): 510–531.
Szrek, H., L.-W. Chao, S. Ramlagan, and K. Peltzer. 2012 (Nov). "Predicting (Un)Healthy Behavior: A Comparison of Risk-Taking Propensity Measures." *Judgment and Decision Making* 7 (6): 716–727.

Viscusi, W. K., and J. Hersch. 2001 (May). "Cigarette Smokers as Job Risk Takers." *The Review of Economics and Statistics* 83 (2): 269–280.
Wack, J., and J. Rodin. 1982. "Smoking and Its Effects on Body Weight and the Systems of Caloric Regulation." *The American Journal of Clinical Nutrition* 35 : 366–380.
Wada, R., and E. Tekin. 2010. "Body Composition and Wages." *Economics and Human Biology* 8 : 242–254.
Weber, E. U., A. R. Blais, and N. E. Betz. 2002. "A Domain-Specific Risk Attitude Scale: Measuring Risk Perceptions and Risk Behaviors." *Judgment and Decision Making* 15 (4): 263–290.
Werle, C., B. Wansink, and C. Payne. 2010. "Just thinking about exercise makes me serve more food. Physical activity and calorie compensation." *Appetite* 56 (2): 332–335.
Werle, C. O. C., B. Wansink, and C. R. Payne. 2011 (Apr). "Just Thinking about Exercise Makes Me Serve More Food. Physical Activity and Calorie Compensation." *Appetite* 56 (2): 332–335.
Wisdom, J., and G. Loewenstein. 2010. "Promoting Healthy Choices: Information Versus Convenience." *American Economic Journal: Applied Economics* 2 : 164–78.
World Health Organization. 2003, http://www.who.int/hpr/NPH/docs/gs_obesity.pdf.

Appendix

A Experimental test to elicit risk preferences

Table 1: Typical payoff matrix in the experimental test.

Pair	*Lottery A*				*Lottery B*				EV^A	EV^B	EV^A-EV^B	*CRRA range if switching to B*
	P_1	£$_1$	P_2	£$_2$	P_1	£$_1$	P_2	£$_2$	£	£	£	
1	10 %	**20**	90 %	**16**	10 %	**38.5**	90 %	**1**	16.40	4.75	11.65	–∞; –1.71
2	20 %	**20**	80 %	**16**	20 %	**38.5**	80 %	**1**	16.80	8.50	8.30	–1.71; –0.95
3	30 %	**20**	70 %	**16**	30 %	**38.5**	70 %	**1**	17.20	12.25	4.95	–0.95; –0.49
4	40 %	**20**	60 %	**16**	40 %	**38.5**	60 %	**1**	17.60	16.00	1.60	–0.49; –0.15
5	50 %	**20**	50 %	**16**	50 %	**38.5**	50 %	**1**	18.00	19.75	–1.75	–0.15; 0.14
6	60 %	**20**	40 %	**16**	60 %	**38.5**	40 %	**1**	18.40	23.50	–5.10	0.14; 0.41
7	70 %	**20**	30 %	**16**	70 %	**38.5**	30 %	**1**	18.80	27.25	–8.45	0.41; 0.68
8	80 %	**20**	20 %	**16**	80 %	**38.5**	20 %	**1**	19.20	31.00	–11.80	0.68; 0.97
9	90 %	**20**	10 %	**16**	90 %	**38.5**	10 %	**1**	19.60	34.75	–15.15	0.97; 1.37
10	100 %	**20**	0 %	**16**	100 %	**38.5**	0 %	**1**	20.00	38.50	–18.50	1.37; ∞

Note: The columns with the expected values for the lotteries and the implied CRRA intervals were not shown to the subjects in the experiment.

Table 2: Payoff matrix of the lotteries included in the experimental test.

Pair	*Lottery A*				*Lottery B*			
	P_1	£$_1$	P_2	£$_2$	P_1	£$_1$	P_2	£$_2$
1	10 %	**20**	90 %	**16**	10 %	**38.5**	90 %	**1**
2	20 %	**20**	80 %	**16**	20 %	**38.5**	80 %	**1**

