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# What You Eat Is What You Are: Risk Attitudes, Time Preferences, and Diet Quality

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## Abstract

This paper explores the relationships between overall diet quality and attitudes toward risk and time using a general population survey. Our survey combines (i) a state-of-the-art food frequency questionnaire with (ii) a choice-based preference module to elicit individual risk and time preferences. The survey was administered to a representative sample of the French population. Using a hierarchical Bayes framework, we jointly estimate individual risk aversion and impatience parameters. We show that risk and time preferences significantly explain individual heterogeneity in key aspects of diet quality, even after controlling for socio-demographic characteristics. We find that more impatient and more risk-seeking individuals have poorer overall diet quality, more impatient individuals have higher daily energy intake, and more risk-seeking individuals consume more alcohol.

**JEL codes:** D91, I12, C11

**Keywords:** health behavior, food consumption, risk preferences, time preferences

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# 1 Introduction

Understanding the determinants of food choices is crucial to tackle the increasing burden of diet-related noncommunicable diseases. (Murray et al., 2020) Traditionally, economists have explained demand for different foods based on price, income, and product characteristics (Dubois et al., 2014), and have considered remaining preference heterogeneities across consumers as exogenous primitives. However, identifying the origins of consumers food preferences is necessary to address the determinants of malnutrition and nutritional inequalities (Darmon and Drewnowski, 2008). A recent strand of work has explored the roles of social and cultural factors in shaping food preferences (Atkin, 2016), but similar evidence drawing on insights from decision theory remain surprisingly elusive.

Diet quality entails mostly delayed and uncertain consequences on well-being and health (Willett, 1994). Risk and time preferences, the two foundational elements of decision theory, should thus be expected to influence dietary habits. For instance, less patient individuals may overlook long-run health damages from consuming junk food, while risk-seeking individuals may be willing to gamble on their health and continue to consume unhealthy drinks. If these phenomena prove widespread, this finding could have important consequences for the design and the evaluation of policies tackling malnutrition - including undernutrition, micronutrient intake inadequacy, and energy imbalance leading to overweight and obesity. In particular, it is possible that impatient and risk-seeking individuals will consume poor quality foods despite being perfectly informed about the health consequences of their choice. This might contribute to explaining the limited shifts in demand caused by policies which treat malnutrition as a problem of imperfect information (Dubois et al., 2021). Insights from the behavioral literature might help to improve the design of nutrition policies (Brownback et al., 2023). Understanding the influence of behavioral primitives on food preferences might improve welfare evaluations related to current public policies (Allcott et al., 2019c) and the credibility of counterfactual analyses based on policy-invariant structural parameters (Meier and Sprenger, 2015; Schildberg-Hörisch, 2018). Finally, it might help to explain the correlation between dietary preferences and income (Allcott et al., 2019a) and the heterogeneous effects of nutritional policies across income groups (Akee et al., 2013; Allcott et al., 2019b).

This paper explores the relationships between overall diet quality and attitudes toward risk and time using a general population survey. To do so, we combine (i) a state-of-the-art food frequency questionnaire with (ii) a choice-based preference module to elicit individual risk and time preferences, and conduct this survey on a representative sample of the French population. Building on recent advances in the empirical literature on hierarchical Bayes methods (Train, 2009; Toubia et al., 2013; Baillon et al., 2020), we simultaneously estimate individual risk and time parameters. Finally, we show that risk and time preferences significantly explains the individual heterogeneity in key aspects of diet quality. We find that both more impatient and more risk-seeking individuals have poorer quality diets and that the former exhibit a higher energy intake while the latter exhibit higher alcohol consumption. We verify that our results hold under several decision model specifications, and examine several sources of endogeneity potentially driving our results including correlated measurement errors (Gillen et al., 2019), contextual confounders, and reverse causation. We argue that these alternative mechanisms are unlikely to generate our results, which lends credence to the conjecture of an underlying causal mechanism.

While economists studying food consumption often rely on field, experimental, or scanner data (Dubois et al., 2014; List and Samek, 2015), these methods generally are unable to measure both at-home and out-of-home consumption or assess the extent of food waste. Therefore, nutritional epidemiologists often favor survey methods that measure the whole

diet at the individual level, and allow to decompose intakes across many nutrients. In this paper, we adopt the latter approach and use a reduced food frequency questionnaire (Affret et al., 2018). Combining the individual frequencies of consumption for each of the 28 food items and their nutrient compositions, we consider three complementary leading indicators of diet quality. First, we include the Daily Energy Intake (DEI) which measures the total calories ingested per day. Second, we compute the Whole Diet Index (WDI) which characterizes the overall quality of the diet in terms of nutritional adequacy with official recommendations. Third, we complement our evaluation of diet quality with the total alcohol intake, a major health driver which is measured in the same questionnaire but not accounted for in the WDI.

To measure risk and time preferences, we designed a module adapted specifically to general population surveys. The module includes eight tasks, four focused on risk preferences and four on time preferences. Each task includes a series of four hypothetical binary choices between a lottery and a certain gain in the risk part, and between a later sure gain and a sooner sure gain in the time part. For each risk (resp. time) prospect, we apply a bisection algorithm to progressively narrow the interval containing the corresponding certain (resp. sooner) equivalent. This preference module offers a balance between simplicity and theoretical consistency (Charness et al., 2013). The tasks are sufficiently simple to be undertaken by the general population, and allow to estimate individual parameters from standard decision theory models. Our elicitation tasks are similar to those of Falk et al. (2018), who elicit one certainty equivalent and one later equivalent using a bisection algorithm with five binary choices. However, in order to estimate structural risk aversion and time discounting, our module collects four certainty equivalents and four sooner equivalents.<sup>1</sup> We conduct this survey on the ELIPSS socio-economic panel, which tracks a representative sample of the general population in France over several years. Conditional on their participation to the surveys, the panelists were granted free internet mobile access (4G) and tablets. This strong incentive to participate allows us to rule out selection bias due to lack of internet access, and yielded a large response rate of 83%.

Using the intervals containing risk and sooner equivalents, we jointly estimate individual risk aversion and impatience parameters using a hierarchical Bayes framework. This method makes use of the population distribution in the estimation of individual parameters, which improves its accuracy and robustness compared to single-subject estimations (Murphy and ten Brincke, 2018). A key feature of our questionnaire is that it allows us to consider a range of decision models, from the classic discounted expected utility model (DEU) to extended hyperbolic discounting rank-dependent utility (HDRDU) models. We rationalize seemingly inconsistent answers across tasks by considering that respondent use noisy certainty and sooner equivalents. These errors are heteroskedastic across individuals, so that each individual is also characterized by the consistency of their equivalents across tasks. We check the stability of the distributions obtained after convergence, and run a sensitivity analysis which shows that our results are not driven by the estimation settings.

Finally, we test the associations between our estimates and diet quality. We find statistically and economically significant associations between our structural estimates and the indicators of diet quality, after controlling for differences in socio-demographic variables. First, our estimations suggest daily energy intake is higher among the most impatient compared to the most patient individuals. Second, we find that less impatient individuals exhibit better diet quality. Third, our estimates indicate that more risk-seeking individuals consume more alcohol. Our results suggest that time preferences play a bigger role explaining cross-

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<sup>1</sup>Eliciting sooner rather than later equivalents has several advantages: (i) it yields equivalents are always bounded upwards, (ii) it allows to homogeneously scan the entire range of the impatience parameter, and (iii) it can be implemented with fixed sooner gains for any time delay.

sectional variations in overall diet quality, and that risk aversion better explains variations in alcohol consumption. This is coherent with the facts that alcohol intoxication has short-run psychotropic effects, whereas most dietary choices have essentially long-run health consequences. We provide a series of robustness checks showing that our results hold both with our main estimates based on a standard DEU model, with estimates based on the extended HDRDU model, and with model-free estimates using the average of equivalents. We also find that substituting these averages by only one certain and one sooner equivalents yield statistically insignificant results for some pairs of equivalents. This highlights the benefits of including several tasks in the questionnaire, as it increases the reliability of the estimations of risk and time preferences and reduces the likelihood of low powered negative results. We then leverage the estimated propensities for errors in risk and time tasks to identify outliers in terms of consistency. Removing the 5% outliers corroborates the previous results and yields that risk-seeking individuals have a significantly poorer diet quality. We check that our results are not spuriously generated by correlations between measurement errors in certainty and sooner equivalents using the instrumental variable estimation method from Gillen et al. (2019). Finally, we examine several alternative mechanisms that could explain our results, including contextual confounders and reverse causation. Although our cross-sectional data delivers results that cannot be conclusive on causality, we argue that it is unlikely that our main results are driven by alternative mechanisms. In addition, we exploit ancillary data from the same panel to obtain additional results on associations with the body mass index (BMI) and the frequency of physical activity, which corroborate our previous findings and the existing evidence in the literature.

This paper makes several contributions. First, our results add directly to the empirical literature on the determinants of individual dietary preferences. There is an emerging stream of research on the influence of social interactions and cultural factors,<sup>2</sup> and the role of personality traits (Lunn et al., 2014) but evidence linking general dietary habits to risk and time preferences is scarce. The existing studies typically provide indirect evidence using only the BMI,<sup>3</sup> which imperfectly captures the health consequences of malnutrition (Kobylińska et al., 2022), or focus on one or few selected product categories such as yogurts (De Marchi et al., 2016), snacks (Bradford et al., 2017), fast food and sweets (Samek et al., 2021), or alcohol (Barsky et al., 1997; Anderson and Mellor, 2008; Sutter et al., 2013). In particular, List et al. (2022) study the relationships between risk and time preferences and sets of healthy or unhealthy foods among a sample of low-income children. In our study, we measure overall diet quality at the general population scale. We are aware of only two existing studies measuring overall diet quality in relation with risk or time preferences: Huston and Finke (2003) focuses on time attitudes and only observe proxies for patience, and Galizzi and Miraldo (2017) focuses on risk attitudes in a sample of 120 students. Our study combines both risk and time preferences, and shows that time preference are more associated with diet quality while alcohol intake is more associated with risk attitudes. These results reflect the facts that alcohol intoxication triggers immediate risks, whereas overall dietary quality has essentially long-run health consequences.<sup>4</sup>

Our paper also contributes to the broader public health literature which documents the behavioral factors of hazardous health choices, such as substance use (Kirby et al., 1999) and smoking (Barsky et al., 1997; Anderson and Mellor, 2008; Burks et al., 2012; Sutter et al.,

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<sup>2</sup>See for instance Fortin and Yazbeck (2015), Atkin (2016), and Lewbel et al. (2022).

<sup>3</sup>See Chabris et al. (2008), Anderson and Mellor (2008), Burks et al. (2012), Sutter et al. (2013), Golsteyn et al. (2014), and Courtemanche et al. (2015).

<sup>4</sup>This is in line with the results on drug use of Blondel et al. (2007), who found that substance users differ from nonusers in risk preferences, but not in time preferences.

2013; Golsteyn et al., 2014). Most of this literature focuses on time preferences (Lawless et al., 2013), and only a handful of articles combine risk and time preferences.<sup>5</sup> Finally, our work relates to the few general population surveys which both leverage choice-based elicitation methods to measure risk or time preferences and assess their external validity (Von Gaudecker et al., 2011; Courtemanche et al., 2015; Bradford et al., 2017; Falk et al., 2018; Meissner et al., 2023) – i.e. their ability to predict economics choices external to the elicitation procedure (Schildberg-Hörisch, 2018). Our preference module relates more closely to Von Gaudecker et al. (2011), who also collect enough observations to allow for stochastic response and structurally estimate model parameters. A key novel feature of our study is to investigate an aspect of real-life behavior – food consumption – largely unexplored with these methods.

The rest of the paper is organized as follows. Section 2.1 presents the sample. In section 3, describes the we describe our questionnaire on risk and time preferences, our decision model, and the estimation method. In section 2 we describe present the diet measurement module and discuss explains how we constructed build our leading indicators of diet quality in section 2. Section 4 discusses comments the estimates of individual risk estimates and the time parameters and provides evidence on their associations with to diet quality. Section 5 concludes

## 2 Measuring diet in the ELIPSS panel

In this section, we present the ELIPSS panel and describe how we build the leading indicators of diet quality for each individual.

### 2.1 The ELIPSS panel

Our survey was conducted in France and involved participants in the ELIPSS panel. ELIPSS is a web-based longitudinal social sciences survey inspired by the Netherlands LISS panel and the US Knowledge panel.<sup>6</sup> Between 2011 and 2019, it was funded by the French agency for research (ANR).<sup>7</sup> The ELIPSS panel target population is francophone residents of metropolitan France, aged between 18 and 79 years on July 1<sup>st</sup> 2016, living in ordinary households (i.e. excluding homeless individuals and individuals living in institutions or communities). According to the 2014 census the eligible population numbered 45.3 million. The panel is composed of 3,331 individuals selected according to a true probability sample of households drawn from the population register by the French National Institute of Statistics and Economic Studies (INSEE). An important feature of this panel is that in exchange for their response to a 30 minute monthly survey all members were provided with touchscreen tablets (Archos) and mobile internet connection (4G). This indirect monetary incentive drastically increased the ELIPSS response rates (over 80% for every survey round) compared to other online surveys or telephone or face to face interviews (de Leeuw et al., 2018). Due to these sampling, material, and incentive particularities, the ELIPSS sample is an accurate representation of the general population in France (Blom et al., 2016; Cornilleau and Duwez, 2021).

The ELIPSS panel is surveyed once a year for socio-demographic information, the other monthly surveys are questionnaires proposed by the successful projects selected by the

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<sup>5</sup>Notable exceptions include Blondel et al. (2007), Sutter et al. (2013), Bradford et al. (2017), Falk et al. (2018), Samek et al. (2021), and List et al. (2022).

<sup>6</sup><https://www.elipss.fr/fr/>

<sup>7</sup>Equipex DIME-SHS (ANR-10-EQPX-19-01)

ELIPSS Scientific committee. Our study uses data from the 2018 annual survey merged with the Psychofood survey (Nebout et al., 2020), which successfully passed the ELIPSS peer-reviewing process. Our survey includes a risk and time preferences module and a diet measurement module. The preference module consists of a series of binary choices allowing to elicit risk and time preferences according to a variety of decision models. We describe this module in section 3. In the diet measurement module, the participants had to fill a food frequency questionnaire. Based on their responses, we computed several diet indicators including energy intakes. This module is described in section 2. The survey was administered on June 6<sup>th</sup>, 2018 to the 2,655 individuals still present in the panel, and the data collection stopped on July 26<sup>th</sup>. A total of 2,199 individuals reached the end of our questionnaire, a high response rate of 83%. The data set included weights correcting for non-response in order to ensure that the sample was representative of the French population.

## 2.2 Frequency of consumption

A frequency questionnaire (FFQ) based on Affret et al., 2018 was used to collect data on respondents diets. This FFQ measures the frequencies of consumption and portion sizes of 28 food items grouped into seven food groups (see table D.1 for the list of the items by food group).

For each food item  $j$ , the frequency of consumption was estimated through a two-stage procedure. The first question was: “On average, over the last 12 months, how often did you eat  $j$ ?” with possible answers “every day”, “every week”, “every month” or “rarely or never”. Individuals who responded “every day” (resp. “week”, “month”) were then asked to answer in a second question to narrow down their frequency of consumption within a period: “Over the last 12 months, on average, how many times every day (resp. “week”, “month”) did you eat  $j$ ?”, and had to enter this frequency manually. Finally, respondents were asked to select their average portion size from several different pictures (see the appendix figure D.1) or expressed in common units (e.g. one standard size yogurt). This third question was: “Over all occasions when you ate that item, what was the average portion size?”. For each item, we combine the respondents’ responses to infer their average daily quantities consumed.

For each individual  $i$  and food item  $j$ , we compute the average daily consumption  $Q_{ij}$  in g/day by multiplying the chosen average portion size in g by the frequency of consumption by day.<sup>8</sup> We do so for each of the 28 food items, including alcohol which we use as a dependent variable in the result section 4.

## 2.3 Daily nutrients intake

We convert the quantities of food items declared in the FFQ into daily intakes of nutrients. This procedure allows us to conduct our main analysis on aggregated variables representing the individuals’ diet rather than on specific food items. The daily intake of nutrient  $n$  by individual  $i$  is computed as follows:

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<sup>8</sup>The declared consumption frequencies expressed per month (resp. week) were converted into a per day frequency by dividing frequencies by 30 (resp. by 7). Portion sizes were either quantified from the FFQ itself (when quantity was available) or with the help of the SUVIMAX book (Hercberg et al., 2002) which provides the conversion between pictures of portion sizes and exact volume for 244 food items generally consumed in France.

$$Intake_{in} = \sum_{j=1}^{28} Q_{ij} N_{jn} \quad (1)$$

where  $Q_{ij}$  is the average daily consumption of food item  $j$  by individual  $i$ , and  $N_{jn}$  is the content of food item  $j$  in nutrient  $n$ . The nutritional compositions  $N_{jn}$  of the 28 food items were provided by the French national INCA2 dietary survey and the French food nutrient composition database CIQUAL.<sup>9</sup>

## 2.4 Diet indicators

We evaluate the respondents' diets over several dimensions. To measure the total quantity of food intake, we compute the Daily Energy Intake (DEI) measured in calories. To assess the overall quality of a diet measured across all nutrients, we use the leading indicator designed in Vieux et al. (2013), which we refer to as the Whole Diet Index (WDI). As alcohol consumption is not accounted for in the WDI albeit having important health impacts, we consider the total alcohol consumption as a separate indicator.

### Daily Energy Intake (DEI)

An excess in energy intake is usually the consequences of consuming foods high in saturated fats or in added sugars. This indicator is known to be associated with bad health outcomes (Bates et al., 2016). We compute the DEI as the sum of all estimated energy intakes from foods. This is obtained by multiplying the estimated amount consumed in grams for each food item by the energy composition of the item (per gram), and summing over items.

### Whole Diet Index (WDI)

We evaluate the overall quality of each respondent' diet using an index designed in Vieux et al. (2013). We begin by computing three scores of nutritional quality which we then combine to produce an aggregated categorical variable, the WDI.

The three scores of nutritional quality, estimated after exclusion of nutrients provided by alcoholic beverages, are the following:

1. Mean Adequacy Ratio (MAR)

The MAR is an indicator of good nutritional quality (Madden et al., 1976). It corresponds to the percentage of Dietary Reference Intakes (DRI) for 20 key nutrients: vitamins A, C, D, E, B12, B2, B6, calcium, potassium, iron, magnesium, proteins, fibers, thiamine, niacin, folates, zinc, copper, iodine, and selenium. For each individual  $i$ , the indicator  $MAR_i$  is given by:

$$MAR_i = \frac{1}{20} \sum_{n=1}^{20} \min \left\{ \frac{Intake_{in}}{DRI_n}, 1 \right\} \quad (2)$$

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<sup>9</sup>Each food from a list of 1,183 foods consumed in the INCA2 survey was matched to each of the 28 FFQ food items. The nutrient composition per gram of each food item was estimated by a weighted mean of all INCA2 foods associated with the FFQ food item. The weight associated to one given INCA2 food corresponded to its consumption level among adults of the INCA2 dietary survey. For instance, if raspberries are consumed in higher quantities than blueberries among French adults, then FFQ nutrient composition of the global "Fruit" item will be more represented by raspberries than blueberries.



where  $\text{DRI}_n$  refers to the age- and gender- specific DRI for nutrient  $n$ . A MAR equal to 100% implies a coverage of all 20 DRIs. The higher the MAR, the better the diet quality. The DRIs are given in the appendix table D.2.

## 2. Mean Excess Ratio (MER)

The MER is an indicator of bad nutritional quality. It is the mean daily percentage of Maximum Recommended Values (MRV) for 3 nutrients that should not be excessively consumed (saturated fats, salt, free sugars. For each individual  $i$ , the indicator  $\text{MER}_i$  is given by:

$$\text{MER}_i = \frac{1}{3} \sum_{n=1}^3 \max\left\{\frac{\text{Intake}_{in}}{\text{MRV}_n}, 0\right\} \quad (3)$$

where  $\text{MRV}_n$  refers to the MRV for nutrient  $n$ . A MER equal to 0% means that none of the maximum daily recommendations for each of the three unfavorable nutrients is exceeded. The lower the MER, the better the diet. The MRVs are given in the appendix table D.2.

## 3. Energy Density (ED)

The ED is the average caloric content of the diet, expressed in kcal per 100 grams. For example, fruit, vegetables, fish, and lean meats have a low energy density while high fat/high sugar foods have a high energy density. This indicator is negatively associated with the nutritional quality of diets (Ledikwe et al., 2006), so that decreasing the ED of the diet is recommended by several public health authorities to prevent obesity and obesity-associated disease conditions. The calculation of the ED is based on all food items consumed excluding beverages (e.g., water, hot beverages, milk, fruit juices, other drinks...). The lower the ED the better the diet quality.

We compute each of the three above scores for each respondent of the Psychofood panel and aggregate them into the WDI:

$$\text{WDI}_i = 1_{\text{MAR}_i > \text{median}_i(\text{MAR})} + 1_{\text{MER}_i < \text{median}_i(\text{MER})} + 1_{\text{ED}_i < \text{median}_i(\text{ED})} \quad (4)$$

where  $\text{median}_i(I)$  is the median of indicator  $I$  over the sample of respondents with the same gender as individual  $i$ . These values are given in the appendix table D.3. We obtain an ordered categorical variable taking values  $\{0, \dots, 3\}$ . The higher the WDI the better the diet. The best (resp. worst) value is 3 (resp. 0), indicating that the individual has a better (resp. worse) value than half the same gender individuals of the sample for all three indicators.

Table 1 describes the distribution of the nutritional indicators across classes of WDI. The first panel gives the average intake by food group and by WDI category. We obtain that individuals with better diets consume more fruits and vegetables, pulses, and less high fat, sugar, and salt foods. The second panel describes the distribution of the indicators DEI, MAR, MER, and ED across WDI categories. The average DEI is higher for the two low quality categories of WDI. We present the distribution of the leading nutritional indicators across socio-demographic characteristics in section 4 (see table 4).

## 2.5 Missing values

Among the 2,199 individuals who reached the end of the preference module, 314 (14%) failed to answer at least one question in the diet module. Among these, 137 individuals

Table 1: Distribution of nutritional indicators

	Whole Diet Index			
	0:Low	1:Intermediate -	2:Intermediate +	3:High
<b>Intake by food group (g/day)</b>			Average	
Fruits and vegetables	172	225	451	634
Cereal-based products and tubers	222	309	276	304
Meat, fish, and eggs	109	144	137	142
Pulses	18.5	28.3	40.7	52.5
Dairy products	246	301	288	272
High fat, sugar, and salt foods	216	221	145	111
Added fats	51.3	46.2	27.5	24.3
Beverages	1,780	1,922	1,877	1,881
Pure alcohol in beverages	8.22	9.07	5.86	5.55
<b>Nutritional quality indicators</b>				
Daily Energy Intake (DEI, cal/day)	1,890	2,149	1,746	1,755
Mean Adequacy Ratio (MAR)	74.5%	80.0%	79.6%	89.5%
Mean Excess Ratio (MER)	21.9%	25.7%	10.8%	1.2%
Energy density (ED, cal/100g)	202	188	139	123
<b>Observations (share)</b>	207 (9.9%)	810 (38.8%)	869 (41.7%)	214 (10.3%)

Note: These statistics are computed without weights. The distribution across WDI groups is close to that of a binomial  $\mathcal{B}(4, 0.5)$  which probabilities are (0:12.5%, 1:37.5%, 2:37.5%, 3:12.5%), albeit with slightly thinner tails. This is in part because the indicators are correlated, with coefficients 0.45 for MAR-MER, -0.11 for MAR-DE, and 0.36 for MER-DE. These correlations are close to those reported in Vieux et al. (2013).

have only missed one of the three questions for only one item (e.g. the average portion size for one item) over the 84 questions pertaining to the 28 item, and 253 individuals who failed to answer five questions or less. For these individuals, the collected data covers most of their diet and allows to reasonably approximate their overall diet quality. To include these individuals in the main analysis, we impute the missing value using the following rules. First, if the individual missed the first question relative to the frequency of consumption for a given item, we impute a frequency of zero. Second, if the individual answered the first question but missed the second question relative to the number of times of consumption, we impute a value of one time per periodicity unit given at question 1. Third, if the individual answered the first two questions but missed the last question relative to the portion size, we impute the average portion size computed over the nonmissing observations.<sup>10</sup> In the appendix, we verify that our qualitative results hold if we drop all individuals with at least one missing item frequency or one imputed value (see table D.4). For our main results presented in section 4, we remove the 5% outliers for the caloric content, therefore excluding 16 individuals with many missing items imputed at zero.

<sup>10</sup>For several categories, an additional question asked the participants to specify the subcategory they consume most often to narrow down the nutritional content of the type of product they consume. These categories are: drinks (juice, sweetened beverages, light beverages, or equally often sweetened and light beverages), hot beverages (coffee, tea, infusion, or equally often coffee and tea), oil (olive, canola, nut, sunflower, peanut, ISO4 (a mix of four oils), or other), and cereal products and bread (whole grain, white grain, both equally often). These subcategories matter in terms of nutritional content. For instance, sweetened beverages are attributed a caloric content of 42 cal/100g, against only 1.3 cal/100g for light beverages. For these additional questions, we impute the missing values at the weighted average among collected answers.

### 3 Measuring risk and time preferences

This section describes our preference module, our general theoretical framework, and the estimation method. We design a parsimonious module to adapt the sophisticated elicitation methods used in lab experiments (Hey and Orme, 1994; Wakker and Deneffe, 1996; Abdellaoui et al., 2007) to a general population survey. Although model-free measurement methods for risk and time attitudes using ordinal scales, such as Likert scales, have recently been shown to be effective at explaining economic behaviors (Dohmen et al., 2011; Falk et al., 2018; Tasoff and Zhang, 2022), economists often favor choice-based and theoretically grounded elicitation methods within the revealed preference paradigm which are more suitable to policy evaluation and welfare analysis. In part because of their high implementation costs at the general population scale, the ability of these structural methods to explain real economic decisions is still subject to investigation (Galizzi et al., 2016; Charness et al., 2020).<sup>11</sup> Our paper contributes to this literature by showing that structural elicitation methods used on several tasks conducted in the general population yield risk and time preferences that significantly explain diet quality.<sup>12</sup> This section describes the preference module, presents the decision model we employ to parameterize risk and time preferences, and finally details our estimation procedure.

#### 3.1 Preference module

Our preference module offers a compromise between simplicity and theoretical consistency. The questionnaire is relatively short (5-10 minutes) and sufficiently simple for a large-scale survey. It collects all the necessary data to estimate a structural decision model.

##### Notation

Let  $z_t$  denote an outcome received at time  $t$  with certainty. When the outcome is received immediately (i.e. at  $t = 0$ ), we simplify the notation by  $z$ . The notation  $(x_t, p, y_t)$  denotes a risk prospect that gives an outcome  $x$  at time  $t$  with probability  $p$  and an outcome  $y$  at time  $t$  with probability  $1 - p$ . We denote by  $\succ$  the preference relation over these objects and use notation  $\sim$  for the indifference. The expected gain of the risk prospect  $(x, p, y)$  is  $xp + (1-p)y$ . The certainty equivalent of the risk prospect  $(x, p, y)$  is the outcome  $c^*$  such that  $c^* \sim (x, p, y)$ . By definition, there is risk aversion (resp. risk-seeking) when  $c^* < xp + (1-p)y$  (resp.  $c^* > xp + (1-p)y$ ). In order to measure time preferences, we consider binary choices of type  $z_t$  vs  $x_{t+\tau}$ , where  $t \geq 0$  and  $\tau > 0$ . The sooner equivalent in  $t$  of a delayed outcome  $x_{t+\tau}$  is the outcome  $c_t^*$  such that  $c_t^* \sim x_{t+\tau}$ . We define the sooner equivalent of a time prospect denoted  $(t, x, t + \tau)$  as the sooner equivalent in  $t$  of the prospect  $x_{t+\tau}$ .