3	30 %	**20**	70 %	**16**	30 %	**38.5**	70 %	**1**
4	40 %	**20**	60 %	**16**	40 %	**38.5**	60 %	**1**
5	50 %	**20**	50 %	**16**	50 %	**38.5**	50 %	**1**
6	60 %	**20**	40 %	**16**	60 %	**38.5**	40 %	**1**
7	70 %	**20**	30 %	**16**	70 %	**38.5**	30 %	**1**
8	80 %	**20**	20 %	**16**	80 %	**38.5**	20 %	**1**
9	90 %	**20**	10 %	**16**	90 %	**38.5**	10 %	**1**
10	100 %	**20**	0 %	**16**	100 %	**38.5**	0 %	**1**
11	10 %	**6**	90 %	**4.80**	10 %	**11.55**	90 %	**0.30**
12	20 %	**6**	80 %	**4.80**	20 %	**11.55**	80 %	**0.30**
13	30 %	**6**	70 %	**4.80**	30 %	**11.55**	70 %	**0.30**
14	40 %	**6**	60 %	**4.80**	40 %	**11.55**	60 %	**0.30**
15	50 %	**6**	50 %	**4.80**	50 %	**11.55**	50 %	**0.30**
16	60 %	**6**	40 %	**4.80**	60 %	**11.55**	40 %	**0.30**
17	70 %	**6**	30 %	**4.80**	70 %	**11.55**	30 %	**0.30**
18	80 %	**6**	20 %	**4.80**	80 %	**11.55**	20 %	**0.30**
19	90 %	**6**	10 %	**4.80**	90 %	**11.55**	10 %	**0.30**
20	100 %	**6**	0 %	**4.80**	100 %	**11.55**	0 %	**0.30**
21	10 %	**200**	90 %	**160**	10 %	**385**	90 %	**10**
22	20 %	**200**	80 %	**160**	20 %	**385**	80 %	**10**
23	30 %	**200**	70 %	**160**	30 %	**385**	70 %	**10**
24	40 %	**200**	60 %	**160**	40 %	**385**	60 %	**10**
25	50 %	**200**	50 %	**160**	50 %	**385**	50 %	**10**
26	60 %	**200**	40 %	**160**	60 %	**385**	40 %	**10**
27	70 %	**200**	30 %	**160**	70 %	**385**	30 %	**10**
28	80 %	**200**	20 %	**160**	80 %	**385**	20 %	**10**
29	90 %	**200**	10 %	**160**	90 %	**385**	10 %	**10**
30	100 %	**200**	0 %	**160**	100 %	**385**	0 %	**10**
31	10 %	**40**	90 %	**32**	10 %	**77**	90 %	**2**
32	20 %	**40**	80 %	**32**	20 %	**77**	80 %	**2**
33	30 %	**40**	70 %	**32**	30 %	**77**	70 %	**2**
34	40 %	**40**	60 %	**32**	40 %	**77**	60 %	**2**
35	50 %	**40**	50 %	**32**	50 %	**77**	50 %	**2**
36	60 %	**40**	40 %	**32**	60 %	**77**	40 %	**2**
37	70 %	**40**	30 %	**32**	70 %	**77**	30 %	**2**
38	80 %	**40**	20 %	**32**	80 %	**77**	20 %	**2**
39	90 %	**40**	10 %	**32**	90 %	**77**	10 %	**2**
40	100 %	**40**	0 %	**32**	100 %	**77**	0 %	**2**

B Instructions for the experimental test.

In the test that follows you will be presented 40 pairs of alternative options. Each pair of options is indicated with a sequential number.

In particular, each pair consists of two lotteries: lottery A, and lottery B.

Both lotteries A and B give you an amount of money (£$_1$) with some probability (P_1), and some other amount of money (£$_2$) with the complementary probability (P_2).

For instance consider the pair of lotteries "0" represented below:

Pair	***Lottery A***				***Lottery B***				***Your Choice***	
	P_1	£$_1$	P_2	£$_2$	P_1	£$_1$	P_2	£$_2$		
0	10 %	**20**	90 %	**16**	10 %	**38.5**	90 %	**1**	A	B

In pair "0" lottery A gives you £20 with probability 10 % and £16 with probability 90 %, while lottery B gives you £38.5 with probability 10 % and £1 with probability 90 %.

In the test, at each pair you will be asked to choose the lottery that you prefer between lottery A and lottery B. You can choose the lottery you prefer by selecting either option "A" or option "B" under "*Your choice*". Please notice that there is no right or wrong answer: we are genuinely interested in what you prefer.

There is an important aspect you may want to consider when choosing your preferred option. At the end of the experiment, one of the 40 pairs of lotteries will be randomly selected. Also, one out of 10 participants in your experimental session will be randomly selected to get paid according to the selected pair of lotteries.

If you will be among the subjects randomly selected to get paid, you will be paid according to the actual outcome of the lottery corresponding to your preferred option (either A or B) in the selected pair.

For instance, imagine that at the end of the experiment, the pair "0" above will be randomly selected for the payment. Also, imagine that you will be among the subjects randomly selected to be paid.

This means that the end of this experimental session you will play either lottery A, if you have chosen A as your preferred option at pair "0", or lottery B, if you have chosen lottery B as your preferred option in that pair.

If you have chosen lottery A as your preferred option in pair "0", you will win either £20 with probability 10 %, or £16 with probability 90 %. On the other hand, if you have chosen lottery B as your preferred option in pair "0", you will win either £38.5 with probability 10 %, or £1 with probability 90 %.

Your preferred lottery will be played for real and you will be paid the corresponding amount of money at the end of the experiment.

Before starting making your choices, please make sure you have fully understood how this test works. You can familiarize with the test by asking yourself which options you prefer between the two lotteries in pair "0":

Pair	*Lottery A*				*Lottery B*				*Your Choice*	
	P_1	£$_1$	P_2	£$_2$	P_1	£$_1$	P_2	£$_2$		
0	10 %	**20**	90 %	**16**	10 %	**38.5**	90 %	**1**	A	B

Please consider now the first pair of options, take your time to decide, select and confirm the option you prefer between A and B, and then move to the next pair of options. Notice that, once you have made your choice, you cannot go back and change your choice.

At this stage, please feel free to ask any question or clarification to the experimenter in the lab. Otherwise, if everything is clear, you are free to start the test whenever you feel like. Please, for each of the following pairs of lotteries, make your choice of the lottery you prefer, by selecting either A or B.

C Construction of the HEI Index

In our questionnaire we assess food intake using recall measures. In particular, we used a self-completed semi-quantitative Food Frequency Questionnaire (FFQ) where we asked subjects to report their frequency of consumption of standard portions of different categories of food and drinks in their last week, with portions' sizes being described and visualized in intuitive ways (e. g. 'a portion is 80 grams, or 3 ounces, about what fits in the palm of your hand'). The FFQ method imposes a low burden on respondents and is directly implementable in self-completed surveys, and as such is used, in the UK, by the NDNS, the BHPS, and the Health in England surveys, among others (36–39). We chose a recall time frame of one week as a compromise between the four-day time frame in the NDNS survey and the two-weeks time window in the LCFS survey. Whilst minimizing the recalling bias, the one-week time frame allows assessing the habitual nutritional intake over a sufficiently representative period of time. Moreover it was chosen also for the sake of direct comparability with the previous study by (11). For a more general discussion on the role of the time windows of recall measures of food consumption, and of collection of food purchasing data see (40,41).

The data collected has been used to calculate the *HEI* that is constructed as a weighted sum of twelve nutritional sub-indexes.

The first six sub-indexes assign 5 points each to subjects whose daily intakes are at least equal, or greater, than the recommended quantities for six "healthy" categories of food: total fruit (*TotFruit*); whole fruit (*WFruit*); total vegetables (*TotVeg*); dark green and orange vegetables, and legumes (*GreenVeg*); total grains (*TotGrains*); whole grains (*WGrains*). Both the intakes and the recommended quantities are expressed in cup equivalents (grams or ounces) per 1,000 kcal. Each of these sub-indexes gives 0 points to subjects who do not consume any quantity at all of the food in the corresponding category, and assigns to subjects whose intakes are less than the recommended amounts, a number of points in between 0 and 5, according to a function linearly increasing in the consumed quantities.

The next three sub-indexes assign 10 points each to subjects whose daily intakes are at least equal, or greater, than the recommended quantities for: milk (*Milk*); meat (*Meat*); and beans and oils (*Oils*). The intakes and the recommended quantities are also expressed in cup equivalents (grams or ounces) per 1,000 kcal. Each of these sub-indexes gives 0 points to subjects who do not consume any quantity at all of the food in the corresponding category, and assigns to intermediate intakes a number of points between 0 and 10, according to a linear function in the consumed quantities.

One further sub-index (*SatFat*) assigns 10 and 0 points to subjects for which the saturated fats represent less than 7 %, and more than the 15 %, of their daily energetic intakes, respectively, and assigns points between 0 and 10 to subjects with intermediate proportions. Another sub-index (*Sodium*) works in a similar way, assigning 10 and 0 points to subjects whose daily intake of sodium is below 0.7 grams, or above 2 grams per 1,000 kcal, respectively, and linearly declining points for the intermediate cases. Finally, one sub-index (*SoFAAS*) assigns 20 and 0 points to subjects for which the so-called "SoFAAS" discretionary calories, derived from Solid Fat, Alcohol and Added Sugars, represent less than 20 %, and more than 50 % of their daily energetic intakes, respectively, and assigns linearly declining points for the intermediate cases.

For the previous version of the *HEI* index, the *USDA* made available online a software that processed a series of inputs such as age, sex, daily intakes of some categories of food and returned the *HEI* score for the subject. No software, or readily available program, was released by *USDA* for the *HEI-2005*.[17] To compute the *HEI* score for each subject in the experiment, we thus wrote our own program following, step by step, the guidelines in the documentation released by the *USDA* panel of experts (29–31). In particular, starting with the weekly intakes of food we expressed all the intakes on a daily base and computed the daily energetic intake for each subject, in kcal; we then considered every single intake and computed its nutritional value and contribution to each of the 12 *HEI* sub-indexes; we summed up the values for all intakes and expressed them in terms of the computed daily energetic intake for each subject; we finally assigned points to each sub-index (e. g. *SatFat*, *SoFAAS*) and computed the overall *HEI*. We have used Stata 11 to program these computations. The program is available on request.

D Estimation of risk preferences

Table 3: Descriptive statistics for the health habits and socio-demographics variables across the 120 subjects by gender.