##### Design

To estimate the risk and time preferences of the respondents, we design a questionnaire to collect their certainty and sooner equivalents for various risk and time prospects. We divide the questionnaire into two parts: (i) a risk part where the outcomes are risky ( $0 < p < 1$ )

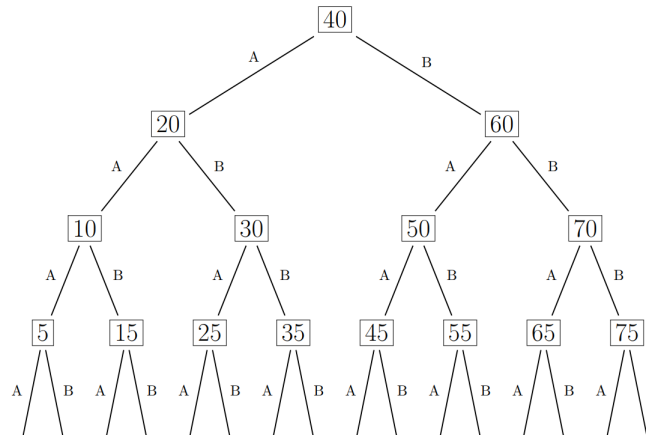
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<sup>11</sup>Only few papers leverage choice-based elicitation methods at the general population level (Von Gaudecker et al., 2011; Courtemanche et al., 2015; Bradford et al., 2017). Studies comparing the respective performance of stated versus revealed preference measures typically focus on experimental samples and limited demographic groups. For instance, Samek et al. (2021) find that stated risk and time preference correlate with BMI among teenagers, but not experimental measures based on a task with multiple price lists.

<sup>12</sup>For comparison, we also include a stated risk preference measure in our survey, which exhibits less explanatory power for our diet indicators (see section 4).

but obtained without delay ( $t = \tau = 0$ ) and (ii) a time part where the outcomes are delayed ( $\tau > 0$ ) but obtained with certainty ( $p = 1$ ). To elicit a respondent's equivalent of a given risk (resp. time) prospect, we ask whether the respondent would choose that prospect instead of a certain (resp. sooner) outcome. For each prospect, the questionnaire includes four successive binary choices following a bisection algorithm to halve the possible range of the equivalent at each question, as illustrated in figure 1.

Figure 1: Bisection algorithm for the risk prospect  $(0, 0.5, 80)$



Note: At the top of the tree, the first question offers €40 against the prospect. If the respondent accepts (path A), the second question offers €20 instead. Alternatively, if she declines (B) the second question offers €60.

Consider for example the risk prospect  $R1 = (80, 0.5, 0)$ , where the respondent has 50% chance to obtain €80 immediately. The first question asks whether the respondent would take €40 immediately with certainty rather than choosing the risk prospect R1. Her answer reveals whether her certainty equivalent for prospect R1 is above or below €40. If she accepts (resp. declines), it implies that her certainty equivalent for this prospect R1 lies within the interval  $(0; 40)$  (resp.  $(40, 80)$ ). The second question is then identical to the first one except that we replace the certainty value by the middle of the interval implied by the first answer. After this second question, the range of the possible values for her certainty equivalent is divided by two. We proceed so four times to obtain intervals of length 5. Note that the lengths of the intervals are identical across prospects, reflecting agnosticism about the distribution of the equivalents.

We consider several prospects for both the risk and the time parts. The main rationale is that measures of both risk and time preferences are notoriously noisy (Frederick et al., 2002; Schildberg-Hörisch, 2018). For that reason, measuring accurately the underlying risk and time preferences requires to disentangle the information on risk and time attitudes from noise, and therefore to collect answers to several tasks. A second motivation is that including several tasks allow to estimate more behavioral traits relative to risk and time preferences (see next section). Although collecting more information generally improves the precision of the estimation, including a large number of tasks may also generate cognitive fatigue, decrease acceptability, and trigger more dropouts. This constraint was partly monitored by the management of ELIPSS who limits the size of surveys sent to the panel. The number of prospects included in our questionnaire results from a trade-off between (i) collecting enough information to adequately measure preferences and (ii) keeping our modules reasonably short and easy to understand by the general population. These constraints led us to consider 4 risk

and 4 time prospects in total, which are listed in table 2. The risk part of the questionnaire thus includes 4 questions following the bisection algorithm for each of the 4 different risk prospects. All outcomes are expressed in euros.<sup>13</sup> For each prospect, the first proposed value is the middle between the high gain and the low gain, so €40 for the risk prospects R1-R3 and €60 for the prospect R4. The time part of the questionnaire mirrors the risk part and consists in the 4 time prospects described in table 2. For each time prospect  $(t, x, t + \tau)$ , we ask 4 questions following the bisection algorithm to elicit the sooner equivalent in  $t$ . The first proposed value is €40 for all 4 time prospects. In the first 3 time prospects, we elicit the quasi-present equivalents with  $t = 1$  day. The last time prospect generates a variation in  $t$  that allows us to measure the extent of present bias (see section 4). During the experiment, the order of the prospects was randomized both across the risk and time parts and within each part.

Table 2: Risk and time prospects

Risk				Time			
Index	$x$	$p$	$y$	Index	$t$	$x$	$t + \tau$
R1	80	0.50	0	T1	1 day	80	3 months
R2	80	0.25	0	T2	1 day	80	6 months
R3	80	0.75	0	T3	1 day	80	12 months
R4	100	0.50	20	T4	6 months	80	12 months

Note: All gains are in euros.

## Incentives

While incentivized choices are the standard in the lab, using real incentives in general population surveys is less systematic (Tasoff and Zhang, 2022).<sup>14</sup> Real incentives dramatically increase the costs of large population studies, while the literature on the significance of hypothetical bias has yielded mixed results (Cohen et al., 2020). Besides monetary costs for the researcher, implementing real incentive-compatible procedures can be cognitively taxing and time consuming (Stantcheva, 2022). It requires to engage the participants in detailed explanations prior to the questionnaire (Baltussen et al., 2012), which may generate cognitive fatigue, noise in the responses, and drop outs before completion. Furthermore, since our primary interest is the relationship between diet and risk and time preferences, the possibility of hypothetical bias may not bear consequences for our results.<sup>15</sup> Finally, to our knowledge there is no incentive compatible method for food questionnaires so that our food data relies

<sup>13</sup>Our paper thus focuses on the external validity of risk and time preferences elicited with monetary outcomes for diet quality. Although we acknowledge that risk and time attitudes may vary across domains so that individuals may behave somewhat differently for monetary and health outcome, Dohmen et al. (2011) conclude that domain-specific preferences assessments are all strongly positively correlated. They also find that domain-specific preferences are the most correlated with the corresponding domain behavior. This results suggests that using hypothetical health outcomes instead of monetary outcomes would only yield stronger associations.

<sup>14</sup> Meissner et al. (2023) is a recent exception, although they draw only a small fraction of the respondents for the payments.

<sup>15</sup>A constant bias would have no impact on our results. If it consists in an additional noise on the equivalents, we can control for it in our procedure allowing for stochastic noise (see section 3.2). Finally, if it causes an idiosyncratic error in our measured risk and time preferences, it may only bias our estimates toward zero, so that our results underestimate would underestimate the true relationships. The role of real incentives in a lab setting is explored by

on declared frequencies of consumption (see section 2). For the sake of consistency between the two modules, and the other reasons listed above, our preference module collects hypothetical choices. As shown below, the answers of the respondents showed general consistency across tasks, suggesting that participants answered our module seriously.

Our preference module is specifically designed for the general population and aims at balancing theoretical consistency with simplicity. Our tasks are kept short and simple (5 to 10 minutes in total) so as to maximize the answer rate (Edwards et al., 2009). Participation was also strongly supported by the fact that all participants were granted tablets and free internet access conditional on their participation to all surveys.

### **Descriptive statistics of the equivalents**

The answers of a given individual for a given prospect yield an interval containing her certainty/sooner equivalent for this prospect. To describe these raw observations, we first compute the middle of this interval for each individual and each prospect. Table 3 gives the average of these middles across individuals, for each prospect. For each prospect, the last two columns give respectively the shares of respondents who answered all questions (4/4) and the number of respondents who answered no questions (0/4). For all prospects, the vast majority (more than 97.5%) of the participants answered all 4 binary choices of the bisection algorithm so that their equivalents can be bounded by an interval of length 5, and only a small minority (under 2%) answered none of the choices. For the latter, we remain agnostic about their equivalents for the corresponding task. We find 18 individuals who missed either all risk tasks (8), all time tasks (3), or both (7). As the data provides no information on their equivalents, we remove these individuals in the rest of the analysis and estimate individual risk and time preferences for  $N=2,181$  individuals. The ranking of these averages across prospects is consistent with the design, as the average certainty equivalent increases with the gain and with the probability of winning this gain. Similarly, the average sooner equivalent decreases with delay  $\tau$ , and increases with the sooner date  $t$ . For all risk prospects, the median certainty equivalent is lower than the expected value, indicating risk aversion. We find statistically significant correlations between 0.1 and 0.2 between the certainty equivalents and the sooner equivalents, which stresses the importance of considering risk and time attitudes jointly to explain economic behaviors (see table D.5 in the appendix).

Table 3: Certainty and sooner equivalents across individuals, in euros

Prospect				Average	Median	S.d.	# Answers	
							4/4	0/4
<b>Risk</b>	$(x; y)$	$p$	$px + (1 - p)y$					
R1	(80;0)	0.50	40	28.3	32.5	17.9	2,155	35
R2	(80;0)	0.25	20	18.0	17.5	15.8	2,147	36
R3	(80;0)	0.75	60	37.2	37.5	20.9	2,150	40
R4	(100;20)	0.50	60	45.1	42.5	18.1	2,149	37
<b>Time</b>	$x$	$t$	$t + \tau$					
T1	80	1 day	3 months	54.0	57.5	20.2	2,159	28
T2	80	1 day	6 months	50.2	57.5	21.6	2,153	34
T3	80	1 day	12 months	44.1	42.5	23.1	2,165	28
T4	80	6 months	12 months	53.0	57.5	20.0	2,167	25

Note: These values are not weighted and computed in the raw data (N=2,199). For example, the answers for the risk prospect R1 yield intervals which middles have an average across respondents of €28.3, a median of €32.5, and a standard deviation of €17.9. 2,155 respondents answered all 4 binary choices for R1 and only 35 answered none.

## 3.2 Model

In this section, we motivate why we need a decision model, present our model for the equivalents, and discuss conceptual and empirical aspects of our framework.

### Motivation

The main motivation for the model is that the sooner equivalents only reflect a combination of risk and time preferences. As noted early in the literature on time preferences (Frederick et al., 2002), the normative benchmark of the discounted expected utility (DEU) model implies that the decreasing marginal utility (i.e. risk preferences) confounds the discount rate. Empirically, this implies that measuring risk and time preferences requires to disentangle the role of the curvature of utility in the intertemporal choices – to the extent that utility is nonlinear. In particular, Andersen et al. (2008) find that ignoring utility curvature in the measurement of time preferences yields to a substantial positive bias in the discount rates. In our case, this suggests that our sooner equivalents are driven both by utility curvature and time preferences.

The second motivation is a practical one: we need to disentangle the signal from the noise in the equivalents. A decision model provides a theoretically sound rule to distinguish the information pertaining to risk and time preferences from the noise, and aggregate that information into a parsimonious set of parameters informing the decision process. In our framework, we build on the seminal works of Hey and Orme (1994) and Bruhin et al. (2010) and consider that individuals have noisy representations of their underlying theoretical equivalents. This framework not only allows to extract the relevant information from the equivalents, but also provides a measure of the noise variance across individuals, i.e. of how precisely they represent their equivalents.

### Behavioral equations

Let gain  $x$  provide individual  $i$  with utility  $u(x, \alpha_i)$ , where  $\alpha_i > 0$  and  $u(\cdot, \alpha_i)$  is a positive and strictly increasing function. A gain  $x$  obtained in period  $t$  grants discounted utility

$D(t, \delta_i)u(x, \alpha_i)$  with  $\delta_i > 0$  and  $D(\cdot, \delta_i)$  a positive and strictly decreasing function. Our objective is to elicit individual preference parameters  $\alpha_i$  and  $\delta_i$  from their indifference levels revealed by their answers. To this aim, we consider a structural equation model for these indifference levels. Under DEU, the theoretical certainty equivalent of respondent  $i$  for the risk prospect  $R = (x, p, y)$ , is denoted  $c_{iR}^*$  and given by equation (5).

$$c_{iR}^* = u(\cdot, \alpha_i)^{-1}[pu(x, \alpha_i) + (1 - p)u(y, \alpha_i)] \quad (5)$$

This equation allows to identify the risk preference parameters  $\alpha_i$ . For each respondent and for each time prospect  $T = (t, x, t + \tau)$ , under DEU, the theoretical sooner equivalent  $c_{iT}^*$  is given by equation (6).

$$c_{iT}^* = u(\cdot, \alpha_i)^{-1} \left[ \frac{D(t + \tau, \delta_i)}{D(t, \delta_i)} u(x, \alpha_i) \right] \quad (6)$$

This equation allows to identify the intertemporal-attitude parameter  $\delta_i$ , given that the parameters  $\alpha_i$  are identified from equation (5). Equations (5) and (6) provide the expected values of the certainty equivalents and the sooner equivalents.

### Specification of noise

In practice respondents may make seemingly inconsistent answers across prospects that violate the monotonicity of preference and in turn the deterministic framework presented above. For instance, the answers of a given respondent may indicate a lower certainty equivalent for prospect R1=(80, 0.5, 0) than for prospect R2=(80, 0.25, 0). We rationalize these apparent mistakes by assuming that the respondents base their answers on noisy certainty and sooner equivalents noted  $c_{iR}$  and  $c_{iT}$ , respectively. We consider the following additive normal errors for the certainty and the sooner equivalents:

$$c_{iR} = c_{iR}^* + \epsilon_{iR} \quad \text{with } \epsilon_{iR} \sim N(0, (\sigma_i^r)^2) \quad \forall R \in \{R1, \dots, R4\}, \quad (7)$$

$$c_{iT} = c_{iT}^* + \epsilon_{iT} \quad \text{with } \epsilon_{iT} \sim N(0, (\sigma_i^t)^2) \quad \forall T \in \{T1, \dots, T4\}. \quad (8)$$

The parameters  $\sigma_i^r > 0$  and  $\sigma_i^t > 0$  characterize the extent to which individual  $i$  deviates from her theoretical equivalents. They allow for seemingly inconsistent answers across prospects, and may also capture possible noise due to our use of hypothetical choices. We further allow for heteroskedasticity as the variances may vary across individuals and across prospect types: each individual has a given error variance for all her certainty equivalents, and another one for all her sooner equivalents. Note that although the realizations of errors  $\epsilon_{iR}$  and  $\epsilon_{iT}$  vary across individuals and prospect type, we assume that the 4 chained binary choices of a given individual pertaining to the same prospect are determined by a single noisy equivalent observed prior to entering the bisection algorithm. This implies that each turns in the bisection tree unequivocally reduces the range of the interval containing the equivalent. Note also that our framework is not a typical random utility model (RUM), a framework that may generate identification issues when individuals are assumed to compare the noisy utilities of two uncertain prospects (Apestegua and Ballester, 2018). We consider that individuals have noisy representations of their underlying equivalents, but precisely



represent the sure gains.<sup>16</sup> In our framework, the respondents only compare noisy equivalents to sure gains, which guarantees that the probability of choosing the sure gain increases monotonically with risk aversion.

In our baseline DEU estimations presented in section 4 we parameterize  $u(x, \alpha_i) = x^{\alpha_i}$  and  $D(t, \delta_i) = e^{-\delta_i t}$ . This yields the following formulas for the equivalents:

$$c_{iR}^* = [px^{\alpha_i} + (1-p)y^{\alpha_i}]^{(1/\alpha_i)} \quad (9)$$

and

$$c_{iT}^* = e^{-\frac{\delta_i}{\alpha_i} \tau} x. \quad (10)$$

with  $\alpha_i > 0$  and  $\delta_i > 0$ .<sup>17</sup> Before turning to the estimation method, we clarify conceptual aspects of our framework.

### Remarks on the model

Classically, we consider that individuals consume their gains at receipt without background consumption (Cohen et al., 2020). Assuming away background consumption is coherent with the rich literature exploring the Rabin’s paradox, which Bleichrodt et al. (2019) conclusively interpret as unilateral evidence in favor of reference-dependence or narrow bracketing. In our case, this would translate as neglecting background consumption in the argument of the utility function. We however acknowledge that risk attitudes may vary with the range of gains. Given that we consider rewards under €100, we only claim to measure small-stakes risk aversion. In support of the consumption-on-receipt assumption, Andersen et al. (2008) and Andreoni et al. (2018) both conclude that intertemporal arbitrage is negligible in ranges of gains and horizons similar to those we consider. Although we cannot rule out some residual heterogeneity in arbitrage and background consumption, we argue that it would merely add noise to our estimation which would be captured by our stochastic component to the extent they affect the equivalents in a separably additive way. If standard, any remaining noise in our estimation of risk and time preferences could only attenuate the associations we set out to measure, and would therefore be unlikely to generate spuriously significant estimates.

The main motivation of our model relies on the role played by nonlinear utility in the sooner equivalents. Although finding curved utility is commonplace in experiments using the DEU framework, allowing probability weighting to explain risk attitudes may decrease utility curvature towards linearity. We explore this possibility in an extension presented in section 4, where we consider an extended rank-dependent expected utility model (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) and allow for present bias (Laibson, 1997). For completeness, in appendix A, we also check other models assuming linear utility only for time tasks or for both tasks, and we obtain similar results.

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<sup>16</sup>Although some recent papers allow for a noisy representation of raw numbers (Khaw et al., 2021), we argue that this noise is likely negligible compared to the one affecting the representation of equivalents, a concept that may be difficult to grasp precisely (e.g. involves the inversion of utility in equation (5)). In support of our assumption, the fact that the bisection algorithm only involves gains that are integers multiples of 5, which are the same across all tasks except R4 (where they are shifted to (20;100)), arguably reduces the risk of numerical misrepresentation.

<sup>17</sup>This proves convenient for our estimation method assuming an prior log-normal distribution for all parameters (see next section). We check in appendix table D.8 that our main results hold also when allowing  $\alpha_i < 0$ . In that specification, the  $\alpha_i$  have a prior normal distribution.

### 3.3 Estimation method

We estimate all individual parameters using a hierarchical Bayes framework. This section first describes and motivates the overall strategy, and then details our implementation of the method.

#### General approach

To assess the link between individual preferences and diet quality, we first estimate all individual parameters as presented in this section. We then regress the diet indicators on the estimated preferences and discuss the causal interpretation of our estimates in section 4. A straightforward way to estimate all individual parameters is to run separate estimations of the parameters for each individual, either by maximizing the individual likelihoods (Hey and Orme, 1994) or by nonlinear least squares (Abdellaoui et al., 2007). However, a recent trend in the literature has highlighted several shortcomings of this method: (i) it may not converge for individuals who do not fit the model well, (ii) it may yield implausible estimates for individuals with inconsistent or extreme answers, (iii) it can be subject to local maxima/minima issues (Nilsson et al., 2011; Murphy and ten Brincke, 2018; Gao et al., 2022). Single-subject estimations has thus often led researchers to consider ex-post bounds and simply remove individuals from the sample with missing or estimates taking implausible values (Bradford et al., 2017). An alternative is to regularize the individual estimates by assuming that they are drawn from a parametric probability distribution – typically normal, lognormal, or discrete – so as to limit the risk of large outliers. Such distributional assumptions are routinely employed in works estimating the distribution of preferences using random parameter models (via maximum simulated likelihood), without actually estimating all individual parameters (Bruhin et al., 2010; Von Gaudecker et al., 2011; l’Haridon and Vieider, 2019; Jagelka, 2023). Using simulations and a test-retest experiment, Murphy and ten Brincke (2018) show that estimating the population distribution in a first stage with a random coefficient model, and then leveraging this distribution to estimate the posterior probabilities of individual parameters, yields more reliable estimations than single-subject estimations. This is because single-subject estimations ignore the plausibility of point estimates with respect to the population distribution. This issue is especially troublesome when the number of observations per individual is constrained to be relatively low, as in general population surveys like ours. We thus adopt such a hierarchical framework and assume that individual parameters are drawn from a population distribution.

Our implementation follows a recent development in the empirical literature in decision theory and behavioral economics that simultaneously estimates individual parameters and their population distribution using the hierarchical Bayes framework. This method has several practical advantages described in Train (2009). First, contrary to the two-step method in Murphy and ten Brincke (2018), the estimation of individual parameters accounts for the sampling error in the estimated population distribution. Second, the estimation of the population distribution is not sensitive to local maxima issues as it does not involve numerical optimization – convergence is assessed by inspecting the stability of the posterior distribution. Third, its computation time does not increase substantially when allowing all individual parameters to be freely correlated. This contrasts with the maximum simulated likelihood method which computing time quickly becomes prohibitive as the number of correlated random coefficients increases, so that it typically requires to restrict the covariance across random coefficients (Von Gaudecker et al., 2011; l’Haridon and Vieider, 2019). Since one of our aim is to disentangle the respective relationships of risk and time preferences with diet quality, it is key not to restrict a priori the correlation between these parameters, which

is more conveniently achieved with a hierarchical Bayes estimation (Ferecatu and Öngüler, 2016). Following this burgeoning literature,<sup>18</sup> we adopt a hierarchical Bayesian approach to jointly estimate individual and population parameters.

## Implementation

Train (2009) provides a general exposition of the hierarchical Bayes method, which we adapt to our case in this section. We denote by  $\theta_i = (\alpha_i, \delta_i, \sigma_i^r, \sigma_i^t)$  the set of individual parameters. The successive answers of individual  $i$  to the bisection procedure for the risk prospect  $R \in \{R1, \dots, R4\}$  yield two bounds  $(c_{iR}^-, c_{iR}^+)$  such that  $c_{iR}^- \leq c_{iR} \leq c_{iR}^+$ . From equation (8), the likelihood function  $l$  for a given observed interval  $(c_{iR}^-, c_{iR}^+)$  conditional on  $\theta_i$  writes:

$$l(c_{iR}^-, c_{iR}^+ | \theta_i) = \Phi\left(\frac{c_{iR}^+ - c_{iR}^*}{\sigma_i^r}\right) - \Phi\left(\frac{c_{iR}^- - c_{iR}^*}{\sigma_i^r}\right) \quad (11)$$

where  $\Phi$  is the cumulative function of the standard normal distribution. Substituting  $\sigma_i^r$  with  $\sigma_i^t$  and index  $R$  with  $T$  in equation (11) yields the likelihood of the observations of the time prospects  $T \in \{T1, \dots, T4\}$  for individual  $i$ . The method accommodates missing answers, as this expression also applies for the 140 individuals who did not complete the bisection algorithm for at least one prospect (i.e. with  $c_{i.}^+ - c_{i.}^- > 5$ ). For these individuals, the estimation is only less precise.

Let  $y_i = (c_{ij}^+, c_{ij}^-)_{j \in \{R1, \dots, R4, T1, \dots, T4\}}$  be the vector of all the observations pertaining to individual  $i$ . The likelihood of the vector  $y_i$  conditional on the individual parameter vector  $\theta_i$  is:

$$l_i(y_i | \theta_i) = \prod_{R=R1}^{R4} l(c_{iR}^-, c_{iR}^+ | \theta_i) \prod_{T=T1}^{T4} l(c_{iT}^-, c_{iT}^+ | \theta_i). \quad (12)$$

We assume that the individual-level parameters  $\theta_i$  are realizations of a random vector  $\theta$  following a positive log normal distribution such that:

$$\log(\theta) \sim \mathcal{N}(\mu, W) \quad (13)$$

where  $\mu$  and  $W$  are the population parameters. We further assume that the population parameters  $\mu$  and  $W$  are random variables themselves and consider the following independent prior distributions:

$$\mu \sim \mathcal{N}(\mu_0, S_0) \quad (14)$$

$$W \sim IW(K, I_K) \quad (15)$$

where  $\mu_0$  and  $S_0$  are nonrandom vectors,  $K$  is the number of individual parameters ( $K = 4$  in the baseline),  $I_K$  is the identity matrix of dimension  $K$ , and  $IW(K, I_K)$  is the inverse Wishart distribution with  $K$  degrees of freedom and scale matrix  $I_K$ .  $S_0$  is large so that the prior distributions of the population means  $\mu$  are flat and that  $\mu_0$  acts as an initial value rather than a prior. We denote by  $N$  the number of individuals with  $\mathcal{I} = \{1, \dots, N\}$  and consider the following posterior distributions given the data:

<sup>18</sup>See Jarnebrant et al. (2009), Nilsson et al. (2011), Toubia et al. (2013), Baillon et al. (2020), Gao et al. (2022), and Alam et al. (2022) for recent applications of the hierarchical Bayes approach to the estimation of behavioral preferences.

$$P(\theta_i|\mu, W, y_i) \propto l_i(y_i|\theta_i)\phi(\log(\theta_i)|\mu, W) \quad \forall i \in \mathcal{I} \quad (16)$$

$$\mu|(W, (y_i)_{i \in \mathcal{I}}) \sim \mathcal{N}\left(\frac{1}{N} \sum_{i \in \mathcal{I}} \log(\theta_i), W/N\right) \quad (17)$$

$$W|(\mu, (y_i)_{i \in \mathcal{I}}) \sim IW\left(K + N, \frac{KI_K + NS}{K + N}\right) \quad (18)$$

with  $S = \sum_{i \in \mathcal{I}} (\log(\theta_i) - \mu)(\log(\theta_i) - \mu)' / N$ . We simulate  $D$  draws of  $\theta$  using the RSGHB R package which implements the Markov chain Monte Carlo (MCMC) algorithm described in Train (2009). The algorithm starts with the initial values  $\theta^0 = 1_K$  and  $W^0 = I_K$  to simulate a draw of vector  $\theta$  with equation (16), uses these simulations to draw new values of  $\mu$  and  $W$  with equations(17) and (18), and iterates. We use the default values of the RSGHB package setting the target acceptance rate at 0.3 and the initial rate at 0.1. We use 10,000 burn-in draws, followed by 50,000 draws of which we select only 1 draw every 5 to mitigate potential autocorrelation issues. Without loss of generality, we divide all gains by the maximum gain € 100 to fasten numerical approximations. We run conservative simulations to evaluate convergence using the diagnostics proposed in Gelman et al. (2013). Using 10 random starting values, we obtain satisfactory convergence for all parameters after only 1,000 burn-in, over 2,000 draws of which we select only 1 draw every 2, and splitting the chains in two parts to assess stationarity. Figure D.2 in the appendix illustrates the stability of the distributions obtained in the baseline specification after 10,000 burn-in iterations. For each individual  $i$ , we obtain  $D = 10,000$  draws  $\hat{\theta}_i^d$  and the estimate of  $\theta_i$  is the mean of these draws  $\hat{\theta}_i = \frac{1}{10,000} \sum_{d=1}^{10,000} \hat{\theta}_i^d$ . In the appendix section B, we run simulations to show the accuracy of the estimation method in terms of parameter recovery, and its stability across sets of estimation parameters.

## 4 Results

This section presents the distribution of the leading diet indicators across socio-demographic characteristics, the estimated individual parameters for risk and time preferences, and our main results linking the two groups of variables.