	Males					Females					Total			
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
Age	66	21.5	4.75	18	43	54	20.43	2.29	18	34	21.02	3.88	18	43
Budget	66	80.22	49.52	20	350	54	66.07	37.86	0	200	73.82	45.20	0	350
NonWhiteD	66	0.21	0.40	0	1	54	0.33	0.47	0	1	0.27	0.44	0	1
Score_HEI	66	51.6	11.17	31.65	72.37	54	54.68	11.36	28.41	75.25	53.19	11.34	28.41	75.25
HEId	66	0.5	0.50	0	1	54	0.63	0.48	0	1	0.57	0.50	0	1
HEIcat	66	1.5	0.50	1	2	54	1.63	0.48	1	2	1.57	0.50	1	2
Score_Sofaas	66	11.1	6.27	0	20	54	12.62	5.90	0	20	11.81	6.15	0	20
BMI	66	21.9	3.38	16.40	40.63	54	22.98	5.60	14.92	48.95	22.39	4.56	14.92	48.95
ObeseD	66	0.0153	0.12	0	1	54	0.06	0.23	0	1	0.03	0.18	0	1
OverwD	66	0.12	0.33	0	1	54	0.20	0.40	0	1	0.16	0.37	0	1
BMIcat	66	2.09	0.45	1	4	54	2.13	0.70	1	4	2.11	0.58	1	4
SportUnits	66	1.11	0.99	0.14	6.43	54	1.55	2.76	0	18.57	1.31	2	0	18.57
Alcohol	66	2.66	3.15	0	20.36	54	1.29	1.38	0	6.14	2.04	2.60	0	20.36
SmokeD	66	0.14	0.34	0	1	54	0.04	0.19	0	1	0.09	0.29	0	1
QuitsmokeD	66	0.17	0.37	0	1	54	0.19	0.39	0	1	0.18	0.38	0	1
ExsmokeD	66	0.23	0.41	0	1	54	0.19	0.39	0	1	0.21	0.41	0	1
ActivesmokeD	66	0.06	0.24	0	1	54	0	0	0	0	0.03	0.18	0	1
NeversmokeD	66	0.7	0.46	0	1	54	0.78	0.42	0	1	0.73	0.44	0	1

Table 4: Correlation matrix between the health habits and socio-demographics variables across the 120 subjects.

	Age	**BMI**	**Budget**	**ParentEduc**	**SportUnits**	**Alcohol**	**smokeD**	**quitsmokeD**	**Score_HEI**
Age	1								
BMI	0.1105***	1							
	(0.0000)								
Budget	0.3191***	–0.073***	1						
	(0.0000)	(0.0000)							
ParentEduc	–0.0586***	–0.0062	0.1283***	1					
	(0.0000)	(0.6693)	(0.0000)						
SportUnits	0.1370***	0.1212***	0.2225***	0.1414***	1				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
Alcohol	–0.1026***	–0.0299**	–0.0029	–0.0328**	–0.0514***	1			
	(0.0000)	(0.0389)	(0.8422)	(0.0232)	(0.0004)				
Smoked	0.0359*	0.0119	0.0575***	0.1041***	–0.0450***	0.1352***	1		

	(0.013)	(0.4125)	(0.0001)	(0.0000)	(0.0018)	(0.0000)			
quitsmokeD	0.1337***	0.0648***	–0.0680***	–0.1215***	0.0149	0.1355***	–0.1463***	1	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3034)	(0.0000)	(0.0000)		
Score_HEI	0.0487***	0.0585***	–0.007	0.0980***	–0.0084	–0.4531***	–0.2413***	–0.0680***	1
	(0.0007)	(0.0001)	(0.6296)	(0.0000)	(0.5604)	(0.0000)	(0.0000)	(0.0000)	

[1] * p<.10, ** p<.05, *** p<.01.

Table 5: Estimated risk preferences by gender.

Women	0.6917	**Men**	0.6682	**Total**	0.6793
	(0.0414)		(0.0251)		(0.0236)

Table 6: Estimated risk preferences and association with health habits for male subjects.

	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**	**Model VIII**
Age	–0.0087	–0.0074	–0.0090	–0.0048	–0.0064	–0.0087	–0.0054	–0.0074
	(0.0063)	(0.0059)	(0.0064)	(0.0064)	(0.0067)	(0.0063)	(0.0062)	(0.00654)
NonWBritD	–0.0371	–0.0291	–0.0378	–0.0553	–0.0662	–0.0371	–0.0421	–0.0492
	(0.0771)	(0.0722)	(0.0784)	(0.0792)	(0.0861)	(0.0771)	(0.0754)	(0.0825)
Budget	–0.0002	–0.0002	–0.0003	–0.0002	–0.0003	–0.0002	–0.0003	–0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
ParentEduc	–0.0714*	–0.0399	–0.0727*	–0.0468	–0.0778**	–0.0714*	–0.0445	–0.0744**
	(0.0377)	(0.0323)	(0.0388)	(0.0318)	(0.0381)	(0.0377)	(0.0305)	(0.0361)
SmokeD	0.0554	–0.0368	0.0577	–0.0332	0.0578	0.0554	–0.0161	0.0706
	(0.106)	(0.0715)	(0.109)	(0.0634)	(0.0997)	(0.106)	(0.0722)	(0.109)
QuitsmokeD	0.0726	0.0863	0.0685	0.0994	0.0814	0.0726	0.0942	0.0762
	(0.0808)	(0.0837)	(0.0809)	(0.0873)	(0.0830)	(0.0808)	(0.0872)	(0.0827)
Alcohol	0.0067	–0.0026	0.0080	–0.0028	0.0067	0.0067	–0.0022	0.0075
	(0.0089)	(0.0055)	(0.0095)	(0.0058)	(0.0091)	(0.0089)	(0.0059)	(0.0097)
SportUnits	0.0705*	0.0490	0.0702*	0.0630*	0.0844**	0.0705*	0.0565*	0.0762*
	(0.0415)	(0.0369)	(0.0423)	(0.0355)	(0.0420)	(0.0415)	(0.0336)	(0.0395)
Score_HEI	0.0056**		0.0060**		0.00571**	0.0056**		0.0056*
	(0.0027)		(0.0028)		(0.0028)	(0.0027)		(0.0029)
ObeseD		–0.510***	–0.553***					
		(0.0378)	(0.0414)					
BMIcat				–0.0798	–0.0766			
				(0.0678)	(0.0670)			
OverwD							–0.0833	–0.0692
							(0.0589)	(0.0608)
Constant	0.749***	0.954***	0.739***	1.079***	0.874***	0.749***	0.928***	0.735***
	(0.220)	(0.169)	(0.222)	(0.193)	(0.236)	(0.220)	(0.165)	(0.216)
Observations	2550	2510	2510	2510	2510	2550	2510	2510