### 4.1 Distribution across socio-demographics

Socio-demographic characteristics include all variables used for the proportional fitting weighting scheme: gender, age, education, location (region), and nationality. These variables are provided by administrative data and are therefore not subject to misreporting. Table 4 shows the frequency of the three main socio-demographic variables, namely gender, age, and education, and their respective average energy intake, diet quality indicator, and alcohol consumption. Column (1) gives the 2014 census share for the target population, i.e. the francophone residents of metropolitan France aged 18-79 on July 1<sup>st</sup>, 2016 and living in ordinary households. The columns (2-4) show that our sample provides an accurate representation of the target population, especially after adjusting for the weights in Column (4).<sup>19</sup> In the columns (5-6), we remove the individuals who missed either all risk or all time tasks,

<sup>19</sup>The corresponding statistics for location and nationality are available upon request. Our weighted sample adequately represents the target population across these characteristics as well.

as well as the 5% outliers for the energy intake in order to correct obvious misreporting.<sup>20</sup> Our reduced sample includes 2,086 individuals and still exhibits an excellent representativity when adjusting for the weights.

Consistent with the INCA3 2017 national survey on food consumption in France (ANSES, 2017), we find that males have a higher daily energy intake and alcohol consumption, that individuals under 45 have on average a slightly higher energy intake and a lower alcohol intake,<sup>21</sup> and that individuals who obtained more advanced diplomas have a higher alcohol intake. The only exception is the pattern for education and daily energy intake, for which INCA3 finds an opposite relationship. Comparing average values, we find an overall under-reporting of calories and alcohol consumption in our survey compared to INCA3. These differences may partly stem from methodological differences: INCA3 is a 3 days recall survey whereas we use a food frequency questionnaire. In our regression analysis presented in section 4.3, we control for systematic under- or over-reporting within socio-demographic groups by fixed effects. The overall diet quality measured by the WDI exhibits the same average across genders,<sup>22</sup> and increases with age and education.

Table 4: Demographics and diet quality

Variable	Census Share (1)	Full sample			Sample after trimming*				
		N (2)	Share (3)	Weight (4)	N (5)	Weight (6)	DEI (7)	WDI (8)	Alcohol (9)
<b>Gender</b>									
Female	51.0%	1,154	52.5%	51.0%	1,096	51.1%	1,881	1.50	4.27
Male	49.0%	1,045	47.5%	49.0%	990	48.8%	2,042	1.50	9.10
<b>Age</b>									
18-22	8.1%	81	3.7%	9.6%	76	9.5%	1,970	1.39	3.89
23-34	19.1%	243	11.1%	17.6%	229	17.4%	1,982	1.49	5.78
35-44	17.5%	488	22.2%	17.5%	467	17.5%	1,979	1.40	5.91
45-54	19.6%	548	24.9%	19.6%	517	19.5%	1,911	1.56	5.93
55-64	17.2%	477	21.7%	17.2%	453	17.3%	1,932	1.53	7.90
65-79	18.5%	362	16.5%	18.6%	344	18.8%	1,993	1.55	9.03
<b>Education</b>									
No highschool	27.8%	292	13.3%	27.8%	268	27.1%	2,038	1.50	6.07
Some highschool	23.4%	497	22.6%	23.3%	468	23.4%	2,125	1.40	6.44
Highschool	33.6%	825	37.5%	33.7%	787	33.9%	1,865	1.49	6.59
College	15.2%	585	26.6%	15.2%	563	15.5%	1,781	1.65	8.00
Total	100%	2,199	100%	100%	2,086	100%	1,960	1.50	6.63

Note: \* In these columns we remove the 5% outliers of the energy intake and the individuals who missed all questions in the preference module. Column (1) gives the shares for the target population according to the 2014 Census, found in the ELIPSS report of Cornilleau and Duwez (2021). (4) and (6) give the weighted shares. The values in Columns (7-9) are weighted averages. The daily energy intake “DEI” is expressed in calorie per day. The column “WDI” gives the average value of the indicator. The daily alcohol intake is expressed in grams of pure alcohol per day. The levels of educations depend the highest diploma obtained, and are defined as follows: “No highschool” includes individual without a diploma and individuals with a pre-highschool diploma: the former CEP (*Certificat d’études primaires* - end of primary school) or the BEPC (*Brevet d’études du premier cycle* - end of middle school); “Some highschool” includes individual with a diploma obtained before the end of highschool: the CAP (*Certificat d’aptitude professionnelle*) or the BEP (*Brevet d’études professionnelles*); “Highschool” includes individuals with the highschool diploma *Baccalauréat* but no college degree (less than 2 years in college); “College” includes individuals with a college degree (at least 3 years of college education).

<sup>20</sup>We keep only the weighted individuals between the 2.5th and 97.5th weighted quantiles of the distribution, computed for each gender (given in appendix table D.3). The daily reference intake for energy is 2,000 calories, so that we removed individuals who reported consuming less than about 40% or more than about 225% of the daily reference value on average over the last year.

<sup>21</sup>In contrast with INCA3, individuals older than 65 have reported a higher energy intake in our sample.

<sup>22</sup>This corroborates the results of Vieux et al. (2013) who report comparable distributions of WDI for men and women.

## 4.2 Individual parameters estimates

In this section, we estimate the risk aversion ( $\alpha_i$ ) and discount rate ( $\delta_i$ ) parameters following the method explained in section 3.3. Table 5 gives summary statistics on the distribution of the estimates. The average of the risk aversion estimates is 0.71 and their median is 0.57. The large majority of respondents are risk averse (84%). These values are in line with other large scale studies (Bradford et al., 2017; Meissner et al., 2023). The median of the estimated standard deviations  $\hat{\sigma}_i^r$  from the certainty equivalents is 13.4, which is large in comparison with the width of the intervals for the certainty equivalents (5 for a complete questionnaire). These large deviations reflect that for many individuals, the hierarchy of the certainty equivalents conflicts with the hierarchy of the expected values across prospects.<sup>23</sup> The median estimated discount rate is 0.037 in our survey, which implies that €1 in 1 month has a present value of €0.96. This discount rate ranges in the higher values reported in the review of Frederick et al. (2002), which likely stem from the fact that we consider rather short delays and small gains (Cohen et al., 2020). The standard deviations  $\hat{\sigma}_i^t$  have a mean of 10.9 exhibit more heterogeneity than the  $\hat{\sigma}_i^r$ . In particular, the minimum  $\hat{\sigma}_i^t$  is small (1.7), which is driven by the fact that many respondents chose the extreme equivalents for all time prospects.<sup>24</sup> In the appendix B, we run simulations to evaluate the parameter recovery performance of our estimation method combined with our data structure.

Table 5: Estimates of the individual parameters

	Min	Q25	Median	Mean	Q75	Max	Std. dev.
<b>Risk</b>							
$\hat{\alpha}_i$	0.15	0.31	0.57	0.71	0.84	8.34	0.81
$\sigma_i^r$	9.1	12.5	13.5	13.6	14.7	22.5	1.7
<b>Time</b>							
$\delta_i$	0.001	0.015	0.037	0.060	0.068	2.247	0.129
$\sigma_i^t$	1.7	5.9	10.4	10.9	14.9	39.8	6.3

Figure 2 shows the cumulative distribution functions of the individual estimates (increasing black curve) together with their densities (dark grey curve). The horizontal grey segments represent the Bayesian credibility intervals of the individual estimates, reflecting uncertainty on their relative ranks. The dotted lines give the mean population estimates and the grey squares give the 95% credibility intervals of the posterior distributions of the individual parameters, thus containing 95% of the individuals.

Panel (a) shows the distribution of the risk coefficient estimates. The distribution is a positive lognormal by design. The estimation yields rank uncertainty across the estimates  $\hat{\alpha}_i$ , as most individuals in the 60% middle of the distribution (from rank 0.3 to rank 0.9) have overlapping 95% credibility intervals for  $\hat{\alpha}_i$ .<sup>25</sup> We account for this uncertainty in our robustness checks. Individuals who gave seemingly inconsistent answers across risk prospects

<sup>23</sup>For instance, 23% of respondents obtained a strictly smaller equivalent for prospect R3 (expected value of 60) than for prospect R2 (20).

<sup>24</sup>47 respondents chose the interval [0,5] for all time prospects and 203 respondents chose the interval [75,80] for all time prospects. This is in part because our bisection algorithm only searches for sooner equivalent that are lower than the later value.

<sup>25</sup>Graphically, only the bottom 30% of the distribution have an upper bound under the average of 0.71, and only the top 10% have a lower bound above this average. Note however that the estimates of the posterior expected individual value  $\mathbb{E}(p_i|\text{data}_i)$  are estimated precisely as their variances are divided by 100.

have larger values of  $\hat{\sigma}_i^r$ , and wider credibility intervals on their risk preference estimates  $\hat{\alpha}_i$ .<sup>26</sup> Because the plotted values are exponentiated, the width of the credibility interval increases with  $\hat{\alpha}_i$ . In Panel (b), the distribution of the time preference estimates  $\hat{\delta}_i$  is less flat, with more individuals having estimates close to zero. Panels (c) and (d) show the distributions of the estimates of the deviations from the certainty and sooner equivalents. For comparability, these two panels have the same x-axis scale. The deviations from the certainty equivalent  $\hat{\sigma}_i^r$  are much more concentrated around their mean, whereas the  $\hat{\sigma}_i^t$  have a flat distribution ranging from 1.7 up to 40. The rank uncertainty is especially important for the estimates  $\hat{\sigma}_i^r$ , for which most individual intervals are overlapping.

The estimation procedure allows for a flexible covariance matrix across individual coefficients. Table 6 shows the resulting correlation coefficients across parameters. Consistent with the results of Ferecatu and Öncüler (2016), we find that the  $\hat{\alpha}_i$  and the  $\hat{\delta}_i$  are strongly positively correlated, so that impatience positively correlates with risk-seeking.<sup>27</sup> We find that the propensity to make errors on the risk part (captured by  $\hat{\sigma}_i^r$ ) is not correlated with time preferences. Similarly, the correlation between the propensity to make errors on the time part (captured by  $\hat{\sigma}_i^t$ ) and the risk aversion coefficient is close to zero. However,  $\hat{\sigma}_i^r$  is negatively correlated with  $\hat{\alpha}_i$ , so that more risk-seeking individuals are more consistent in their answers across risk prospects. This is coherent with the results of Khaw et al. (2021) who, although they use a different framework, do find that respondents making more random choices are more risk-averse. Similarly, we find that  $\hat{\sigma}_i^t$  is positively correlated with impatience  $\hat{\delta}_i$ , so that more impatient individuals are less consistent across time prospects. The propensities to make errors in the risk and in the time part are strongly positively correlated (.57). In the appendix B, we show that these patterns are not generated by our setting and estimation method.

Table 6: Correlations of the estimates across individuals

	$\hat{\alpha}_i$	$\hat{\delta}_i$	$\hat{\sigma}_i^r$
$\hat{\delta}_i$	0.49 [0.46,0.53]		
$\hat{\sigma}_i^r$	-0.43 [-0.46,-0.39]	-0.03 [-0.07, 0.01]	
$\hat{\sigma}_i^t$	-0.08 [-0.13,-0.04]	0.41 [0.37,0.44]	0.54 [0.51,0.57]

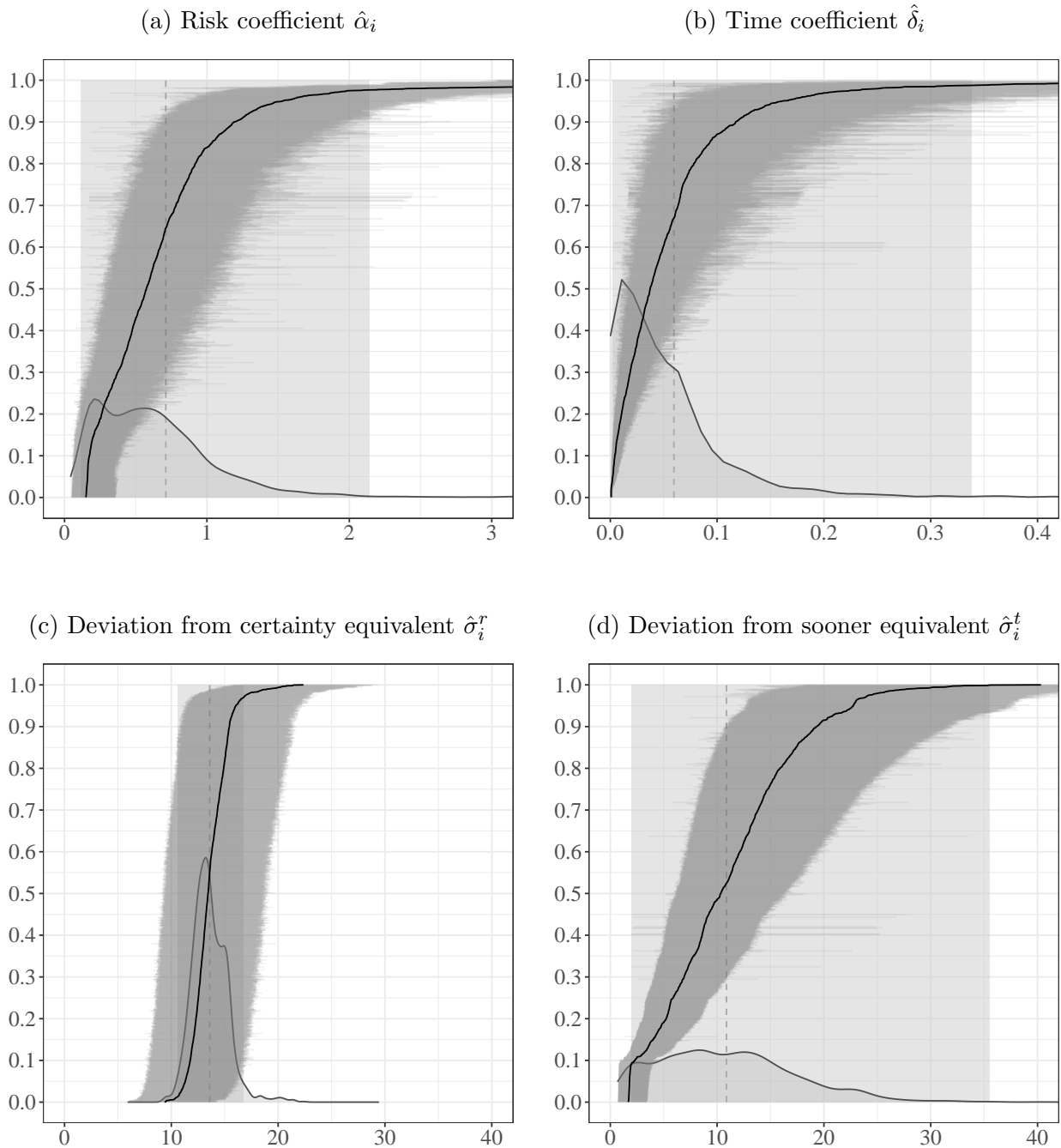
Note: 95% asymptotic confidence intervals based on Fisher's Z transform are given in brackets.

Figure 3 displays the median of preference estimates across socio-demographic variables. It shows that older individuals have lower levels of risk-seeking  $\hat{\alpha}_i$  and impatience  $\hat{\delta}_i$ . Consistent with l'Haridon and Vieider (2019), we also find that older individuals exhibit a higher

<sup>26</sup>There is a large correlation (.77) between the  $\hat{\sigma}_i^r$  and the standard deviations of  $\hat{\alpha}_i$  (calculated across the  $D = 10,000$  draws of  $\hat{\alpha}_i$  for individual  $i$ ). Note that the  $\sigma$  parameters only capture the inconsistency across answers, not the potential noncompletion of the bisection algorithm for a given task. Individuals who fail to complete all risk and time tasks have larger standard deviations of their estimates, but not necessarily larger sigmas.

<sup>27</sup>This may seem inconsistent with the positive correlation between certainty and sooner equivalents (see appendix table D.5), as larger sooner equivalents indicate more patience. But the correlation across certain and sooner equivalents does not identify the sign of the correlation across structural parameters. This is because the sooner equivalents depend both on  $\alpha_i$  and  $\delta_i$  in our main decision model. For completeness, in appendix A, we discuss results obtained when assuming individuals discount raw gains hence omitting the dependence of the sooner equivalents on the  $\alpha_i$ .

Figure 2: Posterior distributions of each individual parameter



Note: For each individual parameter  $p_i \in \{\alpha_i, \delta_i, \sigma_i^r, \sigma_i^t\}$ , the black curve and the dark grey curve respectively give the cumulative distribution function of the individual estimates  $\hat{p}_i$ , and their density. The dotted line is the simple average across individuals. The grey segments represent the 95% credibility interval of  $p_i$  for each individual  $i$ . They are computed by approximating the posterior distribution of  $p_i$  with a lognormal distribution with underlying mean and variance taken at their empirical counterparts across the 10,000 draws  $\log(p_i^d)$ . The shaded rectangle gives the 95% credibility interval of the posterior distribution of  $p_i$  ignoring the data. This interval is computed from the lognormal distribution with underlying mean and variance taken at their empirical counterparts across individuals estimates of  $\log(p_i)$ , neglecting the uncertainty on these population mean and variance.



propensity for errors in the risk tasks ( $\hat{\sigma}_i^r$ ), but not in the time tasks. We also find that education correlate positively with the risk-seeking coefficient  $\hat{\alpha}_i$  and negatively with impatience  $\hat{\delta}_i$  and both standard deviations  $\hat{\sigma}_i^r$  and  $\hat{\sigma}_i^t$ . Consistent with Filippin and Crosetto (2016), we find that the median estimates for risk attitude are comparable across genders. We also find that the median male is more patient than the median female. Finally, males exhibit lower median standard deviations from their certainty and sooner equivalents than women, consistent with l’Haridon and Vieider (2019).

In the appendix figures D.5, we show how the estimated preferences relate to the completion time of the questionnaire and find intuitive patterns supportive of the internal validity of our method. Finally, our questionnaire ended with a series of satisfaction questions designed to evaluate the appreciation of the survey by the panelists. We report in the appendix figure D.6 the result of one such question: “Did you have difficulty understanding the questions?”. We find that the large majority of respondents (76%) reported no difficulty understanding the questions, which suggests that our parsimonious questionnaire generated little cognitive fatigue. We find modest relationships with risk-seeking and impatience, and a clear increasing pattern between both  $\sigma$ s and the difficulties to understand the questions. This suggests that our measure of consistency partly captures the ability of the individuals to understand the questions, and thus to answer in a consistent way across tasks.

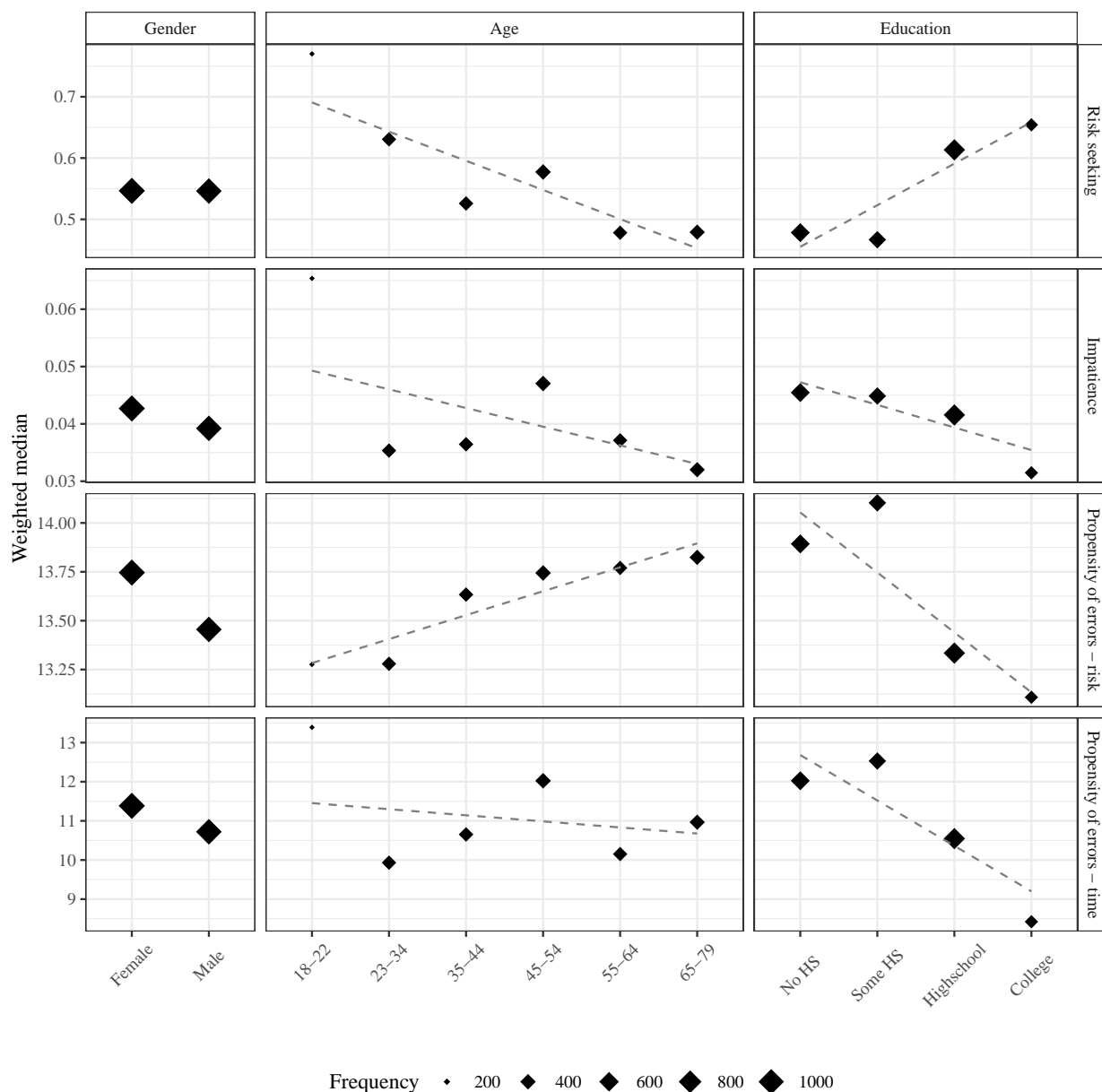
### 4.3 Diet indicators and behavioral preferences

In this section, we provide evidence of the external validity of risk and time preferences for diet quality, i.e. that the estimated preferences are significantly associated with the diet indicators in the general population. Figure 4 depicts the averages of our main dietary indicators for the energy content of the diet (DEI), the overall diet quality (WDI), and alcohol consumption, for each decile of the risk and time estimates distributions.<sup>28</sup> We can see that the average energy intake and diet quality decrease slightly with risk-seeking attitudes, and strongly with impatience. Mean alcohol consumption is higher among deciles corresponding to more risk-seeking and impatient individuals, a pattern that is more salient for risk preferences.

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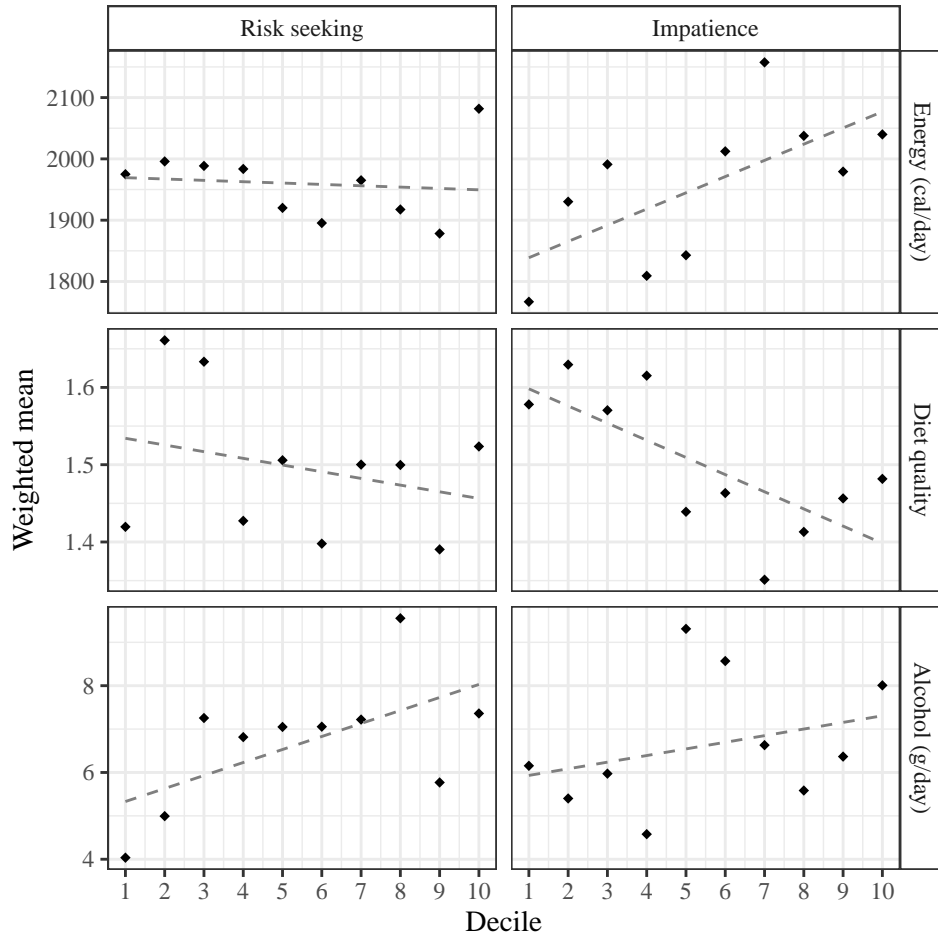
<sup>28</sup>Figure D.3 in the appendix replicates figure 4 for each indicator used to compute the WDI, and figure D.4 give the average quantity consumed of each food group and 8 main nutrients across the estimated risk and time preferences.

Figure 3: Median preferences across socio-demographics



Note: The diamonds give the weighted median of  $\hat{\alpha}_i$ ,  $\hat{\delta}_i$ ,  $\hat{\sigma}_i^r$ , and  $\hat{\sigma}_i^t$  (from top to down) by category, computed using the survey weights. For Age and Education, the dashed lines give the regression slopes of the weighted linear regressions explaining the averages by group.

Figure 4: Main nutritional indicators by decile of risk and time preference



Note: The diamonds represent the weighted averages by decile using the survey weights. The dashed lines represent the regression slopes of the weighted linear regressions explaining the averages by decile.

### Regressions using DEU estimates

We next test the significance of these associations in regressions that include both risk and time attitudes, with and without controlling socio-demographic characteristics. Since the energy intake is continuous and positive, we consider log-linear regressions on the attitudinal regressors estimated by the Ordinary Least Squares (OLS). The second indicator, the diet quality index (WDI) is an ordered categorical variables with four hierarchical levels. We estimate ordered logit models explaining the indicator by the attitudinal variables.<sup>29</sup> Our third and last indicator is the daily alcohol intake, which we explain by attitudinal variables in linear regressions estimated by OLS. Our main attitudinal regressors are normalized measures of risk aversion and impatience estimates respectively  $\hat{\alpha}_i$  and  $\hat{\delta}_i$ . We consider two rescaling transformations. First, we consider the ranks of  $\hat{\alpha}_i$  and  $\hat{\delta}_i$  within the sample. The rank function turns these variables into uniformly distributed variables taking values between 0 and 1. This variable changes aims at facilitating the quantitative interpretation of the estimates. Another advantage is that it mitigates the distortions introduced by outlying

<sup>29</sup>the appendix table D.6 shows estimates of regressions explaining the linear components of the WDI (MAR, MER, and ED). These regressions support the significant association between impatience and diet quality. This suggests that misreporting in the diet questionnaire, which would bias our estimates of the ordered logit models explaining the WDI but not the OLS estimations explaining MAR, MER, and ED, is not a significant concern in our data.

values. As a robustness check, we also ran regressions where the regressors related to the attitudinal variables are the underlying log-parameters of risk and time preferences (which are normally distributed by design) divided by their respective standard deviation across individuals.