[1] Notes: Standard errors in parentheses. * p<.10, ** p<.05, *** p<.01.

Table 7: Estimated risk preferences and association with health habits for male subjects (*continued*).

	Model IX	**Model X**	**Model XI**	**Model XII**	**Model XIII**	**Model XIV**
Age	–0.0055	–0.0087	–0.0073	–0.0061	–0.0091	–0.0078
	(0.0058)	(0.0063)	(0.0059)	(0.0061)	(0.0064)	(0.0062)
NonWBritD	–0.0457	–0.0371	–0.0663	–0.0417	–0.0378	–0.0595

	(0.0738)	(0.0771)	(0.0845)	(0.0751)	(0.0784)	(0.0868)
Budget	–0.0003	–0.0002	–0.0004	–0.0003	–0.0003	–0.0004
	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)
ParentEduc	–0.0512	–0.0714*	–0.0845**	–0.0465	–0.0727*	–0.0811**
	(0.0324)	(0.0377)	(0.0403)	(0.0330)	(0.0388)	(0.0413)
SmokeD	–0.0160	0.0554	0.0884	–0.0257	0.0577	0.0798
	(0.0693)	(0.106)	(0.113)	(0.0720)	(0.109)	(0.118)
QuitsmokeD	0.0902	0.0726	0.0822	0.0877	0.0685	0.0757
	(0.0856)	(0.0808)	(0.0852)	(0.0848)	(0.0809)	(0.0837)
Alcohol	–0.0016	0.0067	0.0092	–0.0018	0.0080	0.0095
	(0.0069)	(0.0089)	(0.0115)	(0.0065)	(0.0095)	(0.0114)
SportUnits	0.0621*	0.0705*	0.0902**	0.0566	0.0702*	0.0839*
	(0.0352)	(0.0415)	(0.0453)	(0.0364)	(0.0423)	(0.0471)
BMI	–0.0161*		–0.0172*	–0.0110		–0.0123
	(0.0088)		(0.0097)	(0.0102)		(0.0108)
Score_HEI		0.0056**	0.0064**		0.0060**	0.0065**
		(0.0028)	(0.0032)		(0.0028)	(0.0032)
Constant	1.294***	0.749***	1.088***	1.184***	0.739***	0.979***
	(0.240)	(0.220)	(0.266)	(0.259)	(0.222)	(0.275)
Observations	2510	2550	2510	2490	2490	2490

Note: *Models XII–XVI* exclude *BMI* outlier above 30. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Estimated risk preferences and association with health habits for female subjects.

	Model XV	Model XVI	Model XVII	Model XVIII	Model XIX	Model XX	Model XXI	Model XXII
Age	0.0243	0.0217	0.0240	0.0204	0.0223	0.0243	0.0261*	0.0288*
	(0.0157)	(0.0146)	(0.0165)	(0.0150)	(0.0162)	(0.0157)	(0.0156)	(0.0170)
Non-WBritD	–0.0176	–0.0181	–0.0166	–0.0043	–0.0015	–0.0176	–0.0478	–0.0469
	(0.0615)	(0.0612)	(0.0636)	(0.0670)	(0.0705)	(0.0615)	(0.0845)	(0.0864)
Budget	0.00056	0.0007	0.0006	0.0006	0.0005	0.0006	0.0007	0.0006
	(0.0008)	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
ParentEduc	–0.0461	–0.0513*	–0.0468	–0.0564*	–0.0526	–0.0461	–0.0418	–0.0368
	(0.0302)	(0.0302)	(0.0331)	(0.0320)	(0.0326)	(0.0302)	(0.0355)	(0.0364)
SmokeD	–0.453***	–0.458***	–0.453***	–0.445***	–0.441***	–0.453***	–0.474***	–0.470***
	(0.0742)	(0.0670)	(0.0746)	(0.0745)	(0.0815)	(0.0742)	(0.0640)	(0.0697)
QuitsmokeD	–0.0160	–0.0186	–0.0172	–0.0238	–0.0241	–0.0160	0.0024	0.0036
	(0.0713)	(0.0739)	(0.0724)	(0.0745)	(0.0738)	(0.0713)	(0.0815)	(0.0795)
Alcohol	0.0840***	0.0771***	0.0837***	0.0792***	0.0855***	0.0840***	0.0734***	0.0807***
	(0.0154)	(0.0123)	(0.0161)	(0.0117)	(0.0155)	(0.0154)	(0.0128)	(0.0161)
SportUnits	–0.088***	–0.088***	–0.088***	–0.085***	–0.086***	–0.088***	–0.090***	–0.089***
	(0.0230)	(0.0235)	(0.0229)	(0.0233)	(0.0227)	(0.0230)	(0.0243)	(0.0240)
Score_HEI	0.00157		0.0015		0.0014	0.0016		0.0017
	(0.0027)		(0.0031)		(0.0026)	(0.0027)		(0.0028)
ObeseD		–0.0361	–0.0127					
		(0.144)	(0.190)					
BMIcat				–0.0211	–0.0197			
				(0.0379)	(0.0386)			
OverwD							0.0519	0.0553
							(0.0722)	(0.0764)
Constant	0.201	0.365	0.215	0.444	0.304	0.201	0.242	0.0685
	(0.426)	(0.298)	(0.481)	(0.351)	(0.454)	(0.426)	(0.347)	(0.476)
Observations	1980	1980	1980	1980	1980	1980	1980	1980