Our main results combining the risk and time preferences in the same regressions are reported in table 7, where the preferences are estimated under the DEU framework. We apply weights in these regressions to correct for potentially endogenous nonresponse (Solon et al., 2015), and report robust standard errors for the weighted linear regressions. The estimations without weights are provided in table D.7 in the appendix and yield similar results. Columns (1-2), (3-4), and (5-6) show estimates reflecting the associations between attitudinal variables and respectively the energy intake (DEI), the diet quality (WDI), and the daily alcohol consumption. In the top two rows the attitudinal variables are rescaled by rank, and in the two rows below they are rescaled by log. Columns (1), (3), and (5) show the direct associations obtained without control variables, whereas columns (2), (4) and (6) show their counterpart using socio-economic variables as control variables, including one dummy for gender, 6 dummies for age, 3 dummies for education, 2 dummies for nationality, and 7 dummies for the regional location. In the log-linear and linear models, the values are the OLS estimates of the coefficients in the regressions. For the ordinal logit models, we show the odds ratios minus 1 to improve the comparison of the direction of the associations across columns. We convert the estimates using the function  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1.

Table 7: Joint association between behavioral parameters and diet quality

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	DEU estimation					
<b>Rank</b>						
Risk seeking: $\text{rank}(\hat{\alpha}_i)$	-0.053 (0.046)	-0.010 (0.048)	-0.024 (0.145)	-0.115 (0.137)	2.957 ** (1.072)	2.594 ** (1.038)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.132 ** (0.044)	0.127 ** (0.044)	-0.408 *** (0.089)	-0.362 ** (0.100)	0.545 (1.073)	1.992 * (1.048)
<b>Log</b>						
Risk seeking: $\log(\hat{\alpha}_i)/s.d.$	-0.011 (0.013)	-0.001 (0.014)	-0.003 (0.042)	-0.029 (0.042)	0.909 ** (0.315)	0.784 ** (0.307)
Impatience: $\log(\hat{\delta}_i)/s.d.$	0.037 ** (0.013)	0.037 ** (0.013)	-0.110 ** (0.039)	-0.097 ** (0.041)	0.188 (0.316)	0.539 * (0.310)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

**Note:** Each column contains the estimates from two regressions using either the rank or the log transformation. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ . The critical values are the corresponding quantiles of a standard normal.

We obtain significant and consistent associations between our rescaled risk and time parameters and the nutritional indicators. The first panel shows that more impatience is significantly associated with more energy intake and lower overall quality diet, after controlling for risk aversion. The estimate in column (2) indicates that the most impatient

individuals have a 13% higher daily energy intake than the most patient individuals, after controlling for differences in socio-demographic variables. In column (4), the estimate indicates that the odds that the most impatient individuals adopt a diet in the better category is 36% lower than that of the most patient individuals, holding the socio-demographic variable constant.<sup>30</sup> This corroborates existing evidence in experimental settings (De Marchi et al., 2016; Bradford et al., 2017; Samek et al., 2021; List et al., 2022) and selected products categories (Bradford et al., 2017). In these regressions, the estimates of the scaled coefficients for risk attitudes  $\hat{\alpha}_i$  are not statistically significant for energy intake and diet quality.

Furthermore, we find a strong and positive association between risk-seeking attitudes and alcohol consumption, in line with Barsky et al. (1997) and Anderson and Mellor (2008). The association between alcohol consumption and time preferences is only weakly statistically significant (10% level) when including covariates. Our results indicate that alcohol consumption positively correlates with impatience within a homogeneous socio-demographic group, but not in the general population. This is because for gender, age, and education, the more patient groups also exhibit higher alcohol consumption levels (see table 4). The fact that alcohol consumption is more strongly associated with risk preferences is consistent with the short-run effects of alcohol intoxication, whereas other dietary choices have essentially long-run health consequences. Our estimates indicate that the average daily consumption of pure alcohol of the less risk-averse individuals is almost 3g higher than the most risk-averse individuals - which amounts to about 2 standard drinks (10g of alcohol in France) per week. The estimations substituting the rank of  $\hat{\delta}_i$  with the standardized log of  $\hat{\delta}_i$  yield the same qualitative results. Failing to control jointly for both risk and time attitudes yields similar results for energy intake, but overestimates the size of the coefficient for risk in the regressions explaining diet quality and alcohol consumption (see appendix table D.9). In the appendix table D.10, we find that the stated risk preferences are less associated with alcohol consumption (not significantly with covariates), so that our revealed preference approach yields estimates with higher external validity in our context.

Taken together, our results provide evidence that impatience is associated with energy intake and diet quality, and that risk attitudes correlate with alcohol intake, even after controlling for socio-demographic variables. In appendix C, we provide supplementary results showing associations of our estimated parameters with the body mass index (BMI) and the frequency of physical activity which corroborate our previous findings and the existing literature. These data are not collected in our survey but in previous annual ELIPSS surveys in 2016 and 2017 and are not systematically reported.

#### 4.4 Robustness to decision model

We check in this section that our results are not driven by our assumptions on the decision model.

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<sup>30</sup>The odds of a probability  $p$  is  $p/(1-p)$ . The odds ratio for a characteristic  $X$  is  $\frac{p_1/(1-p_1)}{p_0/(1-p_0)}$  where  $p_0$  is the probability of moving to the higher category for individuals with  $X = x$ , and  $p_1$  is the same probability for individuals with  $X = x + 1$ , which is constant across categories and values of  $X$  in the ordered logit model. For the ranked variable, the odds ratio compares the odds between the top of the distribution (rank=1) and its bottom (rank=0). The implied difference in probabilities depends on  $p_0$ . For instance, an odds ratio of 1.3 with  $p_0 = 0.5$  implies that  $p_1 \approx 0.565$  so a probability difference of 6.5pp, but for  $p_0 = 0.1$  that difference is only of 2.6pp.

## Regressions using HDRDU estimates

First, we check that we obtain similar results with an extended model accounting for present bias and probability weighting. These models are often referred to as hyperbolic discounting rank-dependent utility (HDRDU) models. We consider the individual-specific probability weighting discounting function  $w(p, \gamma_i) = e^{-(\log(p))^{\gamma_i}}$  following the specification proposed by Prelec (1998), and the quasi-hyperbolic discounting function  $D(t, \beta_i, \delta_i) = \beta_i e^{-\delta_i t}$  if  $t > 0$  and 1 otherwise. For each respondent  $i$ , the certainty equivalent  $c_{iR}^*$  of a risk prospect  $(x, p, y)$  with rank dependence  $x > y$  and the sooner equivalent  $c_{iT}^*$  of a time prospect  $T = (t, x, t + \tau)$  are respectively given by equations(19) and (20).

$$c_{iR}^* = [w(p, \gamma_i)x^{\alpha_i} + (1 - w(p, \gamma_i))y^{\alpha_i}]^{(1/\alpha_i)} \quad (19)$$

$$c_{iT}^* = \beta_i^{1/\alpha_i} e^{-\delta_i \tau / \alpha_i} x \quad (20)$$

In this specification, our estimates of  $\alpha_i$  and  $\delta_i$  account for the possibility of probability weighting and present bias. The estimation is run using the same algorithm, considering a positive lognormal distribution for the  $\gamma_i$  and an initial population mean of 1. Table D.11 in the appendix provides the distribution of these estimates. The top panel of table 8 shows that we obtain similar results using these HDRDU estimates of  $\alpha_i$  and  $\delta_i$ . We cannot include all estimates  $\hat{\alpha}_i$ ,  $\hat{\delta}_i$ ,  $\hat{\gamma}_i$ , and  $\hat{\beta}_i$  together in the same regression because they are highly correlated (see appendix table D.12) so that we cannot identify separately the regression coefficients for  $\hat{\alpha}_i$  and  $\hat{\gamma}_i$ , or  $\hat{\delta}_i$  and  $\hat{\beta}_i$ .<sup>31</sup> In the middle panel of table 8, we show that substituting the ranks of the HDRDU estimated parameters  $\hat{\gamma}_i$  and  $\hat{\beta}_i$  for the DEU parameters  $\hat{\alpha}_i$  and  $\hat{\delta}_i$  yields similar results. We interpret the coefficient for the rank of  $\hat{\gamma}_i$  as reflecting risk-seeking behaviors: over our set of probabilities (0.5,0.25,0.75,0.5) a higher  $\gamma_i$  indicates a relatively more convex curve for the probability transformation function, which implies more risk-seeking behaviors.<sup>32</sup> The results for the present bias estimates  $\hat{\beta}_i$  are qualitatively identical as those for impatience, accounting for the reverse direction of effects: a larger  $\beta_i$  indicates less present bias.

## Regressions using model-free measures

To further check that our results are not driven by functional assumptions, we substitute the estimated risk and time preferences with model-free measures based on the intervals observed for each equivalent. Although these measures are subject to the critic that sooner equivalents are partly determined by utility curvature and thus by risk preferences, we here take the view that this issue is negligible.<sup>33</sup> For each prospect  $R$  and each individual  $i$ , we observe an interval  $(c_{iR}^-, c_{iR}^+)$  bounding the noisy equivalent of individual  $i$  for that prospect. We consider the middle of this interval  $\hat{c}_{iR} = (c_{iR}^- + c_{iR}^+)/2$  as a point estimate of the certainty

<sup>31</sup>Doing so yields nonsignificant estimates and Variance Inflation Factors (VIF) greater than 25, indicating prohibiting levels of correlation across covariates. This is especially severe for the two risk parameter. In the appendix table D.13, we include both time parameters in the same regression and provide suggestive evidence that diet quality may be more associated with present bias than with impatience (as measured by the exponential discounting parameter).

<sup>32</sup>For instance, Wakker (2010) states page 175: “The implications of probability weighting for risk attitude can be compared to those of utility. Concave utility curves enhance risk aversion. Similarly, convex weighting curves enhance pessimism and risk aversion. [...] Under RDU, the degree of risk aversion depends on both utility and probability weighting.”

<sup>33</sup>See also appendix section A where we consider structural models with linear utility, where impatience is accurately measured by sooner equivalents alone.

Table 8: Robustness to other estimations of the rankings

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Using $\hat{\alpha}_i$ and $\hat{\delta}_i$ from the HDRDU model						
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.022 (0.043)	0.020 (0.044)	-0.149 (0.119)	-0.211 (0.114)	2.909 ** (1.049)	2.894 ** (1.020)
Impatience: rank( $\hat{\delta}_i$ )	0.132 ** (0.042)	0.132 ** (0.042)	-0.379 *** (0.088)	-0.340 ** (0.097)	0.659 (1.038)	2.103 ** (1.030)
Using $\hat{\gamma}_i$ and $\hat{\beta}_i$ from the HDRDU model						
Risk seeking: rank( $\hat{\gamma}_i$ )	-0.021 (0.045)	0.025 (0.045)	-0.140 (0.124)	-0.218 * (0.117)	3.079 ** (1.077)	3.199 ** (1.058)
Present bias: rank( $-\hat{\beta}_i$ )	0.112 ** (0.043)	0.100 ** (0.042)	-0.374 ** (0.092)	-0.341 ** (0.100)	0.945 (1.072)	1.920 * (1.042)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

equivalent. Substituting index  $R$  with  $T$  in the previous expressions yields the point estimate  $\hat{c}_{iT}$  of the sooner equivalent for each time prospect. These measures are model-free in the sense that they do not depend on assumptions on the shape of the utility and discounting functions. In the top panel of table 9, we regress the leading indicators on the ranked average middles of these intervals across risk and time prospects, respectively. These model-free results corroborate those of table 7, with an additional statistically significant coefficient found for the link between risk-seeking attitudes and diet quality - which we also recover once correcting for measurement error in the main regressions in the next section.

Finally, we evaluate the role of collecting several equivalents for our results. We consider all 16 possible pairs of one certainty equivalent and one sooner equivalent, run all the regressions for each case, and display the number of estimates statistically significant at the 5% level for each sign in the bottom panel of table 8. The details of all these estimations are given in the appendix table D.14. We find that for many pairs of equivalents, the levels of statistical significance of the estimates are different from our main results. For instance, in 6 out of 16 combinations, the link between energy intake and patience is nonsignificant, which corresponds a false negative rate of 37.5%. This highlights the benefits from collecting several equivalents.

## 4.5 Robustness to measurement errors

In this section, we rule out that our results are driven by variations in the magnitude of measurement errors, correlations of measurement errors across risk and time (i.e. between two independent variables), and correlations of measurement errors across diet indicators and certainty and sooner equivalents (i.e. between dependent and independent variables).

Table 9: Regressions using the raw equivalents

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear (1)	(2)	Ordinal Logit (3)	(4)	Linear (5)	(6)
Model-free: average across prospects						
<b>Ranked average</b>						
Rank of mean $\hat{c}_{iR}$	0.022 (0.042)	0.061 (0.042)	-0.258 ** (0.104)	-0.302 ** (0.101)	3.280 ** (1.073)	3.628 *** (1.046)
Rank of mean $-\hat{c}_{iT}$	0.109 ** (0.041)	0.105 ** (0.042)	-0.366 ** (0.090)	-0.333 ** (0.097)	0.778 (1.034)	1.904 * (1.019)
Number of significant estimates across 16 pairs						
<b>Ranked average</b>						
Rank of mean $\hat{c}_{iR}$	+ 0 ; - 0	+ 4 ; - 0	+ 0 ; - 8	+ 0 ; - 8	+ 16 ; - 0	+ 16 ; - 0
Rank of mean $-\hat{c}_{iT}$	+ 11 ; - 0	+ 10 ; - 0	+ 0 ; - 16	+ 0 ; - 15	+ 0 ; - 0	+ 4 ; - 0

**Note:** The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

### Magnitude of measurement errors

A major advantage of the method is that it accounts explicitly for measurement errors in the raw data, i.e. in the collected certainty and sooner equivalents. Collecting several risk and time equivalents not only allows to estimate behaviorally founded decision models (e.g. allowing for present bias and probability weighting), but it also allows to filter out the measurement errors in the equivalents. However, our data includes individuals who gave extremely inconsistent answers across tasks (see section 4.2). For these individuals, we cannot precisely estimate the risk and time preferences, which may generate an attenuation bias in our main estimations. These individuals can be identified using the estimated  $\sigma$ s, which conveniently measure the respondents' propensities to give inconsistent answers across tasks. We prefer this selection method for outliers rather than the typical alternative of dropping individuals whose choices violate preference monotonicity (see for instance Bradford et al. 2017), as doing so ignores that such inconsistencies may be generated by noisy representation of the equivalents and in practice leads to removing a substantial share of the respondents. In table 10, we remove the 5% outliers for either  $\hat{\sigma}^r$  or  $\hat{\sigma}^t$  and run the same regressions on the remaining 1,916 individuals.<sup>34</sup> We find similar results for energy intake and alcohol, and find that risk-seeking attitudes now significantly correlate with diet quality, together with impatience. This corroborates the findings of Galizzi and Miraldo (2017) focusing on risk preferences, who found that risk aversion was significantly associated with diet quality in a sample of students. By contrast, the appendix table D.10 shows that the stated risk preferences are neither significantly associated with diet quality nor with alcohol intake on the same subsample. This supports the higher external validity of our structural estimation method over the stated preference measure in our context.

<sup>34</sup>Appendix table D.6 reports the results for MAR, MER, and DE, which corroborate our main results.



Table 10: Removing outliers for the propensities to deviate in risk and time tasks

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	DEU estimation					
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.027 (0.049)	0.012 (0.052)	-0.245 * (0.123)	-0.323 ** (0.114)	2.584 ** (1.188)	2.191 * (1.137)
Impatience: rank( $\hat{\delta}_i$ )	0.106 ** (0.048)	0.101 ** (0.047)	-0.455 *** (0.090)	-0.420 ** (0.099)	1.494 (1.232)	2.962 ** (1.187)
Controls		✓		✓		✓
Observations	1,916	1,916	1,916	1,916	1,916	1,916

Note: In these estimations we remove the 5% outliers for  $\hat{\sigma}_i^r$  and  $\hat{\sigma}_i^t$ . Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01.

### Correlation across measurement errors

We check that our results pertaining to the respective roles of risk and time preferences are not driven by the effect described in Gillen et al. (2019), i.e. a bias due to (i) a differential measurement error for risk and time preferences and (ii) correlated true parameters. In their paper, Gillen et al. (2019) show that controlling for a variable measured with error but structurally correlated with the right-hand-side variable of interest may yield spuriously significant estimates. This phenomenon may also apply to our setting with two variables of interest measured with error, if the measurement error is larger for one variable. The solution proposed by Gillen et al. (2019) is to rely on several measures of the same parameter. Although we dispose of only one set of structural estimates for risk and time preferences, our 4 certain and 4 sooner equivalents allow to generate 16 different pairs of certain and sooner equivalents. In the appendix table D.15, we verify that using their estimator on the ranks of the equivalents yields qualitatively identical results the regressions using the mean equivalents.<sup>35</sup> Altogether, properly accounting for measurement errors consistently shows that more risk-seeking individuals and more impatient individuals have lower quality diet, even after controlling differences in socio-demographic characteristics.

We finally address the concern that diet indicators and risk and time preference may be measured with correlated errors. In particular, if late food choices disproportionately affect the answers to the food frequency questionnaire, recent events may influence both the individuals revealed risk and time preferences, and declared food habits. This could for instance be the case for a positive event causing widespread celebrations, which may at least temporarily affect preferences. We are able to test the influence of such an important event, as our data collection period partially overlaps with the 2018 soccer world cup which ended with the victory of the French team on July 15<sup>th</sup>.<sup>36</sup> This event may have at least temporarily affected individuals perceptions (Dohmen et al., 2006), which may in turn have changed their preferences (Malmendier and Nagel, 2011). Although most of respondents answered before the end of the first phase of the competition, we can test the influence of a pivotal game on June 30<sup>th</sup> after which 28% of observations were collected. Controlling for potentially spurious variations caused by this event does not affect our main results (see

<sup>35</sup>We stack 16 replicas of our data set and regress our leading indicators on one pair of certainty and sooner equivalent (each considered in one of the 16 replicas), instrumented by all other equivalents. To ensure a constant variance of the measurement error across the equivalents, we keep only individuals who have completed the bisection algorithm for all risk and time tasks - so that all equivalents are bounded within a interval of width 5.

<sup>36</sup>The dates of our survey (June 6<sup>th</sup> to July 26<sup>th</sup>) were set by the management of the ELIPSS panel.

appendix table D.16). We can thus rule out that our results are driven by correlations across measurement errors spuriously triggered by this event.

## 4.6 Threats to causal interpretation

Having established that the associations between preferences and diet quality are not driven by measurement errors, we now turn to the discussion on the causal interpretation of these estimates. Our main candidate for the causal mechanism explaining the results is that more patient and more risk averse individuals are more sensitive to future health hazards, and therefore more likely to adopt healthier diets. We acknowledge that the nature of the data does not allow to conclusively demonstrate this causal effect, as we cannot fully control for individual-specific unobserved heterogeneity. However, we argue that the nature of the research question – the impact of preferences – rules out the application of the standard tools for causal inference because it is impossible to randomly assign preferences. This leaves us with the alternative strategy of successively addressing threats to a causal interpretation of our estimates. In this Section, we provide an array of evidence suggesting that alternative mechanisms are unlikely to drive our results.

### Exogenous confounding factors

First, our estimates may be driven by unobserved confounding factors causing both risk and time preferences, and our leading indicators of diet quality. Although economists traditionally consider risk and time preferences as exogenous primitives (Stigler and Becker, 1977), a recent body of evidence has shown how these preferences may be influenced by exogenous individual characteristics (Dohmen et al., 2011). Table 7 shows that our estimations are affected only marginally by the inclusion of important potential confounding factors including gender, age, and education. The similarities among our estimates with and without these important drivers of risk and time preferences mitigate concerns about the role of confounding factors.<sup>37</sup>

### A mediating and confounding factor: income

Previous regressions deliberately omit contextual factors that may not be exogenous to risk and time preferences, but may nevertheless confound the link between these preferences and diet quality. Such variables may both confound and mediate the relationship between preferences and diet quality. Perhaps the most important such variable is income, which correlates with diet quality (Darmon and Drewnowski, 2008), likely depends on risk and time preferences (Golsteyn et al., 2014), and may reciprocally influence risk and time preferences (Tanaka et al., 2010; Schildberg-Hörisch, 2018) - although all these causal effects

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<sup>37</sup>Other plausibly exogenous and potentially relevant omitted variables include height and cognitive abilities (Dohmen et al., 2010; Dohmen et al., 2011; Jagelka, 2023). The fact that we control for education, which correlates with both (Case and Paxson, 2008; Gorry, 2017) partially alleviates this concern. Although we do not observe cognitive ability, we argue that our  $\sigma$ s may capture a trait correlated with cognitive ability. These parameters account for the magnitude of individual inconsistencies across answers. Such a measure of inconsistency may capture the ability for decision-making (Choi et al., 2014), which may influence risk and time preferences. In our setting, given the correlation between impatience, the time of completion of the survey, and the  $\sigma$ s, it may also be the case that impatience increases the  $\sigma$ s as it may decrease the time allocated to answer the questions. This would make the  $\sigma$ s a mediator of the effect of impatience, not a confounder. With this caveat, in appendix table D.18 we run regressions controlling by the  $\sigma$ s. We find that the main association between time and our main diet quality remains weakly significant even when including both  $\sigma^r$  and  $\sigma^t$ .

are empirically disputed (Meier and Sprenger, 2015; Schildberg-Hörisch, 2018). To address this concern, we use the income declared by the panelists during the annual survey conducted in April 2018 as a proxy of their income at the time of our survey.<sup>38</sup> This variable was not included in previous regressions because (i) it is plausibly driven by risk and time preferences so would likely mediate their total effects on our diet indicators,<sup>39</sup> (ii) unlike the socio-demographic characteristics obtained via administrative data it is subject to misreporting, and (iii) it has 15% missing values over the 2,086 individuals used in the main regressions.

Table 11: Controlling for a potential mediator: income

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.002 (0.054)	0.023 (0.057)	-0.416 ** (0.109)	-0.438 ** (0.110)	1.773 (1.272)	2.314 * (1.218)
Impatience: rank( $\hat{\delta}_i$ )	0.065 (0.050)	0.066 (0.049)	-0.421 ** (0.108)	-0.433 ** (0.108)	2.230 (1.380)	2.869 ** (1.302)
Log Income per unit	-0.066 ** (0.026)	-0.049 * (0.029)	0.274 ** (0.109)	0.181 * (0.114)	0.380 (0.665)	-1.057 (0.693)
Controls		✓		✓		✓
Observations	1,627	1,627	1,627	1,627	1,627	1,627

Note: In these estimations we remove the 5% outliers for  $\hat{\sigma}^r$  and  $\hat{\sigma}^t$ . Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01.

Table 11 shows that when controlling for income after removing the outliers for the  $\sigma$ s, our main results on diet quality and alcohol are qualitatively unaffected, although the association between energy intake and impatience is no longer statistically significant. We verify that these results are not affected when controlling for location by the size of the city of residence (in addition to the regional fixed effects) in appendix table D.17, with and without the outliers. These additional spatial controls (i) broadly capture spatial variations in relative prices of healthy foods versus unhealthy foods that may mediate the influence of income on diet, and (ii) alleviate concerns on the influence of spatially differentiated macroeconomic shocks which may affect risk preferences (Malmendier and Nagel, 2011). As a byproduct, these regressions provide evidence that the link between income and diet quality is not entirely driven by heterogeneity in risk and time preferences, which contributes to the literature on the causes of nutritional inequalities (Darmon and Drewnowski, 2008).

<sup>38</sup>The respondents state their monthly income, after social security contributions and before income tax, by unit of consumption with intervals delimited by the following thresholds: €650, €950, €1,200, €1,400, €1,650, €1,900, €2,200, €2,500, €3,200. We convert these categories into a quantitative variable using the lower bound of each interval, and, to apply the log transformation, a value of €400 as the minimum for the lowest interval - a value corresponding to the income support in the absence of unemployment benefits. Using a linear scale for income does not affect our results.

<sup>39</sup>We acknowledge that to some extent, socio-demographic variables such as education (Golsteyn et al., 2014) and geographical location (Jaeger et al., 2010) may also be driven by risk and time preferences. Controlling for these variable may thus offset the indirect effects of risk and time preferences on diet quality. The fact that controlling for all socio-demographics has only marginal effects on our point estimates suggest that these mechanisms do not play a major role for our main results. The only exception is our estimation of the relationship between impatience and alcohol intake which becomes strongly significant when controlling for socio-demographic characteristics, as these are correlated with both impatience and alcohol intake. In particular, individuals with higher diplomas are more patient and drink more alcohol, whereas more patient individuals within a class of education drink less alcohol. The total effect of patience on alcohol intake may thus be ambiguous.

## Reverse causation

Finally, we cannot rule out the possibility of a reverse causality effect. One plausible channel for this effect would be that diet quality drives health status which in turn, might affect risk and time preferences. We argue that the plausible direction of this effect does not explain our main results. Both Decker and Schmitz (2016) and Banks et al. (2020) conclude that negative health shocks increase risk aversion, which would in our context generate a positive correlation between diet quality and risk-seeking attitudes. This channel may thus not explain why the more risk-seeking individuals in our data report lower diet quality. The direction of reverse effects may however be different for alcohol consumption, as Corazzini et al. (2015) find that alcohol intoxication increase impatience in experiments - but has no significant effect on risk tolerance consistent to the review of Horn et al. (2022). Reverse causality may thus partly explain why we find that, within socio-demographic groups, more impatient individuals consume more alcohol.

## 4.7 Heterogeneity

In this last section, we explore the heterogeneity of the effects presented above. in table 12 we run the baseline regression with an interaction term between the estimated ranks for risk and time preferences. The coefficients for  $\hat{\alpha}_i$  (resp.  $\hat{\delta}_i$ ) are thus interpreted at the minimal value for  $\hat{\delta}_i$  i.e. extremely patient individuals (resp.  $\hat{\alpha}_i$  i.e. extremely risk-seeking individuals). We find that the estimated coefficients are similarly signed and significant as in the baseline regression, except for alcohol where the estimates are less significant. The interaction term is strongly significant for our main diet indicator, which implies that the association between risk seeking (resp. impatience) and diet fades as impatience (resp. risk. seeking) increases. This feature is coherent with the fact that both risk-seeking and impatience are traits that make individuals be less sensitive to the risk of future negative health outcomes, which mitigates the role of risk and time preferences in the choice of diet quality. In this Table, the values of for the Ordinal Logit estimation are the raw coefficient to facilitate the summation of marginal effects. We obtain that the implied marginal effect of risk seeking only reaches zero for high level of impatience and vice versa: at the median risk and time preference, more risk-seeking and more impatience decreases diet quality.

Finally, in the appendix table D.19, we explore how the associations between diet indicators and risk and time preferences vary across socio-demographic groups. We find that our main results are driven by groups with larger values for the corresponding variables: the results on impatience are driven by more impatient groups (low income, low education), whereas those for risk are driven by more risk seeking groups (high income, high education). Similarly, the results on alcohol are primarily driven by groups consuming more alcohol (high income and education, older individuals, and males).

## 5 Concluding remarks

This paper evaluates the link between individuals risk and time preferences and overall diet quality and alcohol consumption. We employ a standard method in nutritional epidemiology consisting of a food frequency questionnaire which measures the whole diet at the individual level. We represent the individuals' diet with three diet indicators: the daily energy intake, the whole diet indicator, and alcohol consumption. We also design a risk and time preferences module for general population surveys so that the decision tasks are made as cognitively easy as possible. We use a hierarchical Bayes framework to jointly estimate individual

Table 12: Interaction between risk and time attitudes

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	DEU estimation					
<b>Rank</b>						
Risk seeking: $\text{rank}(\hat{\alpha}_i)$	-0.002 (0.085)	0.073 (0.085)	-0.932 ** (0.298)	-1.275 *** (0.306)	3.789 * (2.056)	2.455 (2.034)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.180 ** (0.090)	0.205 ** (0.088)	-1.389 *** (0.289)	-1.528 *** (0.293)	1.339 (2.063)	1.862 (2.084)
Interaction: $\text{rank}(\hat{\alpha}_i) \times \text{rank}(\hat{\delta}_i)$	-0.096 (0.146)	-0.156 (0.140)	1.723 *** (0.490)	2.173 *** (0.497)	-1.584 (3.764)	0.262 (3.707)

Note: Each column contains the estimates from two regressions using either the rank or the log transformation. The standard deviations in brackets are given under their corresponding coefficients. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

risk aversion and impatience parameters. Our interdisciplinary approach allows us to draw on state-of-the-art nutritional epidemiology and behavioral economics methodologies which extends work on the determinants of diet quality.

Our results show significant associations between the risk and time preferences parameters and the diet indicators. More impatience is associated significantly with higher energy intake levels and lower overall diet quality. As for risk attitudes, we find that more risk-seeking individuals have a higher consumption of alcohol. By balancing simplicity and theoretical consistency, we believe that our risk and time preference module would be suited to other general population surveys and could be used to explain other real-life economic behaviors.

Although our cross-sectional data delivers results which cannot be definitely conclusive in terms of causality, we are able to examine and reject several alternative mechanisms which might be generating our results. The stability of our main results to various specifications and sets of control variables lends credence to the conjecture of an underlying causal mechanism. Although an ideal research design would provide a random assignment of risk and time preferences, such an experimental manipulation of preferences might not be feasible. Therefore, observational studies addressing plausible threats to identification using the available data may be a main tool for economists to study the causal effects of preferences on real-life behaviors.

Notwithstanding the risk of hypothetical bias, our results show that hypothetical choice-based measurements have explanatory power for real-life behaviors. Although our risk and time parameters estimates explain dietary habits in a robust manner, exploring the role of real incentives on the validity of these measure would be a fruitful path for future research. In particular, future works could use real data on consumption to address the potential correlation between the hypothetical bias in risk and time equivalents and the reporting bias in dietary habits.

Our results have important implications for public health policies. We contribute to document the psychological determinants of diet quality, a key determinant of health status (Murray et al., 2020). This stream of research advocates accounting for risk and time preferences in the evaluation of the welfare impacts of interventions to tackle the obesity epidemic. Our results contribute to show that targeted public policies based on psychological deter-

minants could be efficient at modifying health behaviors such as dietary habits (Brownback et al., 2023), and suggests new tools to tackle malnutrition as complements to traditional policy tools such as price instruments and information campaigns.

### **CRedit authorship contribution statement**

**Antoine Nebout:** Conceptualization (lead), Funding Acquisition, Investigation (lead), Methodology, Project Administration, Supervision (lead), Writing – Original Draft Preparation (supporting), Writing – Review and Editing. **Noémi Berlin:** Conceptualization (supporting), Investigation (supporting), Methodology, Supervision (supporting), Writing – Original Draft Preparation (supporting), Writing – Review and Editing. **Florent Vieux:** Formal Analysis, Writing – Review and Editing. **Sandrine Péneau:** Writing – Review and Editing. **Nicole Darmon:** Writing – Review and Editing. **Emmanuel Kemel:** Conceptualization (supporting), Formal Analysis, Methodology, Visualization (supporting), Writing – Original Draft Preparation (supporting), Writing – Review and Editing. **Emmanuel Paroissien:** Conceptualization (lead), Formal Analysis, Methodology, Visualization (lead), Writing– Original Draft Preparation (lead), Writing – Review and Editing.

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## References

- Abdellaoui, Mohammed, Han Bleichrodt, and Corina Paraschiv (2007). “Loss aversion under prospect theory: A parameter-free measurement.” *Management science* 53 (10), pp. 1659–1674.
- Affret, Aurélie, Douae El Fatouhi, Courtney Dow, Emmanuelle Correia, Marie-Christine Boutron-Ruault, and Guy Fagherazzi (2018). “Relative validity and reproducibility of a new 44-item diet and food frequency questionnaire among adults: Online assessment.” *Journal of Medical Internet Research* 20 (7), e9113.
- Akee, Randall, Emilia Simeonova, William Copeland, Adrian Angold, and E Jane Costello (2013). “Young adult obesity and household income: effects of unconditional cash transfers.” *American Economic Journal: Applied Economics* 5 (2), pp. 1–28.
- Alam, Jessica, Konstantinos Georgalos, and Harrison Rolls (2022). “Risk preferences, gender effects and Bayesian econometrics.” *Journal of Economic Behavior and Organization* 202, pp. 168–183.
- Allcott, Hunt, Rebecca Diamond, Jean-Pierre Dubé, Jessie Handbury, Ilya Rahkovsky, and Molly Schnell (2019a). “Food deserts and the causes of nutritional inequality.” *Quarterly Journal of Economics* 134 (4), pp. 1793–1844.
- Allcott, Hunt, Benjamin B. Lockwood, and Dmitry Taubinsky (2019b). “Regressive sin taxes, with an application to the optimal soda tax.” *Quarterly Journal of Economics* 134 (3), pp. 1557–1626.
- Allcott, Hunt, Benjamin B Lockwood, and Dmitry Taubinsky (2019c). “Should we tax sugar-sweetened beverages? An overview of theory and evidence.” *Journal of Economic Perspectives* 33 (3), pp. 202–27.
- Andersen, Steffen, Glenn W Harrison, Morten I Lau, and E Elisabet Rutström (2008). “Eliciting risk and time preferences.” *Econometrica* 76 (3), pp. 583–618.
- Anderson, Lisa R and Jennifer M Mellor (2008). “Predicting health behaviors with an experimental measure of risk preference.” *Journal of Health Economics* 27 (5), pp. 1260–1274.
- Andreoni, James, Christina Gravert, Michael A Kuhn, Silvia Saccardo, and Yang Yang (2018). *Arbitrage or narrow bracketing? On using money to measure intertemporal preferences*. Tech. rep. National Bureau of Economic Research.
- ANSES (2017). *Étude individuelle nationale des consommations alimentaires 3 (INCA 3). Avis de l’ANSES Rapport d’expertise collective. Édition scientifique*.
- Apestequia, Jose and Miguel A Ballester (2018). “Monotone stochastic choice models: The case of risk and time preferences.” *Journal of Political Economy* 126 (1), pp. 74–106.
- Atkin, David (2016). “The caloric costs of culture: Evidence from Indian migrants.” *American Economic Review* 106 (4), pp. 1144–81.
- Baillon, Aurélien, Han Bleichrodt, and Vitalie Spinu (2020). “Searching for the reference point.” *Management Science* 66 (1), pp. 93–112.
- Baltussen, Guido, G Thierry Post, Martijn J Van Den Assem, and Peter P Wakker (2012). “Random incentive systems in a dynamic choice experiment.” *Experimental Economics* 15, pp. 418–443.
- Banks, James, Elena Bassoli, and Irene Mammi (2020). “Changing attitudes to risk at older ages: The role of health and other life events.” *Journal of Economic Psychology* 79, p. 102208.
- Barsky, Robert B, F Thomas Juster, Miles S Kimball, and Matthew D Shapiro (1997). “Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study.” *Quarterly Journal of Economics* 112 (2), pp. 537–579.

- Bates, Beverley, Lorna Cox, Sonja Nicholson, Polly Page, Ann Prentice, Toni Steer, and Gillian Swan (2016). *National Diet and Nutrition Survey Results from Years 5 and 6 (combined) of the Rolling Programme (2012/2013 2013/2014)*. Public Health England.
- Bleichrodt, Han, Jason N Doctor, Yu Gao, Chen Li, Daniella Meeker, and Peter P Wakker (2019). “Resolving Rabins paradox.” *Journal of Risk and Uncertainty* 59, pp. 239–260.
- Blom, Annelies G, Michael Bosnjak, Anne Cornilleau, Anne-Sophie Cousteaux, Marcel Das, Salima Douhou, and Ulrich Krieger (2016). “A comparison of four probability-based online and mixed-mode panels in Europe.” *Social Science Computer Review* 34 (1), pp. 8–25.
- Blondel, Serge, Youenn Lohéac, and Stéphane Rinaudo (2007). “Rationality and drug use: An experimental approach.” *Journal of Health Economics* 26 (3), pp. 643–658.
- Bradford, David, Charles Courtemanche, Garth Heutel, Patrick McAlvanah, and Christopher Ruhm (2017). “Time preferences and consumer behavior.” *Journal of Risk and Uncertainty* 55, pp. 119–145.
- Brownback, Andy, Alex Imas, and Michael A. Kuhn (2023). “Behavioral Food Subsidies.” *Review of Economics and Statistics*, pp. 1–47.
- Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper (2010). “Risk and rationality: Uncovering heterogeneity in probability distortion.” *Econometrica* 78 (4), pp. 1375–1412.
- Burks, Stephen, Jeffrey Carpenter, Lorenz Götte, and Aldo Rustichini (2012). “Which measures of time preference best predict outcomes: Evidence from a large-scale field experiment.” *Journal of Economic Behavior and Organization* 84 (1), pp. 308–320.
- Case, Anne and Christina Paxson (2008). “Stature and status: Height, ability, and labor market outcomes.” *Journal of Political Economy* 116 (3), pp. 499–532.
- Chabris, Christopher F., David Laibson, Carrie L. Morris, Jonathon P. Schuldt, and Dmitry Taubinsky (2008). “Individual laboratory-measured discount rates predict field behavior.” *Journal of Risk and Uncertainty* 37 (2), pp. 237–269.
- Charness, Gary, Uri Gneezy, and Alex Imas (2013). “Experimental methods: Eliciting risk preferences.” *Journal of Economic Behavior and Organization* 87, pp. 43–51.
- Charness, Gary, Thomas Garcia, Theo Offerman, and Marie Claire Villeval (2020). “Do measures of risk attitude in the laboratory predict behavior under risk in and outside of the laboratory?” *Journal of Risk and Uncertainty* 60 (2), pp. 99–123.
- Choi, Syngjoo, Shachar Kariv, Wieland Müller, and Dan Silverman (2014). “Who is (more) rational?” *American Economic Review* 104 (6), pp. 1518–1550.
- Cohen, Jonathan, Keith Marzilli Ericson, David Laibson, and John Myles White (2020). “Measuring time preferences.” *Journal of Economic Literature* 58 (2), pp. 299–347.
- Corazzini, Luca, Antonio Filippin, and Paolo Vanin (2015). “Economic behavior under the influence of alcohol: an experiment on time preferences, risk-taking, and altruism.” *PLoS One* 10 (4), e0121530.
- Cornilleau, Anne and Emmanuelle Duwez (2021). *Elipss, un dispositif inédit denquêtes pour la recherche en sciences sociales*.
- Courtemanche, Charles, Garth Heutel, and Patrick McAlvanah (2015). “Impatience, incentives and obesity.” *Economic Journal* 125 (582), pp. 1–31.
- Darmon, Nicole and Adam Drewnowski (2008). “Does social class predict diet quality?” *American Journal of Clinical Nutrition* 87 (5), pp. 1107–1117.
- De Leeuw, Edith, Joop Hox, and Annemieke Luiten (2018). “International nonresponse trends across countries and years: an analysis of 36 years of Labour Force Survey data.” *Survey Methods: Insights from the Field*, pp. 1–11.



- De Marchi, Elisa, Vincenzina Caputo, Rodolfo M Nayga Jr, and Alessandro Banterle (2016). “Time preferences and food choices: Evidence from a choice experiment.” *Food Policy* 62, pp. 99–109.
- Decker, Simon and Hendrik Schmitz (2016). “Health shocks and risk aversion.” *Journal of Health Economics* 50, pp. 156–170.
- Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde (2010). “Are risk aversion and impatience related to cognitive ability?” *American Economic Review* 100 (3), pp. 1238–1260.
- Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G Wagner (2011). “Individual risk attitudes: Measurement, determinants, and behavioral consequences.” *Journal of the European Economic Association* 9 (3), pp. 522–550.
- Dohmen, Thomas J, Armin Falk, David Huffman, and Uwe Sunde (2006). “Seemingly irrelevant events affect economic perceptions and expectations: The FIFA World Cup 2006 as a natural experiment.”
- Dubois, Pierre, Rachel Griffith, and Aviv Nevo (2014). “Do prices and attributes explain international differences in food purchases?” *American Economic Review* 104 (3), pp. 832–867.
- Dubois, Pierre, Paulo Albuquerque, Olivier Allais, Céline Bonnet, Patrice Bertail, Pierre Combris, Saadi Lahlou, Natalie Rigal, Bernard Ruffieux, and Pierre Chandon (2021). “Effects of front-of-pack labels on the nutritional quality of supermarket food purchases: evidence from a large-scale randomized controlled trial.” *Journal of the Academy of Marketing Science* 49 (1), pp. 119–138.
- Edwards, Philip James, Ian Roberts, Mike J. Clarke, Carolyn DiGuseppi, Reinhard Wentz, Irene Kwan, Rachel Cooper, Lambert M. Felix, and Sarah Pratap (2009). “Methods to increase response to postal and electronic questionnaires.” *Cochrane database of systematic reviews* (3).
- Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde (2018). “Global evidence on economic preferences.” *Quarterly Journal of Economics* 133 (4), pp. 1645–1692.
- Ferecatu, Alina and Ayse Öncüler (2016). “Heterogeneous risk and time preferences.” *Journal of Risk and Uncertainty* 53 (1), pp. 1–28.
- Filippin, Antonio and Paolo Crosetto (2016). “A reconsideration of gender differences in risk attitudes.” *Management Science* 62 (11), pp. 3138–3160.
- Fortin, Bernard and Myra Yazbeck (2015). “Peer effects, fast food consumption and adolescent weight gain.” *Journal of Health Economics* 42, pp. 125–138.
- Frederick, Shane, George Loewenstein, and Ted O'Donoghue (2002). “Time discounting and time preference: A critical review.” *Journal of Economic Literature* 40 (2), pp. 351–401.
- Galizzi, Matteo M. and Marisa Miraldo (2017). “Are you what you eat? Healthy behaviour and risk preferences.” *The B.E. Journal of Economic Analysis and Policy* 17 (1).
- Galizzi, Matteo M., Sara R. Machado, and Raffaele Miniaci (2016). “Temporal stability, cross-validity, and external validity of risk preferences measures: Experimental evidence from a UK representative sample.” *working paper*.
- Gao, Xiaoxue Sherry, Glenn W Harrison, and Rusty Tchernis (2022). “Behavioral welfare economics and risk preferences: A Bayesian approach.” *Experimental Economics*, pp. 1–31.
- Gelman, Andrew, John B Carlin, Hal S Stern, and Donald B Rubin (2013). *Bayesian data analysis (3rd ed.)* Chapman and Hall/CRC.

- Gillen, Ben, Erik Snowberg, and Leeat Yariv (2019). “Experimenting with measurement error: Techniques with applications to the caltech cohort study.” *Journal of Political Economy* 127 (4), pp. 1826–1863.
- Golsteyn, Bart HH, Hans Grönqvist, and Lena Lindahl (2014). “Adolescent time preferences predict lifetime outcomes.” *Economic Journal* 124 (580), F739–F761.
- Gorry, Devon (2017). “The influence of height on academic outcomes.” *Economics of Education Review* 56, pp. 1–8.
- Hercberg, Serge, Michèle Deheeger, Paul Preziosi, and Suvimax (2002). *Portions alimentaires-Manuel photos pour l'estimation des quantités*. Paris: Editions Polytechnica.
- Hey, John D. and Chris Orme (1994). “Investigating generalizations of expected utility theory using experimental data.” *Econometrica*, pp. 1291–1326.
- Horn, Tori L., James P. Whelan, and Gregory T. Weil (2022). “Does acute alcohol consumption increase risk-taking while gambling? A systematic review and meta-analysis.” *Addiction* 117 (11), pp. 2780–2790.
- Huston, Sandra J and Michael S Finke (2003). “Diet choice and the role of time preference.” *Journal of Consumer Affairs* 37 (1), pp. 143–160.
- Jaeger, David A., Thomas Dohmen, Armin Falk, David Huffman, Uwe Sunde, and Holger Bonin (2010). “Direct evidence on risk attitudes and migration.” *Review of Economics and Statistics* 92 (3), pp. 684–689.
- Jagelka, Tomáš (2023). “Are economists’ preferences psychologists’ personality traits? A structural approach.”
- Jarnebrant, Peter, Olivier Toubia, and Eric Johnson (2009). “The silver lining effect: Formal analysis and experiments.” *Management Science* 55 (11), pp. 1832–1841.
- Kahneman, Daniel and Amos Tversky (1979). “Prospect theory: An analysis of decision under risk.” *Econometrica* 47 (2), pp. 263–291.
- Khaw, Mel Win, Ziang Li, and Michael Woodford (2021). “Cognitive imprecision and small-stakes risk aversion.” *Review of Economic Studies* 88 (4), pp. 1979–2013.
- Kirby, Kris N, Nancy M Petry, and Warren K Bickel (1999). “Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls.” *Journal of Experimental Psychology: General* 128 (1), p. 78.
- Kobylińska, Milena, Katarzyna Antosik, Agnieszka Decyk, and Katarzyna Kurowska (2022). “Malnutrition in obesity: is it possible?” *Obesity Facts* 15 (1), pp. 19–25.
- Laibson, David (1997). “Golden eggs and hyperbolic discounting.” *Quarterly Journal of Economics* 112 (2), pp. 443–478.
- Lawless, Lydia, Andreas C. Drichoutis, and Rodolfo M. Nayga (2013). “Time preferences and health behaviour: a review.” *Agricultural and Food Economics* 1 (1), pp. 1–19.
- Ledikwe, Jenny H., Heidi M. Blanck, Laura Kettel Khan, Mary K. Serdula, Jennifer D. Seymour, Beth C. Tohill, and Barbara J Rolls (2006). “Low-energy-density diets are associated with high diet quality in adults in the United States.” *Journal of the American Dietetic Association* 106 (8), pp. 1172–1180.
- Lewbel, Arthur, Samuel Norris, Krishna Pendakur, and Xi Qu (2022). “Consumption peer effects and utility needs in India.” *Quantitative Economics* 13 (3), pp. 1257–1295.
- l’Haridon, Olivier and Ferdinand M. Vieider (2019). “All over the map: A worldwide comparison of risk preferences.” *Quantitative Economics* 10 (1), pp. 185–215.
- List, Greta, John A. List, Lina M. Ramirez, and Anya Samek (2022). “Time and risk preferences of children predict health behaviors but not BMI.” *Economics Letters* 218, p. 110724.

- List, John A. and Anya Savikhin Samek (2015). “The behavioralist as nutritionist: Leveraging behavioral economics to improve child food choice and consumption.” *Journal of Health Economics* 39, pp. 135–146.
- Lunn, Trevor E, Caryl A Nowson, Anthony Worsley, and Susan J Torres (2014). “Does personality affect dietary intake?” *Nutrition* 30 (4), pp. 403–409.
- Madden, J. Patrick, S. Jane Goodman, and Helen A. Guthrie (1976). “Validity of the 24-hr. recall. Analysis of data obtained from elderly subjects.” *Journal of the American Dietetic Association* 68 (2), p. 143.
- Malmendier, Ulrike and Stefan Nagel (2011). “Depression babies: Do macroeconomic experiences affect risk taking?” *Quarterly Journal of Economics* 126 (1), pp. 373–416.
- Meier, Stephan and Charles D Sprenger (2015). “Temporal stability of time preferences.” *Review of Economics and Statistics* 97 (2), pp. 273–286.
- Meissner, Thomas, Xavier Gassmann, Corinne Faure, and Joachim Schleich (2023). “Individual characteristics associated with risk and time preferences: A multi country representative survey.” *Journal of Risk and Uncertainty* 66 (1), pp. 77–107.
- Murphy, Ryan O. and Robert H.W. ten Brincke (2018). “Hierarchical maximum likelihood parameter estimation for cumulative prospect theory: Improving the reliability of individual risk parameter estimates.” *Management Science* 64 (1), pp. 308–326.
- Murray, Christopher J.L., Aleksandr Y. Aravkin, Peng Zheng, Cristiana Abbafati, Kaja M. Abbas, Mohsen Abbasi-Kangevari, Foad Abd-Allah, Ahmed Abdelalim, Mohammad Abdollahi, Ibrahim Abdollahpour, et al. (2020). “Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019.” *Lancet* 396 (10258), pp. 1223–1249.
- Nebout, Antoine, Equipe Psychofood, and Equipe ELIPSS (2020). *Comportements alimentaires et traits psychologiques (2018)*. Version V2. DOI: 10.21410/7E4/ZAJ6MT. URL: <https://doi.org/10.21410/7E4/ZAJ6MT>.
- Nilsson, Håkan, Jörg Rieskamp, and Eric-Jan Wagenmakers (2011). “Hierarchical Bayesian parameter estimation for cumulative prospect theory.” *Journal of Mathematical Psychology* 55 (1), pp. 84–93.
- Prelec, Drazen (1998). “The probability weighting function.” *Econometrica*, pp. 497–527.
- Samek, Anya, Andre Gray, Ashlesha Datar, and Nancy Nicosia (2021). “Adolescent time and risk preferences: Measurement, determinants and field consequences.” *Journal of Economic Behavior and Organization* 184, pp. 460–488.
- Schildberg-Hörisch, Hannah (2018). “Are risk preferences stable?” *Journal of Economic Perspectives* 32 (2), pp. 135–54.
- Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge (2015). “What are we weighting for?” *Journal of Human Resources* 50 (2), pp. 301–316.
- Stantcheva, Stefanie (2022). “How to run surveys: A guide to creating your own identifying variation and revealing the invisible.” *Annual Review of Economics* 15.
- Stigler, George J and Gary S Becker (1977). “De gustibus non est disputandum.” *American Economic Review* 67 (2), pp. 76–90.
- Sutter, Matthias, Martin G Kocher, Daniela Glätzle-Rützler, and Stefan T Trautmann (2013). “Impatience and uncertainty: Experimental decisions predict adolescents’ field behavior.” *American Economic Review* 103 (1), pp. 510–31.
- Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen (2010). “Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam.” *American Economic Review* 100 (1), pp. 557–71.
- Tasoff, Joshua and Wenjie Zhang (2022). “The performance of time-preference and risk-preference measures in surveys.” *Management Science* 68 (2), pp. 1149–1173.

- Toubia, Olivier, Eric Johnson, Theodoros Evgeniou, and Philippe Delquié (2013). “Dynamic experiments for estimating preferences: An adaptive method of eliciting time and risk parameters.” *Management Science* 59 (3), pp. 613–640.
- Train, Kenneth E. (2009). *Discrete choice methods with simulation*. Cambridge university press.
- Tversky, Amos and Daniel Kahneman (1992). “Advances in prospect theory: Cumulative representation of uncertainty.” *Journal of Risk and Uncertainty* 5 (4), pp. 297–323.
- Vieux, Florent, Louis-Georges Soler, Djilali Touazi, and Nicole Darmon (2013). “High nutritional quality is not associated with low greenhouse gas emissions in self-selected diets of French adults.” *American Journal of Clinical Nutrition* 97 (3), pp. 569–583.
- Von Gaudecker, Hans-Martin, Arthur Van Soest, and Erik Wengström (2011). “Heterogeneity in risky choice behavior in a broad population.” *American Economic Review* 101 (2), pp. 664–694.
- Wakker, Peter and Daniel Deneffe (1996). “Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown.” *Management science* 42 (8), pp. 1131–1150.
- Wakker, Peter P. (2010). *Prospect Theory*. Cambridge Books. Cambridge University Press.
- Willett, Walter C. (1994). “Diet and health: what should we eat?” *Science* 264 (5158), pp. 532–537.

## Appendix A Model with discounted monetary gains

This section presents the results of a model where the time prospects are assumed not to be affected by the shape of the utility function. This model is commonly used in the experimental literature on time preferences, and considers that individuals only discount raw monetary gains, not their utility. This assumption implies that either individuals have two different utility functions: a nonlinear function for risky prospects (allowing non neutral risk attitudes) and a linear function for time prospects with sure gains at different points in time, or either that individuals have a linear utility function and are risk neutral. We investigate both frameworks in the following subsections. Regardless of whether the utility is linear or not for the risky prospects, the sooner equivalent for time prospect  $T$  of individual  $i$  becomes:

$$c_{iT}^* = e^{-\delta'_i \tau} x \quad (21)$$

### A.1 Linear utility only for time prospects

In this section, we consider a linear utility for time prospects, and the same power utility function for the risk prospect. This specification implies that individuals have a different utility function for risk and time prospect, an assumption notably explored in Abdellaoui et al. (2013). The Tables and Figures of this Appendix are the counterparts of those presented in the main text. Table A.1 shows that the discounting estimates increase, with a median of 0.067 against 0.037 in the main text. This is consistent with the analysis of Andersen et al. (2008) and stems from the fact that in this discounted gain specification, the coefficient  $\delta'_i$  arguably identifies the ratio  $\delta_i/\alpha_i$  from the discounted utility framework in the main text, although with a different prior distribution.<sup>40</sup>

Table A.1: Individual parameters with discounted gains

	Min	Q25	Median	Mean	Q75	Max	Std. dev.
<b>Risk</b>							
$\hat{\alpha}_i$	0.15	0.31	0.57	0.71	0.84	8.32	0.80
$\hat{\sigma}_i^r$	9.2	12.5	13.5	13.6	14.7	22.5	1.7
<b>Time</b>							
$\hat{\delta}'_i$	0.004	0.027	0.068	0.099	0.132	0.589	0.101
$\hat{\sigma}_i^t$	1.7	5.8	10.4	10.9	14.8	39.8	6.3

Note: For individual  $i$  and parameter  $p_i \in \{\alpha_i, \delta'_i, \sigma_i^r, \sigma_i^t\}$ ,  $\hat{p}_i = \mathbb{E}(p_i | \text{data}_i)$ , i.e. the estimate is the mean of the posterior distribution, computed as the mean across 10,000 draws.

Table A.2 gives the resulting correlation matrix. The correlation between  $\hat{\delta}'_i$  and the  $\hat{\alpha}_i$  is much smaller in absolute value and negative, and the estimates  $\hat{\delta}'_i$  are now positively correlated with the  $\hat{\sigma}_i^r$ . Both correlations are consistent with the fact that the  $\delta'_i$  in this specification identify the ratio  $\delta_i/\alpha_i$  in the baseline specification, as the  $\hat{\alpha}_i$  are negatively correlated with the  $\hat{\sigma}_i^r$ . The correlation between the deviations  $\hat{\sigma}_i^r$  and  $\hat{\sigma}_i^t$  is unaffected by the change of specification.

Table A.3 shows we obtain similar results in this specification with a discounted monetary gain, although now the transformed  $\hat{\alpha}_i$  are significantly associated with diet quality. This also stems from the fact that in this specification, risk attitudes and time preferences are both partly captured by  $\hat{\delta}'_i$ .

<sup>40</sup>The discounted gain framework assumes a lognormal distribution for this ratio whereas the discounted utility framework assumes a ratio of lognormal distributions. The absolute difference between (i) the  $\hat{\delta}'_i$  estimated in the discounted gains framework and (ii) the ratio  $\hat{\delta}_i/\hat{\alpha}_i$  estimated in the main text is below 0.0026 for 90% of the respondents, with a median absolute difference at 0.0002.