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Estimated risk preferences and association with health habits for female subjects (*continued*).

	Model XXIII	Model XXIV	Model XXV	Model XXVI	Model XXVII	Model XXVIII
Age	0.0231	0.0243	0.0245	0.0286**	0.0358**	0.0363**
	(0.0146)	(0.0157)	(0.0157)	(0.0137)	(0.0156)	(0.0152)
NonWBritD	–0.0089	–0.0176	–0.0055	–0.0452	–0.0537	–0.0607
	(0.0583)	(0.0615)	(0.0622)	(0.0661)	(0.0606)	(0.0635)
Budget	0.0006	0.0006	0.0005	0.0005	0.0003	0.0003
	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0007)
ParentEduc	–0.0541*	–0.0461	–0.0512*	–0.0405	–0.0253	–0.0229
	(0.0291)	(0.0302)	(0.0294)	(0.0311)	(0.0310)	(0.0310)
SmokeD	–0.448***	–0.453***	–0.445***	–0.446***	–0.437***	–0.440***
	(0.0708)	(0.0742)	(0.0770)	(0.0716)	(0.0833)	(0.0854)
QuitsmokeD	–0.0210	–0.0160	–0.0218	–0.0015	0.0060	0.0082
	(0.0710)	(0.0713)	(0.0709)	(0.0733)	(0.0686)	(0.0689)
Alcohol	0.0781***	0.0840***	0.0839***	0.0742***	0.0900***	0.0902***
	(0.0118)	(0.0154)	(0.0152)	(0.0117)	(0.0153)	(0.0153)
SportUnits	–0.087***	–0.088***	–0.087***	–0.086***	–0.088***	–0.088***
	(0.0233)	(0.0230)	(0.0227)	(0.0236)	(0.0223)	(0.0223)
BMI	–0.0036		–0.0034	–0.0009		0.0015
	(0.0036)		(0.00393)	(0.00720)		(0.0067)
Score_HEI		0.0016	0.0013		0.0039	0.0041
		(0.0027)	(0.0026)		(0.0029)	(0.0026)
Constant	0.423	0.201	0.303	0.225	–0.219	–0.276
	(0.303)	(0.426)	(0.419)	(0.333)	(0.442)	(0.435)
Observations	1980	1980	1980	1910	1910	1910

Note: *Models XXVI–XXVIII* exclude *BMI* outliers above 30. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Estimated risk preferences: smoking and gender.

	All	Active smokers	Never smoked	Non-smokers Ex-smokers	Total	Smoke or used to smoke
Women	0.6917	0.4804	0.6536	0.8675	0.6977	0.8184
	(0.0415)	(0.1634)	(0.0298)	(0.1499)	(0.0423)	(0.1405)
Men	0.6681	0.5814	0.6672	0.7288	0.6806	0.6702
	(0.0251)	(0.0609)	(0.0299)	(0.0669)	(0.0271)	(0.0469)
Total	0.6793	0.5651	0.6604	0.7965	0.6891	0.7279
	(0.0236)	(0.0551)	(0.021)	(0.0861)	(0.0251)	(0.0644)

E Tables for subsample of subjects less than 24 years old

Table 11: Estimated risk preferences and association with health habits for male subjects less than 24 years old.