Table A.2: Correlation matrix of the estimates across individuals

	$\hat{\alpha}_i$	$\hat{\delta}'_i$	$\hat{\sigma}_i^r$
$\hat{\delta}'_i$	-0.13 [-0.17,-0.08]		
$\hat{\sigma}_i^r$	-0.42 [-0.46,-0.38]	0.47 [0.44,0.51]	
$\hat{\sigma}_i^t$	-0.08 [-0.13,-0.04]	0.91 [0.90,0.91]	0.56 [0.53,0.59]

Note: The 95% confidence interval are given in brackets.

Table A.3: Main regression with the estimates of the discounted gain model

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk seeking: rank( $\hat{\alpha}_i$ )	0.022 (0.044)	0.062 (0.044)	-0.270 ** (0.105)	-0.312 ** (0.102)	3.262 ** (1.081)	3.727 *** (1.055)
Impatience: rank( $\hat{\delta}'_i$ )	0.120 ** (0.042)	0.117 ** (0.043)	-0.366 ** (0.092)	-0.322 ** (0.102)	0.524 (1.045)	1.871 * (1.037)
Controls	✓		✓		✓	
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

## A.2 Linear utility for risk and time with probability weighting

In this section, we consider a linear utility function for both risk and time prospects. As the curvature of utility no longer explains the cross-individual heterogeneity in risky choices, we allow for probability weighting to explain risk preferences. This specification is motivated by experiments showing that, when allowing for both nonlinear utility and probability weighting, the curvature of utility was typically linear for small gains ( $\sim \text{€}25$ , Abdellaoui et al. 2011) – with larger gains ( $\geq \text{€}200$ ) other experiments found a significantly curved utility (Abdellaoui et al., 2019). In our main HDRDU specification, we do find that allowing for probability weighting reduces the curvature of the utility, but we lack identifying variation to discriminate both parameters and therefore consider in this section the assumption that utility may linear for both risk and time.

We estimate two models with linear utility and probability weighting, allowing for present bias or not. The summary statistics are reported in table A.4, and the corresponding results of our main regressions are reported in table A.5. We find that our main results hold in both specifications. When allowing for present bias, we find as in the main HDRDU specification that  $\beta$  and  $\delta$  are highly correlated, and are unable to clearly disentangle their respective contribution to the overall association between time preferences and diet preferences.

Table A.4: Individual parameters with linear utility and probability weighting

	Min	Q25	Median	Mean	Q75	Max	Std. dev.
<b>Without present bias: RDU</b>							
<b>Risk</b>							
$\hat{\gamma}_i$	0.05	0.14	0.24	0.28	0.35	1.64	0.18
$\sigma_i^r$	7.9	13.6	16.3	17.4	20.9	35.2	4.9
<b>Time</b>							
$\delta_i$	0.004	0.027	0.067	0.099	0.132	0.532	0.100
$\sigma_i^t$	1.8	5.8	10.4	10.9	14.9	39.2	6.4
<b>With present bias: HDRDU</b>							
<b>Risk</b>							
$\hat{\gamma}_i$	0.05	0.14	0.24	0.28	0.35	1.62	0.19
$\sigma_i^r$	7.7	13.5	16.2	17.3	20.9	35.4	4.9
<b>Time</b>							
$\delta_i$	0.003	0.017	0.050	0.083	0.103	0.496	0.099
$\beta_i$	0.76	0.82	0.86	0.87	0.92	1.01	0.07
$\sigma_i^t$	2.0	5.2	9.1	9.4	12.6	37.3	5.2

Note: For individual  $i$  and parameter  $p_i \in \{\alpha_i, \delta'_i, \sigma_i^r, \sigma_i^t\}$ ,  $\hat{p}_i = \mathbb{E}(p_i | \text{data}_i)$ , i.e. the estimate is the mean of the posterior distribution, computed as the mean across 10,000 draws.

Table A.5: Main regression with linear utility and probability weighting

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Without present bias: RDU</b>						
<b>Rank</b>						
Risk seeking: $\text{rank}(\hat{\gamma}_i)$	-0.062 (0.047)	-0.015 (0.049)	-0.343 ** (0.098)	-0.441 *** (0.087)	3.264 ** (1.050)	3.391 ** (1.053)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.099 ** (0.043)	0.103 ** (0.043)	-0.384 ** (0.092)	-0.358 ** (0.099)	0.812 (1.056)	2.065 ** (1.040)
<b>Log</b>						
Risk seeking: $\log(\hat{\gamma}_i)/s.d.$	-0.025 * (0.013)	-0.012 (0.014)	-0.083 ** (0.038)	-0.128 ** (0.038)	0.961 ** (0.302)	0.915 ** (0.301)
Impatience: $\log(\hat{\delta}_i)/s.d.$	0.027 ** (0.012)	0.029 ** (0.012)	-0.105 ** (0.037)	-0.099 ** (0.039)	0.237 (0.293)	0.530 * (0.285)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086
<b>With present bias: HDRDU</b>						
<b>Only <math>\delta</math></b>						
Risk seeking: $\text{rank}(\hat{\gamma}_i)$	-0.060 (0.047)	-0.012 (0.049)	-0.344 ** (0.097)	-0.441 *** (0.087)	3.202 ** (1.058)	3.338 ** (1.063)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.102 ** (0.043)	0.108 ** (0.044)	-0.396 *** (0.090)	-0.371 ** (0.096)	0.802 (1.068)	2.038 * (1.048)
<b>Only <math>\beta</math></b>						
Risk seeking: $\text{rank}(\hat{\gamma}_i)$	-0.077 * (0.046)	-0.031 (0.049)	-0.300 ** (0.100)	-0.409 *** (0.089)	3.149 ** (1.016)	3.082 ** (1.025)
Present bias: $\text{rank}(-\hat{\beta}_i)$	0.079 * (0.043)	0.079 * (0.042)	-0.383 *** (0.089)	-0.365 ** (0.094)	1.033 (1.022)	2.014 ** (0.997)
<b>Both <math>\delta</math> and <math>\gamma</math></b>						
Risk seeking: $\text{rank}(\hat{\gamma}_i)$	-0.044 (0.048)	0.008 (0.048)	-0.328 ** (0.105)	-0.424 *** (0.094)	2.871 ** (1.136)	3.170 ** (1.141)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.235 (0.151)	0.273 * (0.155)	-0.257 (0.339)	-0.177 (0.382)	-1.937 (3.322)	0.625 (3.269)
Present bias: $\text{rank}(-\hat{\beta}_i)$	-0.135 (0.148)	-0.169 (0.148)	-0.190 (0.357)	-0.242 (0.341)	2.798 (3.185)	1.446 (3.114)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

**Note:** The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.



## Appendix B Parameter recovery

This section presents the results of a simulation to assess the precision of the baseline estimation procedure with the dimensions of our data set ( $N=2,000$  individuals). The structural means and standard deviations are chosen to mimic the distributions of the parameters obtained in our baseline estimations in the main text. In the simulation, we consider a diagonal covariance matrix across the 4 parameters, so that we can test how much of the correlation obtained in the estimations is driven by our setting. The results in this section are based on a single simulated data set and a single estimation. The values may vary at the margin for other simulations, but repeating the simulation and the estimation yields the same qualitative conclusions.

**Population and individual parameters** Table B.1 gives the summary statistics of a parameter recovery estimation over the simulated values. We obtain a slight bias toward zero for all log parameters, with marginal consequences on the rank uncertainty of the preference parameters. The resulting rank uncertainty is more substantial on the error parameters  $\sigma_i^r$  and  $\sigma_i^t$ , which we do not rely on to test our associations in the main text. The bias for the ranked parameters of interest in the main text is null.

Table B.1: Summary statistics of estimated values

	Log parameters			
	$\log(\alpha_i)$	$\log(\delta_i)$	$\log(\sigma_i^r)$	$\log(\sigma_i^t)$
Structural mean	-0.700	-3.600	2.600	2.100
Sample mean	-0.681	-3.660	2.595	2.071
Estimated mean	-0.623	-3.537	2.434	1.799
	[-0.656;-0.589]	[-3.594;-3.481]	[2.411;2.457]	[1.760;1.837]
Structural s.d.	0.700	1.300	0.100	0.700
Sample s.d.	0.714	1.321	0.102	0.700
Estimated s.d.	0.680	1.215	0.293	0.701
	[0.653;0.708]	[1.170;1.260]	[0.271;0.316]	[0.665;0.738]
Mean ind. error	0.058	0.123	-0.160	-0.272
Absolute mean ind. error	0.261	0.423	0.194	0.445
	Exponentiated parameters			
	$\alpha_i$	$\delta_i$	$\sigma_i^r$	$\sigma_i^t$
Sample mean	0.649	0.059	13.465	10.129
Estimated mean	0.674	0.061	11.877	7.658
	[0.519;0.555]	[0.027;0.031]	[11.144;11.668]	[5.814;6.281]
Sample s.d.	0.498	0.105	1.381	7.901
Estimated s.d.	0.446	0.086	1.861	4.608
Mean individual error	0.025	0.001	-1.588	-2.471
Absolute mean ind. error	0.158	0.022	2.175	3.788
	Ranked parameters			
	$\text{rank}(\alpha_i)$	$\text{rank}(\delta_i)$	$\text{rank}(\sigma_i^r)$	$\text{rank}(\sigma_i^t)$
Mean rank error	0.000	0.000	0.000	0.000
Absolute mean rank error	0.102	0.089	0.303	0.179

Note: The ‘‘Structural mean’’ and ‘‘s.d.’’ are the means and standard deviations used to simulate the sample values. The ‘‘Sample’’ values are calculated over the simulated values. The ‘‘Estimated’’ values are calculated over the estimates.

**Covariance** Table B.2 shows the nondiagonal elements of 6 correlation matrices. Panels A.1 and A.2 give the correlation matrices over the simulated sample, for structural (exponentiated) and log parameters, respectively. Because the structural covariance used to simulate the data is

diagonal, these values are all close to zero. Panel B gives the counterparts of these covariances over the estimates of the simulated sample, together with 95% confidence intervals. Most estimated correlation coefficients are not significant or close to zero as expected, but some are spuriously significant so suffer from a bias due to our setting. The most concerning bias is for  $\hat{\alpha}_i$  and  $\hat{\sigma}_i^r$  which are positively and substantially correlated. One may then worry that these biases may be large enough to cause the coefficients we obtain in table 6 in the main text.

For comparison purposes, Panel C thus reproduces the correlation matrix from the main text, and its counterpart with log parameters. We find that the spurious correlations we obtain in the simulations are much smaller than the one we estimate in our survey data, or of opposite sign. This suggests that the few spurious correlations due to our estimation method and setting cannot explain alone the significant correlation coefficients obtained with our survey data.

Table B.2: Recovery of the nondiagonal elements of the correlation matrix

A: Correlation matrix in the simulated independent sample							
A.1: Structural parameters			A.2: Log parameters				
	$\alpha_i$	$\delta_i$	$\sigma_i^r$		$\log(\alpha_i)$	$\log(\delta_i)$	$\log(\sigma_i^r)$
$\delta_i$	0.01			$\log(\delta_i)$	0.01		
$\sigma_i^r$	-0.01	-0.02		$\log(\sigma_i^r)$	-0.01	-0.02	
$\sigma_i^t$	-0.03	-0.02	0.05	$\log(\sigma_i^t)$	-0.03	-0.02	0.05

B: Estimated correlation matrix over the simulated independent sample							
B.1: Structural parameters			B.2: Log parameters				
	$\hat{\alpha}_i$	$\hat{\delta}_i$	$\hat{\sigma}_i^r$		$\widehat{\log(\alpha_i)}$	$\widehat{\log(\delta_i)}$	$\widehat{\log(\sigma_i^r)}$
$\hat{\delta}_i$	0.07 [0.02;0.13]			$\widehat{\log(\delta_i)}$	-0.02 [-0.07, 0.02]		
$\hat{\sigma}_i^r$	0.32 [0.24;0.40]	0.08 [-0.01;0.16]		$\widehat{\log(\sigma_i^r)}$	0.51 [0.48,0.54]	0.09 [0.04,0.13]	
$\hat{\sigma}_i^t$	-0.09 [-0.15;-0.03]	0.21 [0.15;0.27]	0.00 [-0.10;0.09]	$\widehat{\log(\sigma_i^t)}$	-0.10 [-0.15,-0.06]	0.07 [0.02,0.11]	-0.01 [-0.05, 0.04]

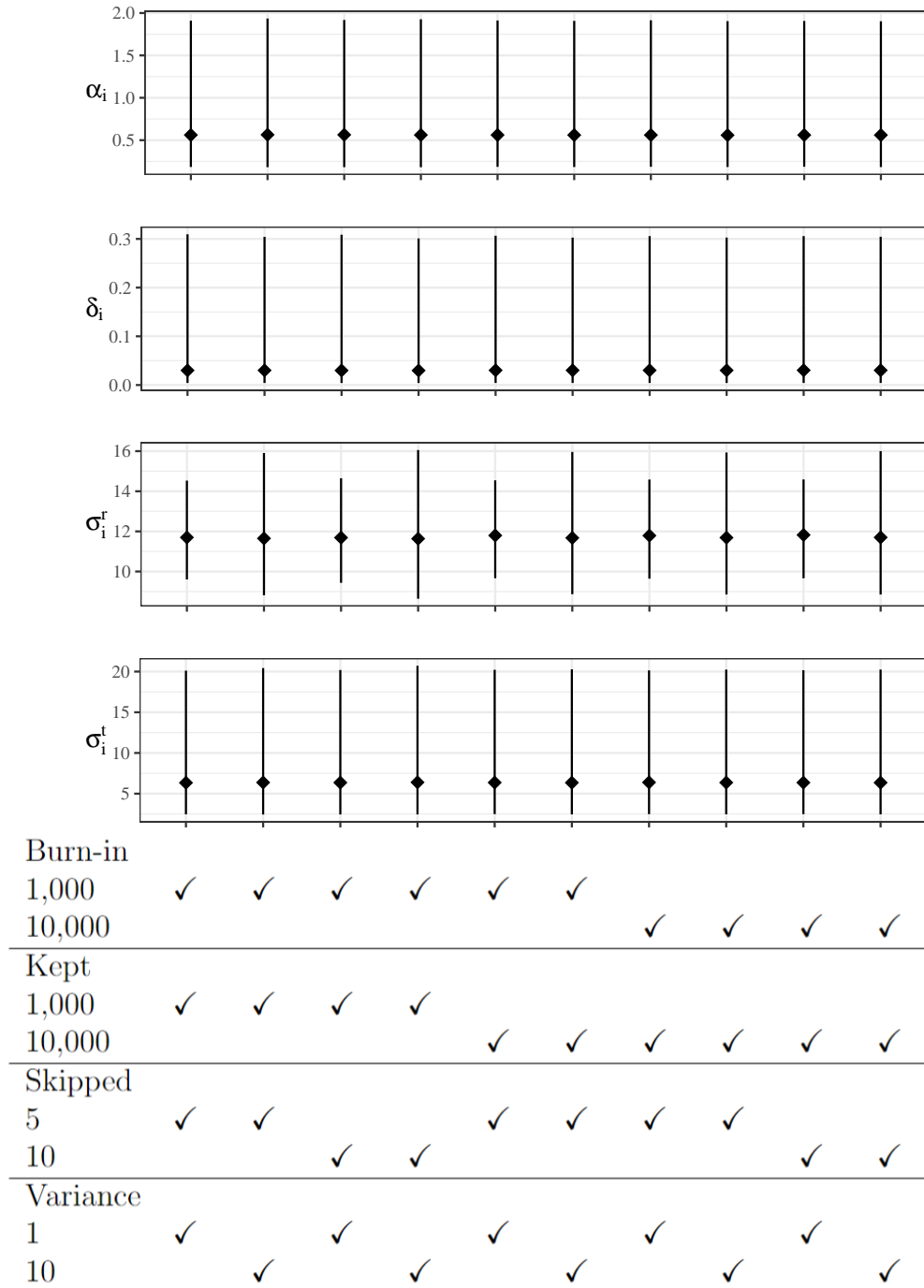
C: Estimated correlation matrix in the baseline estimation in the main text							
C.1: Structural parameters			C.2: Log parameters				
	$\hat{\alpha}_i$	$\hat{\delta}_i$	$\hat{\sigma}_i^r$		$\widehat{\log(\alpha_i)}$	$\widehat{\log(\delta_i)}$	$\widehat{\log(\sigma_i^r)}$
$\hat{\delta}_i$	0.45 [0.40;0.49]			$\widehat{\log(\delta_i)}$	0.49 [0.46,0.52]		
$\hat{\sigma}_i^r$	-0.32 [-0.42;-0.21]	0.05 [-0.06;0.15]		$\widehat{\log(\sigma_i^r)}$	-0.39 [-0.42,-0.35]	0.02 [-0.02, 0.06]	
$\hat{\sigma}_i^t$	-0.10 [-0.15;-0.04]	0.79 [0.76;0.82]	0.33 [0.23;0.42]	$\widehat{\log(\sigma_i^t)}$	-0.08 [-0.13,-0.04]	0.43 [0.39,0.46]	0.57 [0.54,0.60]

**Note:** The 95% confidence intervals over the structural parameters in Panels A-C.1 are obtained using the Fisher's Z transform are given in brackets. The ones for the log parameters in Panels A-C.2 are given by the quantiles over the 10,000 draws.

**Sensitivity analysis** Lastly, figure B.1 shows that the distributions of the individual estimates do not vary substantially across 10 sets of estimations parameters: number of burn-in simulations, number of simulations kept, number of simulations skipped to mitigate autocorrelation, and prior

variance. The only exception is the variance of  $\sigma_i^r$  which is slightly larger when choosing a larger prior variance (equal to 10 times the identity matrix).

Figure B.1: Stability of the estimation across 10 sets of parameters



Note: For all estimations and all parameters, the figure gives the median and the 95% middle interval of the distribution across the  $N=2,000$  individuals in the simulated data. We consider estimations using 1,000 or 10,000 burn-in simulations, keeping 1,000 or 10,000 simulations in total, every 5 or 10 simulations to mitigate autocorrelation, and with a diagonal prior variance of 1 or 10.

## Appendix C Results on BMI and physical activity

In this section, we use ancillary data on other indicators to support the external validity of our individual estimates. First, we consider the Body Mass Index (BMI) as an indicator of balance between diet and physical activity, which association with time preferences is documented in the literature (Chabris et al., 2008; Sutter et al., 2013; Golsteyn et al., 2014). The BMI was provided by the ELIPSS panel from their general survey which was then merged to our Psychofood survey data. It was calculated based on self-declared height and weight. Around 12% of the respondents have a missing value for BMI in the 2018 ELIPSS survey. To improve the power of regressions explaining this variable, we use the BMI from the previous ELIPSS survey in 2017 for a majority of these individuals. This yields 1,815 observations of BMI in our sample without the outliers for the  $\sigma$ s. The raw data are truncated under 18.5 and above 35 to guarantee anonymity. For each individual  $i$ , we consider a categorical variable  $BMI_i$  reflecting the nutritional status of the individual according the World Health Organization (WHO) definition: i) underweight if  $BMI_i \leq 18.5$ , ii) normal weight if  $18.5 < BMI_i < 25$ , iii) overweight if  $25 \leq BMI_i < 30$ , and iv) obese if  $BMI_i \geq 30$ .<sup>41</sup> We also include an indicator of frequency of physical activity with five different categories: “less than once a month”, “one to to three times a month”, “once a week”, “several times a week”, and “every day or so”. This is nonmissing for 1,903 individuals in our sample. We order these categories so that higher values indicate more frequent physical activity.

Table C.1: Results with the baseline DU model

Dependent variable Model	BMI		Physical activity	
	Ordinal Logit		Ordinal Logit	
	(1)	(2)	(3)	(4)
Risk seeking: $\text{rank}(\hat{\alpha}_i)$	-0.278 *	0.025	-0.074	-0.016
	(0.124)	(0.187)	(0.145)	(0.162)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.500 **	0.552 **	-0.305 **	-0.335 **
	(0.264)	(0.288)	(0.110)	(0.108)
Controls		✓		✓
Observations	1,815	1,815	1,903	1,903

Note: The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

Table C.1 gives the associations of the estimated parameters with supplementary health indicators from the ELIPSS annual survey, after removing the 5% outliers for the  $\sigma$ s as in the main text. Consistent with the empirical literature on weight status and time preferences (Chabris et al., 2008; Sutter et al., 2013; Golsteyn et al., 2014; Courtemanche et al., 2015), we find that more impatient individuals are more likely to have a higher BMI. We obtain a statistically significant at the 10% level and negative estimates indicating that more risk-seeking individuals have a lower BMI in our sample. When controlling for socio-demographic variables, the estimate is no longer statistically significant. This is in line with Anderson and Mellor (2008) and Galizzi and Miraldo (2017) who found mixed results on the relationship between risk aversion and BMI, depending on

<sup>41</sup>Lagged BMI values are strong predictors of current BMI. The absolute difference between the 2017 BMI and the 2018 BMI is under 0.6 for half the sample, and under 2 for 90% of the sample.

the specification.<sup>42</sup> Consistent with our results on BMI, we find that more impatient individuals practice physical activities significantly less often, whereas we find no significant association with risk attitudes.

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<sup>42</sup>The literature remains altogether inconclusive on the link between risk preferences and BMI. In a sample of children and teenager, Sutter et al. (2013) find an association with a opposite direction between certainty equivalents and BMI. More recently, Samek et al. (2021) and List et al. (2022) obtains insignificant association between risk preferences and BMI.

## Appendix D Supplementary tables and figures

Table D.1: List of the 28 food items aggregated into 7 food groups

<b>Food group</b>	<b>Item</b>
Fruit and vegetables	Cooked vegetables
	Raw vegetables
	Fruit
Cereal-based products and tubers	Bread
	Pasta, rice
	Breakfast cereals
	Potatoes
Meat, eggs, fish and pulses	Poultry
	Meat
	Eggs
	Fish
	Pulses
Dairy product	Milk
	Yogourt
	Cheese
High fat, sugar, salt processed foods	Fries
	Pizza, quiches, lasagna
	Breaded
	Savory snacks
	Sweet snacks
	Sweetened deserts
	Cured meat
Added Fats	Vegetable oils
	Other fats
Beverages	Water
	Hot Beverages
	Other beverages
	Alcohol

Table D.2: Dietary recommendations

Nutrient	Gender	Age	Value	Unit
<b>Dietary Reference Intakes (for the MAR index)</b>				
Fiber	All	All	30.0	g
Vitamin B12	All	All	2.4	mcg
Vitamin C	All	All	110.0	mg
Vitamin E	All	All	12.0	mg
Vitamin D	All	All	5.0	mcg
Potassium	All	All	3100.0	mg
Iodine	All	All	150.0	mcg
Calcium	All	18-54	900.0	mg
	All	55-79	1200.0	mg
Vitamin B2	Male	All	1.6	mg
	Female	All	1.5	mg
Proteins	Male	All	60.0	g
	Female	All	50.0	g
Vitamin A	Male	All	800.0	mcg ER
	Female	All	600.0	mcg ER
Vitamin B1	Male	All	1.3	mg
	Female	All	1.1	mg
Vitamin B3	Male	All	14.0	mg
	Female	All	11.0	mg
Vitamin B6	Male	All	1.8	mg
	Female	All	1.5	mg
Vitamin B9	Male	All	330.0	mcg
	Female	All	300.0	mcg
Iron	Male	All	9.0	mg
	Female	All	16.0	mg
Magnesium	Male	All	420.0	mg
	Female	All	360.0	mg
Zinc	Male	18-54	12.0	mg
	Male	55-79	11.0	mg
	Female	18-54	10.0	mg
	Female	55-79	11.0	mg
Copper	Male	18-54	2.0	mg
	Male	55-79	1.5	mg
	Female	All	1.5	mg
Selenium	Male	18-54	60.0	mcg
	Male	55-79	70.0	mcg
	Female	18-54	50.0	mcg
	Female	55-79	60.0	mcg
<b>Maximum Recommended Values (for the MER index)</b>				
Saturated fatty acids	All	All	22.0	g
Free sugars	All	All	50.0	g
Sodium	All	All	3153.0	mg

Note: Most values are based on WHO and FAO (2003). The values for saturated fatty acids and free sugars are from Scientific Committee for Food (1993), and that for potassium is from Martin (2001).



Table D.3: Quantiles by gender

Gender	Used for the WDI			Quantiles of energy	
	MAR	MER	DE	Q <sub>2.5%</sub>	Q <sub>97.5%</sub>
Female	83.10	4.19	155.39	779	4,505
Male	82.99	8.13	168.23	737	4,541

Note: These values are the medians of the MAR, MER, and DE used to compute the WDI, and the 2.5% and 97.5% quantiles used to remove outliers. The values are computed over the full sample (N=2,199). The quantiles of energy are in cal/day.

Table D.4: Including or removing diet outliers and imputed values

Dependent variable Model	Energy Log-Linear		Diet quality Ordinal Logit		Alcohol Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Including diet outliers and imputed values</b>						
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.060 (0.053)	-0.019 (0.056)	-0.048 (0.138)	-0.143 (0.129)	3.220 ** (1.063)	2.784 ** (1.010)
Impatience: rank( $\hat{\delta}_i$ )	0.168 ** (0.052)	0.155 ** (0.050)	-0.428 *** (0.085)	-0.377 ** (0.096)	0.869 (1.092)	2.355 ** (1.079)
Controls		✓		✓		✓
Observations	2,179	2,179	2,179	2,179	2,179	2,179
<b>Removing diet outliers and imputed values</b>						
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.052 (0.051)	-0.007 (0.052)	-0.162 (0.135)	-0.256 * (0.125)	3.066 ** (1.189)	2.790 ** (1.148)
Impatience: rank( $\hat{\delta}_i$ )	0.120 ** (0.048)	0.119 ** (0.047)	-0.358 ** (0.105)	-0.282 * (0.122)	1.484 (1.189)	2.809 ** (1.159)
Controls		✓		✓		✓
Observations	1,803	1,803	1,803	1,803	1,803	1,803

Note: This Table replicates table 7 including or removing the diet outliers and the individuals who required diet imputation. The results are qualitatively unaffected. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

Table D.5: Correlation across equivalents

Certainty equivalents	Sooner equivalents			
	T1	T2	T3	T4
R1	0.15 [0.11,0.19]	0.16 [0.12,0.20]	0.14 [0.10,0.18]	0.16 [0.12,0.20]
R2	0.09 [0.05,0.13]	0.11 [0.07,0.15]	0.12 [0.08,0.16]	0.08 [0.04,0.12]
R3	0.17 [0.13,0.21]	0.16 [0.12,0.21]	0.15 [0.11,0.20]	0.20 [0.16,0.24]
R4	0.09 [0.05,0.14]	0.09 [0.05,0.13]	0.07 [0.03,0.11]	0.10 [0.06,0.14]

Note: This Table gives the correlation between the center of the intervals bounding the certainty equivalents and the sooner equivalents. We find that all certainty equivalents are slightly positively correlated with all sooner equivalents. This is not inconsistent with the correlations across structural parameters in the main text as the sooner equivalents depend both on the discount factor and on the curvature of the utility function. These model-free correlations do not identify the correlation between structural parameters. 95% asymptotic confidence intervals based on Fisher's Z transform are given in brackets. These values are computed over the full sample (N=2,199).

Table D.6: OLS regressions on MAR, MER, and ED

Dependent variable Model	Adequacy ratio		Excess ratio		Energy density	
	Linear		Linear		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Equivalents: Main sample					
Rank of mean $\hat{c}_{iR}$	1.188 (1.491)	1.910 (1.522)	-2.784 (3.498)	-2.196 (3.646)	1.843 (4.228)	4.453 (4.160)
Rank of mean $-\hat{c}_{iT}$	2.142 (1.523)	1.827 (1.548)	9.138 ** (3.580)	7.719 ** (3.604)	9.951 ** (4.224)	10.183 ** (4.133)
	DEU estimates: Main sample					
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.411 (1.634)	0.365 (1.753)	-9.952 ** (4.278)	-8.331 * (4.311)	-4.171 (4.294)	-1.319 (4.398)
Impatience: rank( $\hat{\delta}_i$ )	2.581 (1.627)	2.441 (1.607)	11.394 ** (3.776)	9.477 ** (3.654)	10.241 ** (4.202)	9.873 ** (4.248)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086
	DEU estimates: Without outliers for the $\sigma_s$					
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.108 (1.791)	0.658 (1.906)	-4.368 (3.975)	-2.676 (4.261)	-1.479 (4.522)	0.871 (4.645)
Impatience: rank( $\hat{\delta}_i$ )	1.144 (1.824)	0.777 (1.782)	8.843 ** (3.664)	7.125 * (3.816)	11.048 ** (4.527)	11.651 ** (4.540)
Controls		✓		✓		✓
Observations	1,916	1,916	1,916	1,916	1,916	1,916

Note: These regressions explain the intermediary indicators used to compute the WDI. The top panel report regressions on the sample used in the table 7, while report regressions on the sample used in the table 10. These estimates corroborate our main regressions where impatient individuals have a significantly worse diet quality. Within these indicators, risk-seeking attitudes measured by DEU estimates are associated with the excess ratio only when including the outliers for the  $\sigma_s$ , and only weakly so when controlling for covariates (10% level). Without the outliers for the  $\sigma_s$ , we find that risk seeking is not significantly associated with the components of the WDI, suggesting that the aggregation is required to reveal the significant association between risk seeking and diet quality in table 10. The standard deviations in brackets are given under their corresponding coefficients. The standard errors are robust. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

Table D.7: Main estimation without weights

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Equivalentents					
Rank of mean $\hat{c}_{iR}$	0.020 (0.029)	0.041 (0.030)	-0.342 ** (0.094)	-0.398 *** (0.089)	4.963 *** (1.062)	4.870 *** (1.049)
Rank of mean $-\hat{c}_{iT}$	0.083 ** (0.029)	0.064 ** (0.029)	-0.290 ** (0.102)	-0.231 * (0.113)	0.153 (1.023)	1.185 (1.045)
	DEU estimation					
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.041 (0.031)	-0.007 (0.032)	-0.183 (0.125)	-0.295 ** (0.113)	4.651 *** (1.025)	3.993 *** (1.032)
Impatience: rank( $\hat{\delta}_i$ )	0.100 ** (0.030)	0.078 ** (0.031)	-0.367 ** (0.096)	-0.302 ** (0.109)	0.521 (1.042)	1.665 (1.067)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: Each column contains the estimates from two regressions using either the rank or the log transformation. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). These estimations do not use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

Table D.8: Main estimation allowing for  $\alpha < 0$ 

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	DEU estimation					
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.052 (0.047)	-0.009 (0.048)	-0.073 (0.142)	-0.171 (0.132)	2.741 ** (1.133)	2.267 ** (1.084)
Impatience: rank( $\hat{\delta}_i$ )	0.111 ** (0.044)	0.106 ** (0.044)	-0.302 ** (0.108)	-0.242 * (0.122)	1.068 (1.125)	2.458 ** (1.077)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: In these regression, we consider a utility function allowing for  $\alpha_i \leq 0$ . For  $\alpha_i = 0$  it yields  $\log(x)$ , and for  $\alpha_i < 0$  it yields  $(-x)_{i}^{\alpha}$ . This allows for more curvature of the utility function. We re-estimate the  $\hat{\alpha}_i$ , run the same regressions as in the main text, and find similar results. For Each column contains the estimates from two regressions using either the rank or the log transformation. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). These estimations do not use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

Table D.9: Separate associations between behavioral parameters and diet quality

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk seeking: $\text{rank}(\hat{\alpha}_i)$	-0.005 (0.044)	0.038 (0.044)	-0.184 (0.114)	-0.247 ** (0.109)	3.152 ** (1.035)	3.342 *** (1.005)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.113 ** (0.041)	0.123 ** (0.040)	-0.413 *** (0.083)	-0.390 *** (0.089)	1.621 (1.033)	2.973 ** (1.013)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: This Table replicates the top panel of table 7 using either only risk estimates or time estimates in each regression, so that each estimate is from a different regression - we use the same format to ease comparisons. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ . The critical values are the corresponding quantiles of a standard normal.

Table D.10: Stated risk preference measure

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-linear		Ordered logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>With outliers for the <math>\sigma</math>s</b>						
<b>Only stated risk</b>						
Stated risk seeking: rank	0.092 ** (0.042)	0.074 * (0.042)	-0.083 (0.132)	-0.111 (0.131)	2.432 ** (1.167)	1.386 (1.137)
<b>With estimated impatience</b>						
Stated risk seeking: rank	0.075 * (0.043)	0.054 (0.044)	0.015 (0.149)	-0.021 (0.147)	2.214 * (1.166)	0.877 (1.140)
Impatience: rank( $\hat{\delta}_i$ )	0.100 ** (0.043)	0.113 ** (0.041)	-0.415 *** (0.084)	-0.387 *** (0.091)	1.247 (1.023)	2.815 ** (1.012)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086
<b>Without outliers for the <math>\sigma</math>s</b>						
<b>Only stated risk</b>						
Stated risk seeking: rank	0.071 (0.044)	0.053 (0.045)	-0.127 (0.134)	-0.166 (0.130)	2.073 (1.291)	1.256 (1.246)
<b>With estimated impatience</b>						
Stated risk seeking: rank	0.054 (0.046)	0.034 (0.047)	0.004 (0.157)	-0.042 (0.153)	1.645 (1.293)	0.522 (1.248)
Impatience: rank( $\hat{\delta}_i$ )	0.085 * (0.047)	0.099 ** (0.045)	-0.512 *** (0.076)	-0.499 *** (0.080)	2.219 * (1.143)	3.750 *** (1.123)
Controls		✓		✓		✓
Observations	1,916	1,916	1,916	1,916	1,916	1,916

Note: In these estimations we control for the stated risk preference measure, with or without the 5% outliers for  $\hat{\sigma}_i^r$  and  $\hat{\sigma}_i^t$ . The stated risk preferences are measured via the standard Lickert scale from 0 to 10, which we rank between zero and 1 for comparison with our main regressions. We show regressions with and without the ranked estimated impatience parameter. These regressions indicate that the stated risk aversion has less explanatory power than our structural estimate for diet quality and alcohol consumption. Contrary to our structural estimates for risk, the stated measure positively and significantly correlates with energy intake in a bivariate setting but only weakly so when including socio-demographics or when controlling for time preferences. Over the sample without the outliers for the estimated  $\sigma$ s, the stated risk measure is not associated with our diet indicators, contrary to our estimated risk measure. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01.

Table D.11: Individual parameters in the extended HDRDU model

	Min	Q25	Median	Mean	Q75	Max	Std. dev.
<b>Risk</b>							
$\hat{\alpha}_i$	0.23	0.55	0.79	0.85	1.02	4.44	0.48
$\hat{\gamma}_i$	0.18	0.33	0.45	0.47	0.56	1.42	0.19
$\sigma_i^r$	8.1	10.5	11.3	11.7	12.3	23.6	1.9
<b>Time</b>							
$\delta_i$	0.002	0.014	0.039	0.057	0.075	1.123	0.079
$\beta_i$	0.77	0.85	0.89	0.90	0.94	1.03	0.06
$\sigma_i^t$	1.8	5.1	8.9	9.1	12.1	37.7	5.0

Note: These summary statistics describe the distribution of the estimated individual parameters in the extended HDRDU model. This estimation yields comparable distribution of the parameters, albeit slightly higher values for  $\hat{\alpha}_i$  and lower values for the  $\sigma$ s.

Table D.12: Correlations of the estimates in the HDRDU model

	$\hat{\alpha}_i$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\beta}_i$	$\hat{\sigma}_i^r$
$\hat{\gamma}_i$	0.94 [0.94,0.95]				
$\hat{\delta}_i$	0.26 [0.22,0.30]	0.34 [0.31,0.38]			
$\hat{\beta}_i$	-0.12 [-0.16,-0.08]	-0.27 [-0.31,-0.23]	-0.60 [-0.63,-0.57]		
$\hat{\sigma}_i^r$	0.22 [0.18,0.26]	0.19 [0.15,0.23]	0.43 [0.39,0.46]	-0.34 [-0.38,-0.30]	
$\hat{\sigma}_i^t$	-0.10 [-0.14,-0.06]	-0.04 [-0.09, 0.00]	0.64 [0.61,0.66]	-0.69 [-0.71,-0.67]	0.57 [0.54,0.60]

Note: 95% asymptotic confidence intervals based on Fisher's Z transform are given in brackets. The very large correlation between  $\hat{\alpha}_i$  and  $\hat{\gamma}_i$  is caused by a combination of factors: (i)  $\alpha_i$  and  $\gamma_i$  both increase the theoretical certainty equivalents for all tasks except R2 -although our model is identified using R4; (ii) the certainty equivalent for R2 is relatively less precisely bounded by our bisection algorithm which includes only 4 intervals for risk-averse individuals; (iii) the respondents all exhibit a large propensity for errors  $\hat{\sigma}_i^r$  compared to the identifying variation potentially generated by the influence of  $\gamma_i$  on the R2 equivalents (+/-€5 at the median  $\hat{\alpha}_i$ ).

Table D.13: Suggestive evidence on distinct associations: discounting vs. present bias

Dependent variable Model	Energy Log-Linear		Diet quality Ordinal Logit		Alcohol Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Separate regressions using the standardized log estimates</b>						
Risk seeking: $\log(\hat{\alpha}_i)/s.d.$	-0.004 (0.012)	0.007 (0.012)	-0.018 (0.038)	-0.039 (0.038)	0.892 ** (0.292)	0.855 ** (0.287)
Impatience: $\log(\hat{\delta}_i)/s.d.$	0.036 ** (0.012)	0.037 ** (0.012)	-0.109 ** (0.036)	-0.097 ** (0.038)	0.246 (0.298)	0.607 ** (0.295)
Risk seeking: $\log(\hat{\gamma}_i)/s.d.$	-0.003 (0.013)	0.009 (0.013)	-0.031 (0.039)	-0.058 (0.039)	0.988 *** (0.296)	0.983 *** (0.293)
Present bias: $-\log(\hat{\beta}_i)/s.d.$	-0.032 ** (0.012)	-0.029 ** (0.012)	0.152 *** (0.049)	0.136 ** (0.050)	-0.239 (0.300)	-0.539 * (0.292)
<b>Including both time parameters in the same regression (VIF&gt;5)</b>						
<b>Rank</b>						
Risk seeking: $\text{rank}(\hat{\alpha}_i)$	-0.021 (0.043)	0.021 (0.044)	-0.148 (0.119)	-0.210 (0.115)	2.834 ** (1.048)	2.856 ** (1.023)
Impatience: $\text{rank}(\hat{\delta}_i)$	0.181 * (0.102)	0.195 * (0.106)	-0.191 (0.257)	-0.059 (0.306)	-3.076 (2.496)	-0.297 (2.466)
Present bias: $\text{rank}(-\hat{\beta}_i)$	0.055 (0.103)	0.071 (0.104)	0.346 (0.431)	0.491 (0.487)	-4.208 * (2.508)	-2.699 (2.428)
<b>Log</b>						
Risk seeking: $\log(\hat{\alpha}_i)/s.d.$	-0.004 (0.012)	0.006 (0.012)	-0.024 (0.038)	-0.046 (0.038)	0.906 ** (0.291)	0.869 ** (0.286)
Impatience: $\log(\hat{\delta}_i)/s.d.$	0.048 (0.029)	0.055 * (0.031)	0.107 (0.108)	0.135 (0.113)	-0.660 (0.740)	-0.138 (0.739)
Present bias: $-\log(\hat{\beta}_i)/s.d.$	0.013 (0.030)	0.020 (0.030)	0.273 ** (0.126)	0.291 ** (0.130)	-1.008 (0.728)	-0.830 (0.718)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: We do not show regressions including estimates of the two parameters for risk ( $\alpha$  and  $\gamma$ ) because doing so yields VIFs greater than 25 indicating a prohibiting level of multicollinearity – doing so yields estimates that are mostly nonsignificant. Because the two time parameters ( $\delta$  and  $\beta$ ) are slightly less correlated, including both of them in the same regression yields lower VIFs between 5 and 6 (for both the rank and the log transformations). This falls below the commonly used threshold of 10 but still indicates highly inflated standard errors due to correlated regressors, which suggest caution in the interpretation. For comparison with our main results we control for heterogeneous risk attitudes with  $\hat{\alpha}$  (using  $\hat{\gamma}$  yields the same results). With these caveats, these regressions provide suggestive evidence that present bias (measured by  $\beta$ ) is relatively more associated with diet quality than impatience (measured by the exponential discounting parameter  $\delta$ ), both in terms of magnitude of the point estimates in the top panel and in terms of statistical significance in the bottom panel when using the normalized log transformation. This suggests that outliers for present bias and impatience exhibit different pattern for diet quality, which variations are mitigated with the rank transformation. We also find suggestive evidence that the exponential discounting parameter is slightly more associated with energy intake than present bias. All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.



Table D.14: Main regressions when using only one pair of ranked equivalents

Dependent variable Model	Energy Log-Linear		Diet quality Ordinal Logit		Alcohol Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Rank( $\hat{c}_{iR}$ ) at R1	0.006 (0.042)	0.044 (0.043)	-0.097 (0.126)	-0.173 (0.119)	3.016 ** (1.072)	3.197 ** (1.046)
Rank( $-\hat{c}_{iT}$ ) at T1	0.075 * (0.043)	0.064 (0.044)	-0.305 ** (0.098)	-0.281 ** (0.104)	1.189 (1.010)	2.014 ** (0.985)
Rank( $\hat{c}_{iR}$ ) at R1	0.010 (0.042)	0.049 (0.043)	-0.121 (0.123)	-0.194 (0.116)	3.023 ** (1.077)	3.225 ** (1.055)
Rank( $-\hat{c}_{iT}$ ) at T2	0.084 ** (0.041)	0.080 ** (0.040)	-0.365 ** (0.089)	-0.341 ** (0.094)	0.955 (1.060)	1.608 (1.024)
Rank( $\hat{c}_{iR}$ ) at R1	0.013 (0.042)	0.052 (0.043)	-0.105 (0.126)	-0.184 (0.118)	2.953 ** (1.080)	3.243 ** (1.057)
Rank( $-\hat{c}_{iT}$ ) at T3	0.104 ** (0.042)	0.098 ** (0.042)	-0.278 ** (0.102)	-0.261 ** (0.107)	0.459 (1.006)	1.620 * (0.979)
Rank( $\hat{c}_{iR}$ ) at R1	0.014 (0.041)	0.052 (0.042)	-0.120 (0.124)	-0.189 (0.117)	2.929 ** (1.074)	3.180 ** (1.052)
Rank( $-\hat{c}_{iT}$ ) at T4	0.108 ** (0.041)	0.111 ** (0.043)	-0.338 ** (0.093)	-0.306 ** (0.099)	0.305 (1.092)	1.302 (1.079)
Rank( $\hat{c}_{iR}$ ) at R2	-0.029 (0.042)	-0.001 (0.043)	0.062 (0.149)	-0.003 (0.142)	3.194 ** (1.165)	2.599 ** (1.158)
Rank( $-\hat{c}_{iT}$ ) at T1	0.070 (0.043)	0.059 (0.043)	-0.289 ** (0.100)	-0.266 ** (0.106)	1.285 (1.034)	2.030 ** (1.009)
Rank( $\hat{c}_{iR}$ ) at R2	-0.028 (0.043)	0.001 (0.043)	0.053 (0.147)	-0.009 (0.141)	3.141 ** (1.163)	2.534 ** (1.161)
Rank( $-\hat{c}_{iT}$ ) at T2	0.079 * (0.041)	0.074 * (0.041)	-0.347 ** (0.091)	-0.321 ** (0.097)	0.923 (1.076)	1.484 (1.039)
Rank( $\hat{c}_{iR}$ ) at R2	-0.023 (0.043)	0.006 (0.043)	0.060 (0.149)	-0.006 (0.142)	3.102 ** (1.139)	2.586 ** (1.133)
Rank( $-\hat{c}_{iT}$ ) at T3	0.098 ** (0.043)	0.092 ** (0.043)	-0.256 ** (0.105)	-0.237 * (0.110)	0.505 (0.996)	1.541 (0.964)
Rank( $\hat{c}_{iR}$ ) at R2	-0.026 (0.042)	0.003 (0.042)	0.061 (0.148)	0.000 (0.142)	3.050 ** (1.156)	2.477 ** (1.150)
Rank( $-\hat{c}_{iT}$ ) at T4	0.102 ** (0.042)	0.104 ** (0.043)	-0.318 ** (0.095)	-0.284 ** (0.102)	0.239 (1.103)	1.147 (1.085)
Rank( $\hat{c}_{iR}$ ) at R3	-0.002 (0.043)	0.042 (0.043)	-0.330 ** (0.092)	-0.370 ** (0.089)	3.316 *** (0.983)	3.663 *** (0.965)
Rank( $-\hat{c}_{iT}$ ) at T1	0.074 * (0.043)	0.063 (0.044)	-0.329 ** (0.094)	-0.300 ** (0.101)	1.139 (0.996)	1.984 ** (0.972)
Rank( $\hat{c}_{iR}$ ) at R3	0.001 (0.043)	0.045 (0.042)	-0.344 ** (0.091)	-0.384 *** (0.088)	3.314 *** (0.986)	3.686 *** (0.971)
Rank( $-\hat{c}_{iT}$ ) at T2	0.083 ** (0.041)	0.078 * (0.041)	-0.389 *** (0.085)	-0.362 ** (0.091)	0.879 (1.044)	1.571 (1.012)
Rank( $\hat{c}_{iR}$ ) at R3	0.006 (0.044)	0.049 (0.043)	-0.336 ** (0.092)	-0.379 *** (0.089)	3.275 *** (0.985)	3.727 *** (0.971)
Rank( $-\hat{c}_{iT}$ ) at T3	0.103 ** (0.043)	0.097 ** (0.042)	-0.309 ** (0.097)	-0.288 ** (0.103)	0.437 (0.995)	1.630 * (0.972)
Rank( $\hat{c}_{iR}$ ) at R3	0.009 (0.043)	0.053 (0.042)	-0.353 ** (0.090)	-0.389 *** (0.087)	3.279 *** (0.987)	3.728 *** (0.974)
Rank( $-\hat{c}_{iT}$ ) at T4	0.107 ** (0.042)	0.111 ** (0.043)	-0.373 *** (0.088)	-0.338 ** (0.095)	0.385 (1.085)	1.432 (1.079)
Rank( $\hat{c}_{iR}$ ) at R4	0.057 (0.043)	0.086 ** (0.042)	-0.258 ** (0.103)	-0.299 ** (0.101)	2.327 ** (1.087)	2.654 ** (1.080)
Rank( $-\hat{c}_{iT}$ ) at T1	0.081 * (0.043)	0.067 (0.043)	-0.323 ** (0.095)	-0.293 ** (0.102)	1.101 (1.011)	1.958 ** (0.987)
Rank( $\hat{c}_{iR}$ ) at R4	0.058 (0.044)	0.088 ** (0.042)	-0.260 ** (0.103)	-0.303 ** (0.101)	2.287 ** (1.072)	2.614 ** (1.069)
Rank( $-\hat{c}_{iT}$ ) at T2	0.089 ** (0.041)	0.082 ** (0.040)	-0.373 *** (0.087)	-0.344 ** (0.093)	0.752 (1.040)	1.435 (1.004)
Rank( $\hat{c}_{iR}$ ) at R4	0.059 (0.044)	0.089 ** (0.042)	-0.250 ** (0.104)	-0.295 ** (0.102)	2.230 ** (1.094)	2.601 ** (1.088)
Rank( $-\hat{c}_{iT}$ ) at T3	0.108 ** (0.043)	0.099 ** (0.041)	-0.288 ** (0.100)	-0.263 ** (0.106)	0.224 (1.009)	1.391 (0.978)
Rank( $\hat{c}_{iR}$ ) at R4	0.062 (0.043)	0.090 ** (0.042)	-0.264 ** (0.102)	-0.301 ** (0.101)	2.222 ** (1.084)	2.578 ** (1.083)
Rank( $-\hat{c}_{iT}$ ) at T4	0.113 ** (0.041)	0.112 ** (0.042)	-0.350 ** (0.090)	-0.309 ** (0.098)	0.119 (1.089)	1.127 (1.079)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: These estimates are from regressions combining all possible pairs of risk and time equivalents. Each estimate is from a separate regression. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*: $p < 0.10$ ; \*\*: $p < 0.05$ ; \*\*\*: $p < 0.01$ . The critical values are the corresponding quantiles of a standard normal.

Table D.15: IV estimation à la Gillen et al. (2019)

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Linear		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk seeking: $\text{rank}(\hat{c}_{iR})$	0.045 (0.043)	-0.067 ** (0.034)	6.798 *** (1.367)			
Impatience: $\text{rank}(\hat{c}_{iT})$	0.066 * (0.035)	-0.063 ** (0.029)	1.721 (1.234)			
Controls	✓	✓	✓			
Clusters	1,972	1,972	1,972			

Note: The diet quality is here measured with a dummy indicating a WDI of 2 or more. The standard errors are clustered at the individual level. These estimations include only individuals who have completed the bisection algorithm for all risk and time tasks. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01.

Table D.16: Controlling for a contextual factor: the soccer world cup

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk seeking × Pre 1/8 round	-0.058 (0.053)	-0.015 (0.055)	0.191 (0.208)	0.114 (0.202)	2.806 ** (1.149)	2.687 ** (1.135)
Impatience × Pre 1/8 round	0.103 ** (0.051)	0.106 ** (0.050)	-0.497 *** (0.089)	-0.466 *** (0.097)	-0.603 (1.207)	0.841 (1.165)
Post 1/8 round	-0.062 (0.069)	-0.040 (0.066)	-0.078 (0.199)	-0.037 (0.211)	-1.561 (1.513)	-0.969 (1.517)
Risk seeking × Post 1/8 round	-0.039 (0.094)	0.002 (0.089)	-0.410 * (0.168)	-0.515 ** (0.141)	3.186 (2.440)	2.327 (2.364)
Impatience × Post 1/8 round	0.213 ** (0.091)	0.186 ** (0.090)	-0.075 (0.270)	0.054 (0.314)	3.731 * (2.232)	5.171 ** (2.147)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: These regressions tests whether our results are driven by changes triggered by the victory of France over Argentina during the soccer world cup. We use the ranked estimates from the DEU model in these regressions. The variable “Post 1/8 round” is a dummy variable equal to one if the respondent started the questionnaire the day after the game or later, and zero otherwise. We do find significant variations in the associations after this game: diet quality becomes only associated with risk attitudes and declared alcohol consumption more associated with impatience after this game. However, our main results hold over the period prior to this game (which contains 72% of observations), where individuals’ perceptions are not influenced by this event. The figures for Ordinal Logit models are the estimates transformed by  $(x \mapsto \exp(x) - 1)$ , which gives the odds ratios minus 1. The standard deviations in brackets are given under their corresponding coefficients. For Ordinal Logit models, the standard deviations of the odds ratios are computed using the Delta-method. The linear models are estimated by OLS, the other models by maximum likelihood. The standard errors for linear models are robust. For Ordinal Logit models, the significance levels pertain to the raw estimates. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01. The critical values are the corresponding quantiles of a standard normal.

Table D.17: Controlling for income and location

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-linear		Ordered logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	<b>With outliers for the <math>\sigma</math>s</b>					
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.017 (0.052)	-0.022 (0.052)	-0.175 (0.146)	-0.176 (0.146)	2.440 ** (1.116)	2.425 ** (1.125)
Impatience: rank( $\hat{\delta}_i$ )	0.107 ** (0.045)	0.106 ** (0.045)	-0.397 ** (0.106)	-0.391 ** (0.107)	1.954 * (1.168)	1.939 * (1.167)
Log Income per unit	-0.049 * (0.028)	-0.052 * (0.028)	0.057 (0.094)	0.059 (0.094)	-0.548 (0.621)	-0.512 (0.609)
Log city size		-0.002 (0.003)		-0.018 * (0.010)		0.066 (0.061)
Log city size $\times$ Log Income per unit		0.005 (0.005)		-0.003 (0.015)		0.026 (0.105)
Controls	✓	✓	✓	✓	✓	✓
Observations	1,764	1,763	1,764	1,763	1,764	1,763
	<b>Without outliers for the <math>\sigma</math>s</b>					
Risk seeking: rank( $\hat{\alpha}_i$ )	0.023 (0.057)	0.016 (0.056)	-0.438 ** (0.110)	-0.447 ** (0.109)	2.314 * (1.218)	2.286 * (1.232)
Impatience: rank( $\hat{\delta}_i$ )	0.066 (0.049)	0.066 (0.049)	-0.433 ** (0.108)	-0.426 ** (0.109)	2.869 ** (1.302)	2.864 ** (1.302)
Log Income per unit	-0.049 * (0.029)	-0.054 * (0.030)	0.181 * (0.114)	0.165 (0.112)	-1.057 (0.693)	-1.006 (0.676)
Log city size		-0.003 (0.003)		-0.024 ** (0.010)		0.063 (0.066)
Log city size $\times$ Log Income per unit		0.008 (0.005)		0.021 (0.018)		0.016 (0.121)
Controls	✓	✓	✓	✓	✓	✓
Observations	1,627	1,626	1,627	1,626	1,627	1,626

Note: In these estimations we control for the potential influence of city size interacted with income, with or without the 5% outliers for  $\hat{\sigma}_i^r$  and  $\hat{\sigma}_i^t$ . The interaction term broadly controls for differentiated macroeconomic conditions in rural and urban across the income gradient. These results corroborate the regressions including only income in the main text. Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01.

Table D.18: Controlling for the precision parameters  $\hat{\sigma}$ s

Dependent variable Model	Energy		Diet quality		Alcohol	
	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
Using the estimates from the DEU model						
<b>Only risk parameters</b>						
Risk seeking: rank( $\hat{\alpha}_i$ )	0.070 (0.053)	0.103 ** (0.052)	-0.308 ** (0.123)	-0.296 * (0.127)	2.272 (1.481)	3.209 ** (1.443)
Imprecision for risk: rank( $\hat{\sigma}_i^r$ )	0.129 ** (0.054)	0.118 ** (0.056)	-0.238 (0.139)	-0.109 (0.166)	-1.512 (1.508)	-0.238 (1.502)
<b>Only time parameters</b>						
Impatience: rank( $\hat{\delta}_i$ )	0.032 (0.077)	0.093 (0.075)	-0.461 ** (0.128)	-0.513 ** (0.119)	5.376 ** (1.840)	6.057 *** (1.766)
Imprecision for time: rank( $\hat{\sigma}_i^t$ )	0.099 (0.076)	0.037 (0.078)	0.111 (0.262)	0.325 (0.324)	-4.612 ** (1.804)	-3.843 ** (1.760)
<b>Both risk and time parameters</b>						
Risk seeking: rank( $\hat{\alpha}_i$ )	0.010 (0.077)	0.039 (0.078)	0.074 (0.284)	0.074 (0.288)	1.338 (2.018)	1.565 (1.943)
Impatience: rank( $\hat{\delta}_i$ )	0.085 (0.135)	0.100 (0.129)	-0.552 * (0.205)	-0.547 * (0.210)	1.544 (3.704)	2.672 (3.576)
Imprecision for risk: rank( $\hat{\sigma}_i^r$ )	0.073 (0.068)	0.069 (0.065)	-0.086 (0.205)	0.030 (0.235)	-2.096 (1.965)	-1.336 (1.916)
Imprecision for time: rank( $\hat{\sigma}_i^t$ )	0.021 (0.135)	0.004 (0.130)	0.365 (0.636)	0.400 (0.659)	-0.265 (3.929)	-0.228 (3.815)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: Because the  $\sigma$ s are highly correlated with our main parameters, we arguably lack identifying variation to disentangle the relationships between our diet indicators and each parameter. With this caveat, when including all four parameters in the same regressions, we find that the main association between time and our main diet quality remains weakly significant even when including both  $\sigma^r$  and  $\sigma^t$ . Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:p<0.10; \*\*:p<0.05; \*\*\*:p<0.01.