	Model Ib	Model IIb	Model IIIb	Model IVb	Model Vb	Model Vib	Model VIIb	Model VIIIb
Age	–0.0056	–0.0111	–0.0092	–0.0050	–0.0042	–0.0038	–0.0072	–0.0058
	(0.0260)	(0.0269)	(0.0246)	(0.0270)	(0.0249)	(0.0239)	(0.0272)	(0.0248)
Non-WhiteBritD	–0.101	–0.0991	–0.104	–0.107	–0.113*	–0.109	–0.102	–0.109
	(0.0742)	(0.0745)	(0.0660)	(0.0758)	(0.0686)	(0.0664)	(0.0746)	(0.0675)
Budget	–0.0003	–0.0004	–0.0008	–0.0003	–0.0006	–0.0006	–0.0003	–0.0006

	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
ParentEduc	–0.0726*	–0.0723*	–0.111**	–0.0767*	–0.112**	–0.109**	–0.0773**	–0.111**
	(0.0375)	(0.0385)	(0.0470)	(0.0392)	(0.0476)	(0.0460)	(0.0391)	(0.0468)
SmokeD	0.0903	0.0809	0.199	0.0716	0.187	0.202	0.0998	0.207
	(0.0991)	(0.0969)	(0.127)	(0.0916)	(0.124)	(0.128)	(0.0980)	(0.128)
QuitsmokeD	0.110	0.112	0.0941	0.109	0.0958	0.0957	0.103	0.0922
	(0.114)	(0.115)	(0.104)	(0.115)	(0.105)	(0.105)	(0.117)	(0.106)
Alcohol	0.0013	0.0016	0.0119	0.0007	0.0097	0.0108	0.0009	0.0099
	(0.0062)	(0.0067)	(0.0097)	(0.0064)	(0.0089)	(0.0089)	(0.0066)	(0.0091)
SportUnits	0.0010	–0.0049	0.0170	0.0134	0.0307	0.0204	0.0096	0.0264
	(0.0351)	(0.0344)	(0.0333)	(0.0347)	(0.0348)	(0.0335)	(0.0330)	(0.0328)
ObeseD		–0.537***	–0.576***					
		(0.0653)	(0.0650)					
Score_HEI			0.0062**		0.0057**	0.0058**		0.0056**
			(0.0027)		(0.0027)	(0.0027)		(0.0028)
BMI Cat				–0.0689	–0.0530			
				(0.0757)	(0.0730)			
OverwD							–0.0967*	–0.0673
							(0.0546)	(0.0565)
Constant	1.079*	1.204*	0.952	1.212*	0.969	0.844	1.130*	0.905
	(0.638)	(0.667)	(0.581)	(0.690)	(0.612)	(0.562)	(0.675)	(0.587)
Observations	2,160	2,120	2,120	2,120	2,120	2,160	2,120	2,120

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Estimated risk preferences and association with health habits for male subjects less than 24 years old (*continued*).

	Model IXb	Model Xb	Model XIb	Model XIIb	Model XIIIb	Model XIVb
Age	–0.0196	–0.0038	–0.0168	–0.0187	–0.0092	–0.0159
	(0.0332)	(0.0239)	(0.0284)	(0.0322)	(0.0246)	(0.0277)
NonWhiteBritD	–0.0880	–0.109	–0.101	–0.0914	–0.104	–0.101
	(0.0729)	(0.0664)	(0.0651)	(0.0720)	(0.0661)	(0.0642)
Budget	–0.0005	–0.0006	–0.0008	–0.0005	–0.0008	–0.0008
	(0.0010)	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)
ParentEduc	–0.0844*	–0.109**	–0.119**	–0.0801*	–0.111**	–0.117**
	(0.0452)	(0.0460)	(0.0504)	(0.0449)	(0.0470)	(0.0504)
SmokeD	0.0870	0.202	0.203*	0.0817	0.199	0.201*
	(0.0885)	(0.128)	(0.119)	(0.0908)	(0.127)	(0.121)
QuitsmokeD	0.114	0.0957	0.110	0.114	0.0941	0.104
	(0.118)	(0.105)	(0.109)	(0.118)	(0.104)	(0.108)
Alcohol	0.0009	0.0108	0.0092	0.0012	0.0119	0.0106
	(0.0082)	(0.0089)	(0.0097)	(0.0078)	(0.0097)	(0.0097)
SportUnits	0.0174	0.0204	0.0402	0.0081	0.0170	0.0307
	(0.0334)	(0.0335)	(0.0360)	(0.0330)	(0.0334)	(0.0355)
BMI	–0.0193*		–0.0183*	–0.0133		–0.0119
	(0.0100)		(0.0099)	(0.0119)		(0.0108)
Score_HEI		0.0058**	0.0059**		0.0062**	0.0062**
		(0.00270)	(0.00274)		(0.00276)	(0.00273)
Constant	1.812*	0.844	1.526*	1.662*	0.952	1.356*
	(0.978)	(0.562)	(0.814)	(0.979)	(0.581)	(0.809)
Observations	2,120	2,160	2,120	2,100	2,100	2,100

Note: *Models XIIb–XVIb* exclude *BMI* outlier above 30. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Estimated risk preferences and association with health habits for female subjects.

	Model XVb	Model XVIb	Model XVIIb	Model XVIIIb	Model XIXb	Model XXb	Model XXIb	Model XXIIb
Age	0.0065	0.0051	0.0063	0.0052	0.0063	0.0065	0.0088	0.0108
	(0.0223)	(0.0226)	(0.0227)	(0.0226)	(0.0221)	(0.0223)	(0.0250)	(0.0245)
Non-WhiteBritD	–0.0023	–0.0057	–0.0016	0.0031	0.0079	–0.0023	–0.0315	–0.0288
	(0.0614)	(0.0592)	(0.0624)	(0.0658)	(0.0706)	(0.0614)	(0.0835)	(0.0867)
Budget	0.0010	0.0011	0.0010	0.0010	0.0009	0.0010	0.0012	0.0010
	(0.0010)	(0.0010)	(0.001)	(0.0009)	(0.0009)	(0.0010)	(0.0011)	(0.0010)
ParentEduc	–0.0491	–0.0562*	–0.0497	–0.0594*	–0.0534	–0.0491	–0.0476	–0.0406
	(0.0318)	(0.0316)	(0.0334)	(0.0330)	(0.0333)	(0.0318)	(0.0377)	(0.0382)
SmokeD	–0.463***	–0.472***	–0.463***	–0.461***	–0.454***	–0.463***	–0.489***	–0.482***
	(0.0939)	(0.0822)	(0.0940)	(0.0888)	(0.101)	(0.0939)	(0.0793)	(0.0885)
quitsmokeD	–0.0429	–0.0436	–0.0439	–0.0455	–0.0476	–0.0429	–0.0242	–0.0243
	(0.0763)	(0.0794)	(0.0775)	(0.0802)	(0.0786)	(0.0763)	(0.0885)	(0.0857)
Alcohol	0.0847***	0.0747***	0.0845***	0.0764***	0.0859***	0.0847***	0.0714***	0.0815***
	(0.0155)	(0.0129)	(0.0159)	(0.0122)	(0.0157)	(0.0155)	(0.0129)	(0.0162)
SportUnits	–0.0985***	–0.0969***	–0.0984***	–0.0943***	–0.0962***	–0.0985***	–0.0985***	–0.0992***
	(0.0260)	(0.0273)	(0.0259)	(0.0276)	(0.0258)	(0.0260)	(0.0285)	(0.0273)
Score_HEI	0.0024		0.0023		0.0023	0.0024		0.0024
	(0.0027)		(0.0029)		(0.0026)	(0.0027)		(0.0028)
ObeseD		–0.0369	–0.0114					
		(0.108)	(0.153)					
BMI Cat				–0.0161	–0.0143			
				(0.0344)	(0.0348)			
OverwD							0.0491	0.0514
							(0.0678)	(0.0742)
Constant	0.500	0.696	0.511	0.734	0.557	0.500	0.589	0.381
	(0.542)	(0.469)	(0.568)	(0.488)	(0.546)	(0.542)	(0.537)	(0.609)
Observations	1,960	1,960	1,960	1,960	1,960	1,960	1,960	1,960

Notes: Standard errors in parentheses. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Estimated risk preferences and association with health habits for female subjects less than 24 years old (*continued*).

	Model XXIIIb	Model XXIVb	Model XXVb	bModel XXVIb	Model XXVIIb	Model XXVIIIb
Age	0.0079	0.0065	0.0080	0.0174	0.0223	0.0227
	(0.0225)	(0.0223)	(0.0215)	(0.0245)	(0.0219)	(0.0220)
Non-WhiteBritD	–0.0010	–0.0023	0.0053	–0.0339	–0.0412	–0.0471
	(0.0574)	(0.0614)	(0.0620)	(0.0680)	(0.0610)	(0.0665)
Budget	0.0010	0.0010	0.000	0.0007	0.0006	0.0006
	(0.0009)	(0.0010)	(0.0009)	(0.0010)	(0.0009)	(0.0009)
ParentEduc	–0.0574*	–0.0491	–0.0524*	–0.0447	–0.0275	–0.0254
	(0.0307)	(0.0318)	(0.0305)	(0.0341)	(0.0328)	(0.0333)
SmokeD	–0.462***	–0.463***	–0.456***	–0.456***	–0.442***	–0.445***
	(0.0851)	(0.0939)	(0.0958)	(0.0829)	(0.0981)	(0.0999)
QuitsmokeD	–0.0431	–0.0429	–0.0464	–0.0197	–0.0145	–0.0124
	(0.0770)	(0.0763)	(0.0758)	(0.0827)	(0.0742)	(0.0752)
Alcohol	0.0757***	0.0847***	0.0849***	0.0733***	0.0910***	0.0911***
	(0.0124)	(0.0155)	(0.0152)	(0.0121)	(0.0154)	(0.0154)
SportUnits	–0.0953***	–0.0985***	–0.0971***	–0.0921***	–0.0953***	–0.0954***
	(0.0271)	(0.0260)	(0.0255)	(0.0278)	(0.0250)	(0.0251)
BMI	–0.0029		–0.0027	–0.0009		0.00133
	(0.0032)		(0.0034)	(0.0071)		(0.0066)
Score_HEI		0.00247	0.0022		0.00452	0.00468*

		(0.002)	(0.0026)		(0.0029)	(0.0026)
Constant	0.710	0.500	0.555	0.452	0.0102	–0.0402
	(0.451)	(0.542)	(0.506)	(0.551)	(0.545)	(0.570)
Observations	1,960	1,960	1,960	1,890	1,890	1,890

Notes: *Models XXVIb–XXVIIIb* exclude *BMI* outliers above 30. Standard errors in parentheses. *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.