Table D.19: Heterogeneity across income, education, age, and gender

Dependent variable Model	Energy Log-Linear		Diet quality Ordinal Logit		Alcohol Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Heterogeneity across income</b>						
<b>Interaction with income deviation</b>						
Risk seeking: rank( $\hat{\alpha}_i$ )	-0.028 (0.049)	0.001 (0.050)	-0.246 * (0.128)	-0.260 * (0.132)	2.318 ** (1.145)	2.780 ** (1.124)
Impatience: rank( $\hat{\delta}_i$ )	0.085 * (0.045)	0.088 ** (0.043)	-0.395 ** (0.105)	-0.400 ** (0.107)	1.187 (1.215)	2.019 * (1.161)
Log Income per unit	-0.064 (0.051)	-0.045 (0.055)	0.760 ** (0.305)	0.648 ** (0.301)	-0.757 (1.452)	-2.453 * (1.420)
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ $\Delta$ Log Income	0.211 ** (0.085)	0.244 ** (0.086)	-0.592 ** (0.117)	-0.659 *** (0.100)	3.688 * (2.039)	3.590 * (1.968)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ $\Delta$ Log Income	-0.185 ** (0.086)	-0.220 ** (0.084)	-0.027 (0.276)	0.073 (0.309)	-0.030 (2.160)	0.511 (2.127)
<b>Income categories</b>						
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ Low income	-0.126 (0.077)	-0.122 (0.076)	0.222 (0.296)	0.231 (0.303)	0.949 (1.781)	1.685 (1.719)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ Low income	0.267 *** (0.069)	0.273 *** (0.068)	-0.612 *** (0.090)	-0.602 *** (0.095)	1.753 (1.698)	3.345 ** (1.696)
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ High income	0.017 (0.054)	0.065 (0.055)	-0.359 ** (0.134)	-0.398 ** (0.133)	3.329 ** (1.379)	2.991 ** (1.366)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ High income	-0.033 (0.055)	-0.025 (0.055)	-0.148 (0.183)	-0.174 (0.183)	0.358 (1.479)	0.865 (1.390)
Controls		✓		✓		✓
Observations	1,764	1,764	1,764	1,764	1,764	1,764
<b>Heterogeneity across education, age, and gender</b>						
<b>Education categories</b>						
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ not completed HS	-0.020 (0.069)	-0.035 (0.073)	0.048 (0.210)	0.111 (0.231)	2.377 * (1.414)	1.898 (1.436)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ not completed HS	0.204 ** (0.064)	0.196 ** (0.071)	-0.544 *** (0.089)	-0.483 ** (0.113)	0.081 (1.416)	0.729 (1.560)
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ completed HS	-0.017 (0.050)	0.017 (0.057)	-0.215 (0.159)	-0.330 * (0.156)	2.894 ** (1.382)	3.597 ** (1.448)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ completed HS	0.018 (0.050)	0.057 (0.052)	-0.166 (0.169)	-0.203 (0.176)	1.428 (1.413)	3.225 ** (1.388)
<b>Age categories</b>						
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ under 45yo	-0.086 (0.072)	-0.053 (0.082)	-0.028 (0.198)	0.200 (0.272)	1.717 (1.385)	1.504 (1.554)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ under 45yo	0.166 ** (0.072)	0.146 ** (0.072)	-0.469 ** (0.109)	-0.149 (0.197)	-0.176 (1.380)	1.413 (1.426)
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ above 45yo	-0.026 (0.050)	0.025 (0.053)	0.038 (0.201)	-0.331 * (0.139)	4.828 *** (1.367)	3.553 ** (1.408)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ above 45yo	0.103 ** (0.050)	0.113 ** (0.051)	-0.354 ** (0.123)	-0.502 *** (0.105)	1.165 (1.398)	2.520 * (1.483)
<b>Gender categories</b>						
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ Female	-0.064 (0.062)	0.005 (0.069)	-0.094 (0.182)	-0.210 (0.173)	1.014 (1.189)	2.334 ** (1.179)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ Female	0.072 (0.060)	0.094 (0.064)	-0.389 ** (0.123)	-0.470 ** (0.119)	-1.512 (1.133)	0.902 (1.055)
Risk seeking: rank( $\hat{\alpha}_i$ ) $\times$ Male	-0.045 (0.056)	-0.025 (0.064)	0.046 (0.203)	-0.010 (0.211)	4.688 ** (1.551)	2.887 (1.759)
Impatience: rank( $\hat{\delta}_i$ ) $\times$ Male	0.202 *** (0.058)	0.159 ** (0.059)	-0.421 ** (0.111)	-0.249 (0.160)	3.273 ** (1.627)	3.017 * (1.781)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

**Note:** In these regressions, we add interaction terms between the risk and time parameters and selected socio-demographics: income, education, age, and gender. We find that the relationship between preferences and diet quality varies across socio-demographic groups. The general pattern is that our main results are driven by groups with larger values for the corresponding variables: the results on impatience are driven by more impatient groups (low income, low education), whereas those for risk are driven by more risk seeking groups (high income, high education). Similarly, the results on alcohol are primarily driven by groups consuming more alcohol (high income and education, older individuals, and males). Controls include gender (1 dummy), age (6 dummies), education (3), nationality (2), and living area (7). All estimations use weights. Significance: \*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ .

Figure D.1: Screenshot of a question from the food frequency questionnaire

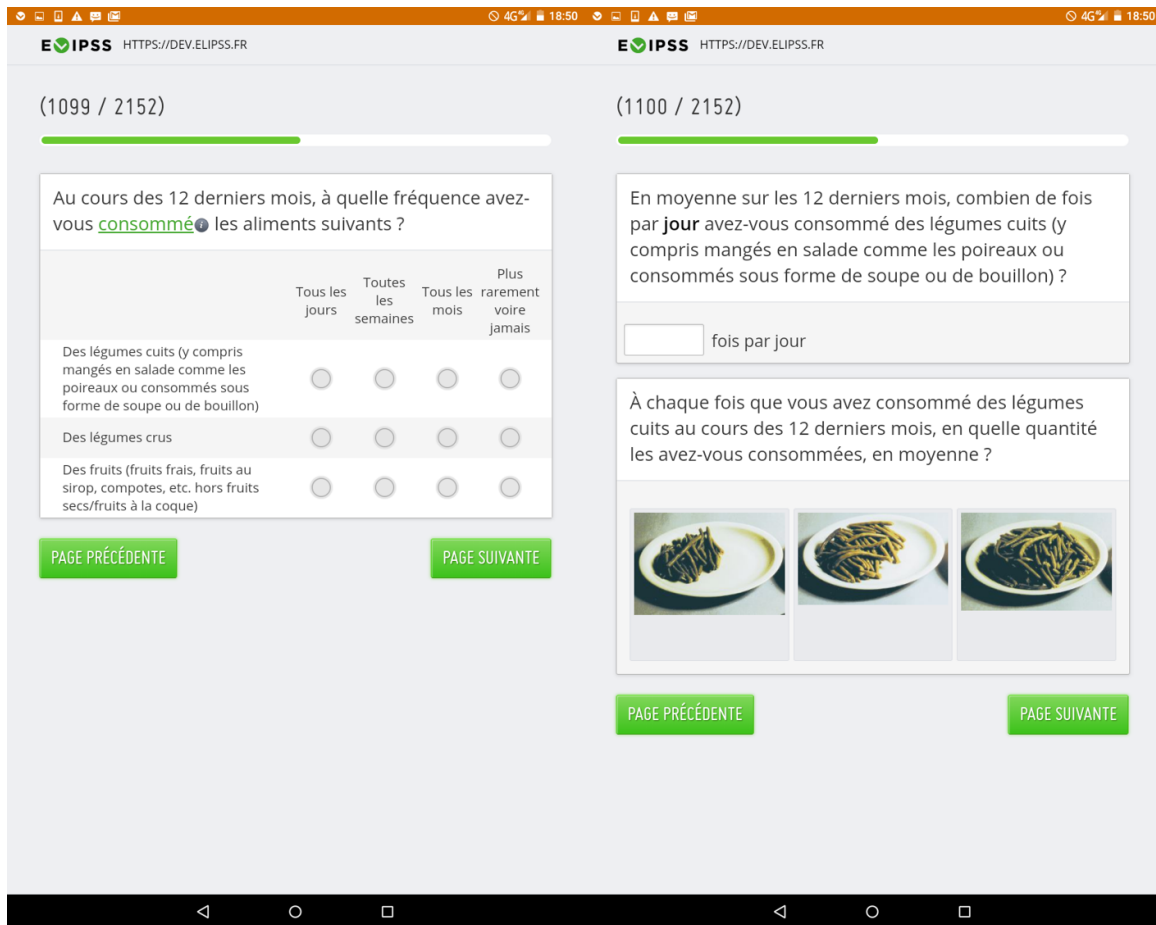
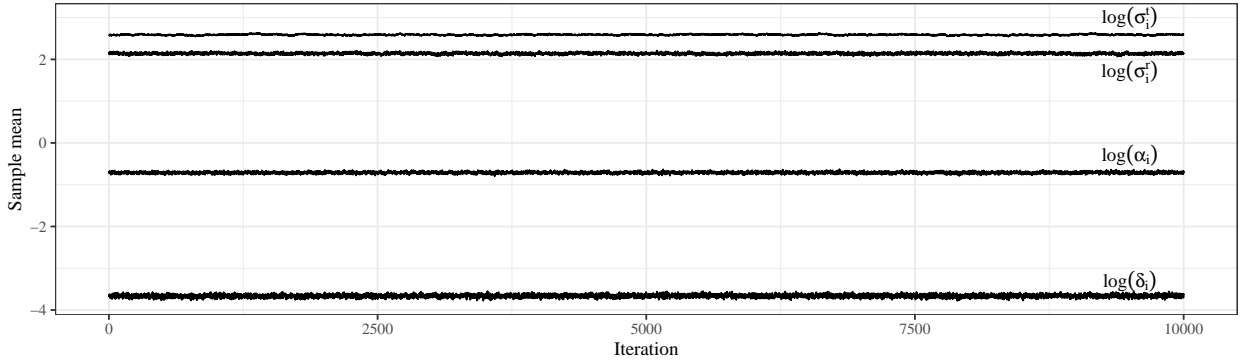
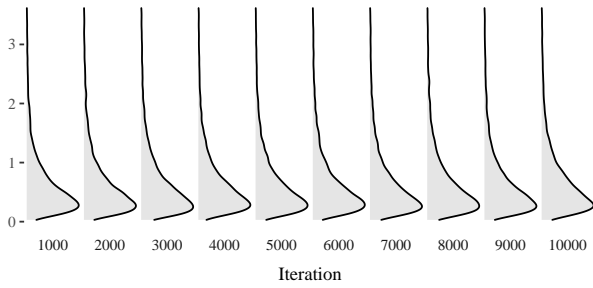


Figure D.2: Stability of the distributions of the draws across the  $D = 10,000$  iterations

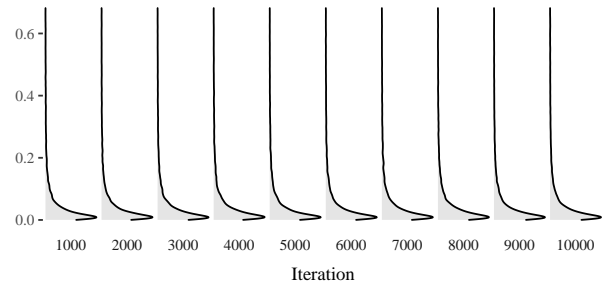
(a) Sample means of the normally distributed underlying log-parameter



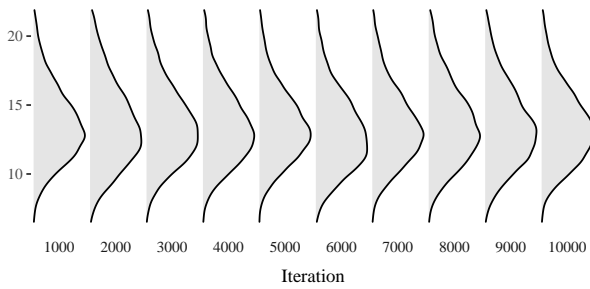
(b) Distributions of  $\hat{\alpha}_i$



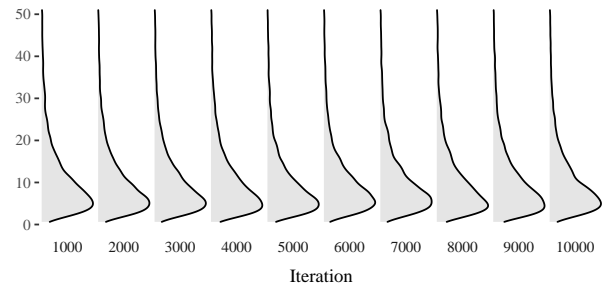
(c) Distributions of  $\hat{\delta}_i$



(d) Distributions of  $\hat{\sigma}_i^r$

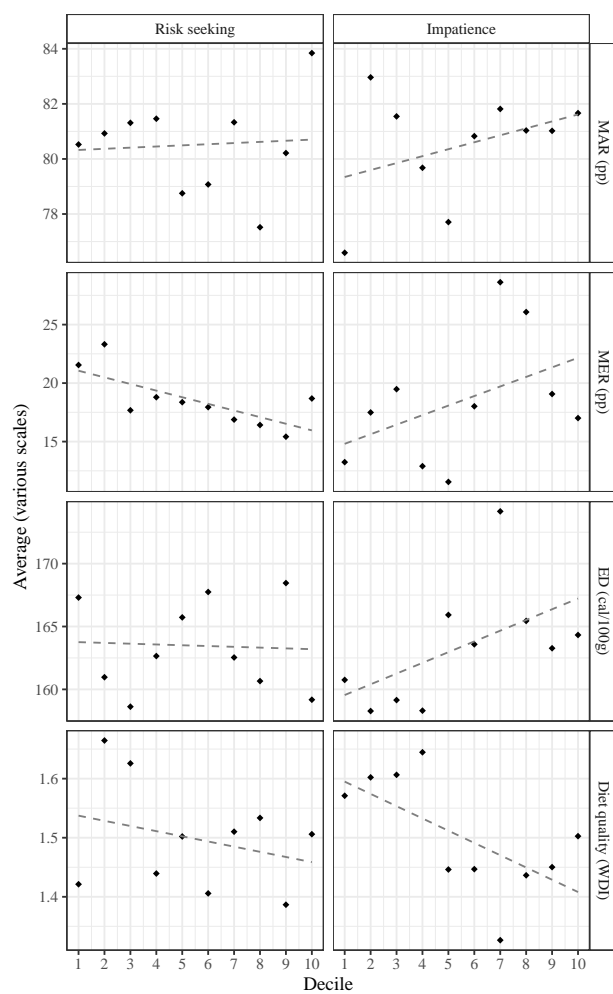


(e) Distributions of  $\hat{\sigma}_i^t$



Note: This Figure illustrates the stability of the distribution of draws across the  $D = 10,000$  draws kept for the baseline estimation, after 10,000 burn in iterations. Panel (a) gives the mean across individual draws of each parameter at each iteration. Panels (b) to (e) give the estimated distributions under the 99<sup>th</sup> percentile every 1,000 iterations.

Figure D.3: Components of the WDI index by decile of risk and time preference



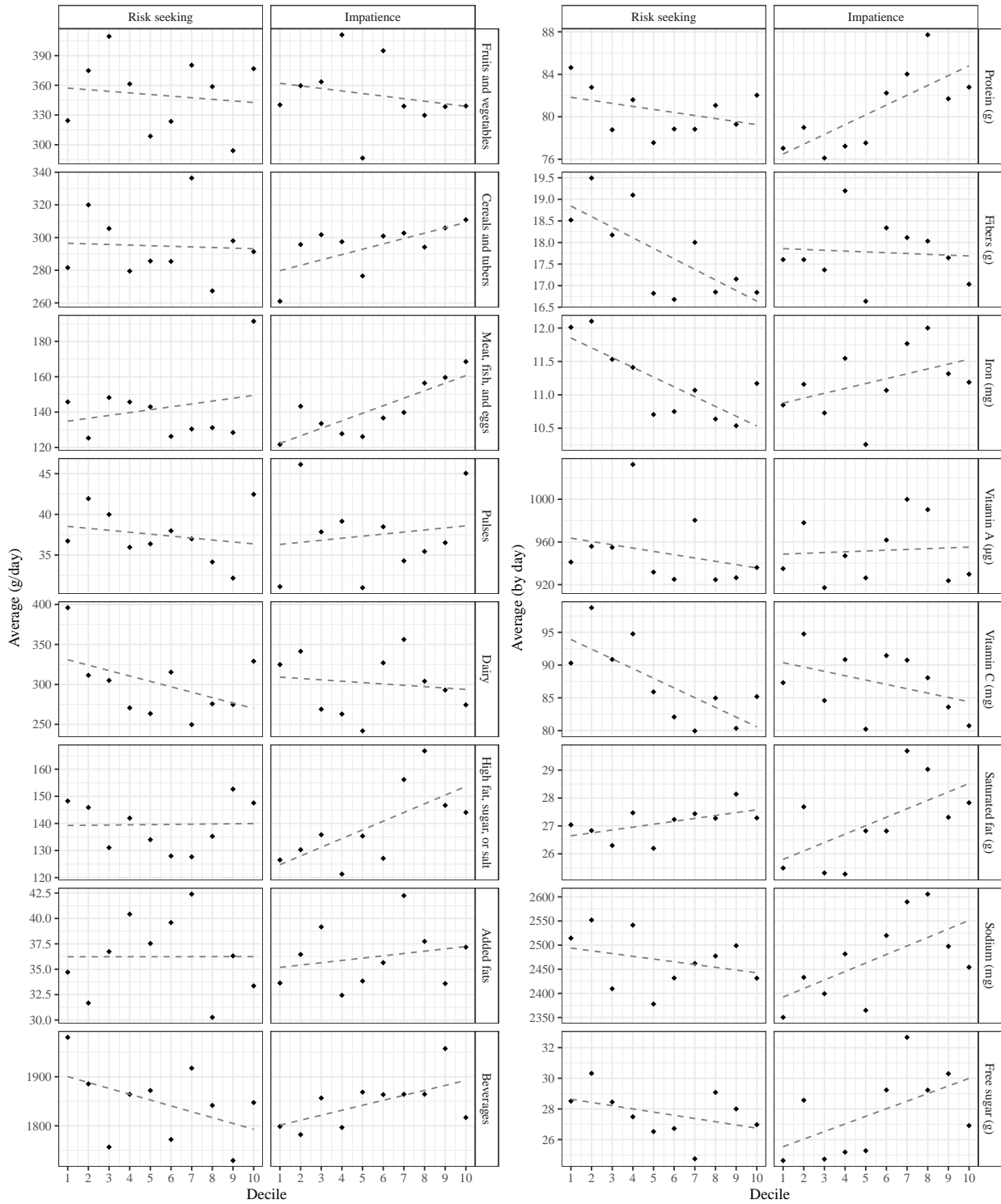
Notes: This Figure shows the distribution of the intermediate indicators used to compute the WDI across deciles of estimated risk and time parameters.



Figure D.4: Food groups and nutrients by decile of risk and time preference

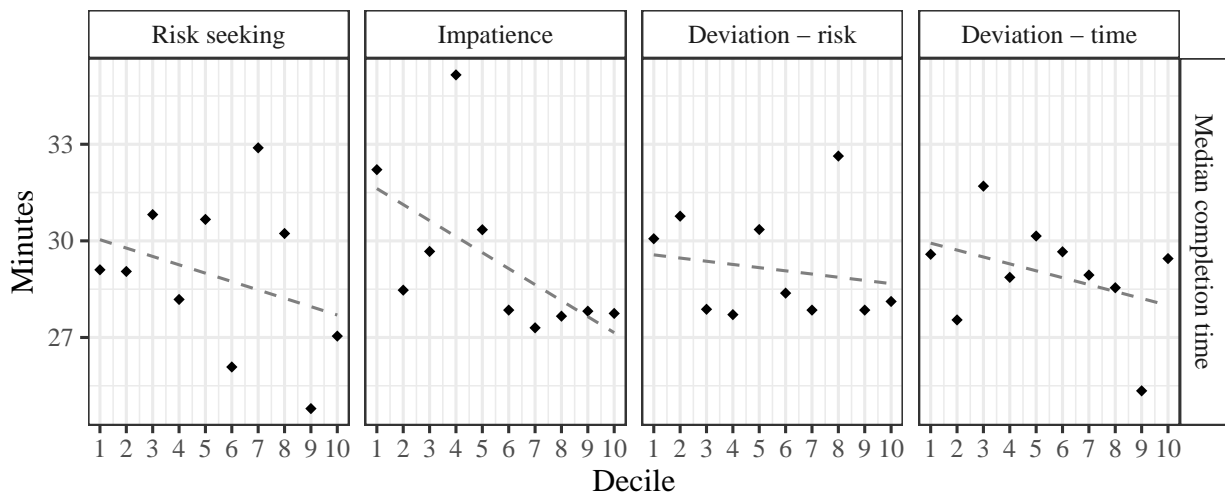
(a) Food groups

(b) Nutrients



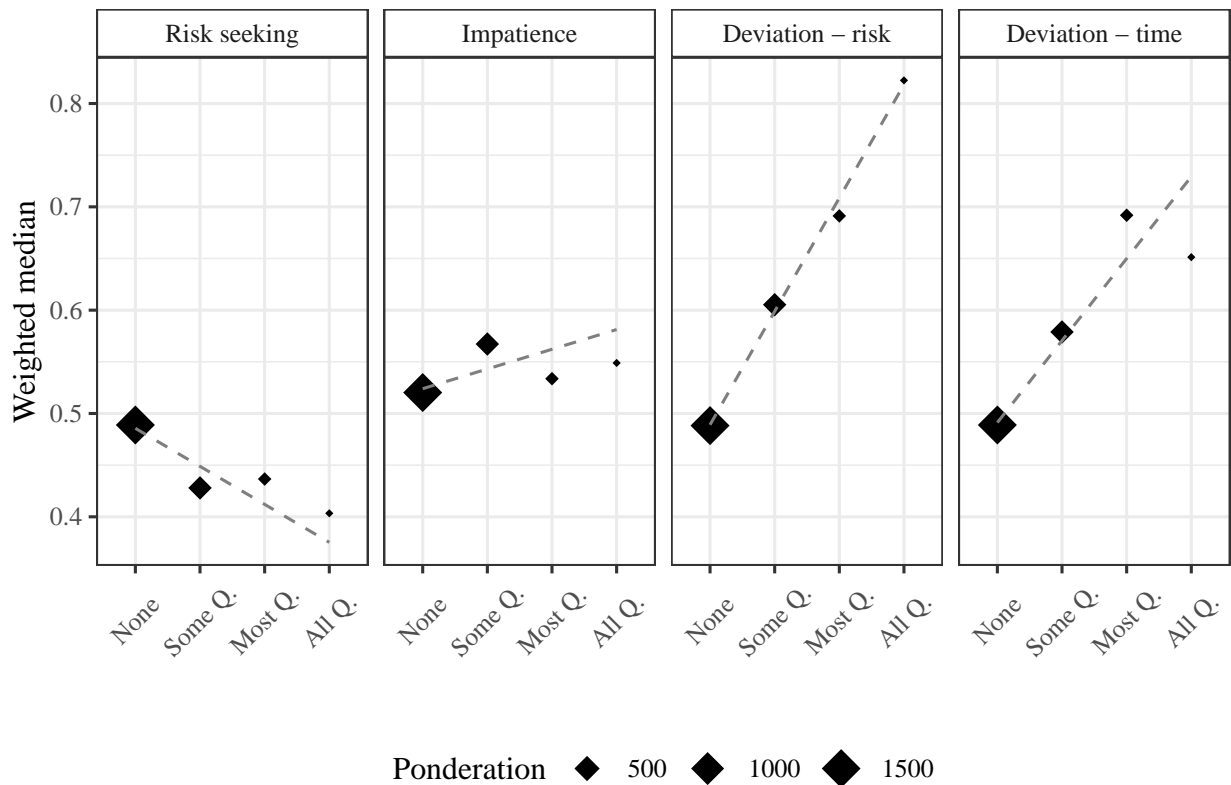
Note: This Figure gives the average quantity consumed daily by food group and for main nutrients across deciles of estimated risk and time parameters.

Figure D.5: Completion time



Note: The diamonds give the weighted median completion by decile of  $\hat{\alpha}_i$ ,  $\hat{\delta}_i$ ,  $\hat{\sigma}_i^r$ , and  $\hat{\sigma}_i^t$  (from left to right), computed using the survey weights. We find intuitive patterns which support the internal validity of our method. In particular, the median completion time decreases with impatience, so that less patient individuals typically completed the questionnaire faster. We also find that more risk-seeking individuals completed the questionnaire faster, which may stem from the fact that risk-seeking attitude and impatience are positively correlated in our sample. Finally, we find that less consistent individuals for risk and time exhibited lower median completion times, which may explain their lower consistency across tasks. A similar pattern was found by Von Gaudecker et al. (2011).

Figure D.6: Difficulties to understand the questions



Note: The diamonds give the weighted medians of  $\hat{\alpha}_i$ ,  $\hat{\delta}_i$ ,  $\hat{\sigma}_i^r$ , and  $\hat{\sigma}_i^t$  (from left to right), computed using the survey weights. We find that most individuals had no difficulty answering all the questions. Furthermore, the individuals who had difficulty to understand “some,” “most,” or “all questions” gave more inconsistent answers across tasks, reflected in larger median  $\sigma$ s.

## Appendix references

- Abdellaoui, Mohammed, Aurélien Baillon, Laetitia Placido, and Peter P Wakker (2011). “The rich domain of uncertainty: Source functions and their experimental implementation.” *American Economic Review* 101 (2), pp. 695–723.
- Abdellaoui, Mohammed, Han Bleichrodt, Olivier l’Haridon, and Corina Paraschiv (2013). “Is there one unifying concept of utility? An experimental comparison of utility under risk and utility over time.” *Management Science* 59 (9), pp. 2153–2169.
- Abdellaoui, Mohammed, Emmanuel Kemel, Amma Panin, and Ferdinand M. Vieider (2019). “Measuring time and risk preferences in an integrated framework.” *Games and Economic Behavior* 115, pp. 459–469.
- Martin, Ambroise (2001). “The “apports nutritionnels conseillés” (ANC) for the French population.” *Reproduction Nutrition Development* 41 (2), pp. 119–128.
- Scientific Committee for Food (1993). “Nutrient and energy intakes for the European Community.” *Reports of the Scientific Committee for Food, 31st Series*, p. 248.
- WHO and FAO (2003). “Diet, nutrition and the prevention of chronic diseases.” *Joint WHO /FAO Expert Consultation. World Health Organization Technical Report Series* 916 (i–viii), pp. 1–149.