Risk, Time, and Diet Quality: Evidence from a General Population Survey

Antoine Nebout[†*] Noémi Berlin[‡] Emmanuel Kemel[§]

Emmanuel Paroissien[†]

[†] *University Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics. 22 Place de l'Agronomie, 91120 Palaiseau, France.*

[‡] *CNRS, EconomiX, University of Paris Nanterre. 200 Avenue de la République, 92000 Nanterre, France.*

[§] *CNRS & HEC Paris. 1 Rue de la Libération, 78350 Jouy-en-Josas, France. kemel@hec.fr*

Abstract

This paper explores the relationships between overall diet quality and attitudes toward risk and time using a general population survey. We combine a state-of-the-art food frequency questionnaire and a choice-based preference module to elicit individual risk and time preferences. The online questionnaire was administered to a socioeconomic panel representative of the French population. We show that risk and time preferences are associated with individual heterogeneity in key aspects of diet quality, a result that holds across a wide range of robustness checks. Using a hierarchical Bayes framework, we jointly estimate individual risk aversion and impatience parameters and show that associations hold for both model-free and structural estimates of risk and time preferences. We further show that these associations account for a substantial share of the heterogeneity in dietary outcomes beyond sociodemographic controls. However, despite their importance for individual heterogeneity, behavioral preferences explain little of the observed socioeconomic gradients in diet quality.

JEL: D91, I12, C11, I14

Keywords: diet quality, risk attitudes, time preferences, survey, nutritional inequality

1 Introduction

Dietary choices involve delayed and uncertain health impacts. Risk and time preferences, the two foundational elements of decision theory, are therefore expected to play an important role in dietary choices. For instance, less patient individuals may neglect their long-term health and focus on the short-term costs and benefits of their food choices, while risk-seeking individuals may

[*] Corresponding author: antoine.nebout@inrae.fr.

be willing to gamble with their health by consuming unhealthy products. If widespread, these phenomena could have significant consequences for the design and evaluation of nutrition policies. In particular, impatient and risk-seeking individuals may adopt low-quality diets even when fully informed about their health consequences. These behaviors may help explain why information-based policies often generate only modest behavioral responses (Dubois et al., 2021). Conversely, interventions that foster patience (Alan and Ertac, 2018) may yield downstream benefits for diet quality and long-run health outcomes. These mechanisms may also rationalize why dietary habits persist over time, even following a health diagnosis (Hut and Oster, 2022). Moreover, if behavioral preferences correlate both with diet quality and socioeconomic status, they may contribute to the well-documented nutritional inequalities across income and education (Darmon and Drewnowski, 2008). Yet, despite these potentially important policy implications, empirical evidence linking diet quality, and risk and time preferences remains fragmented and largely indirect.

This paper shows that risk and time preferences are strongly associated with key dimensions of diet quality. We combine a state-of-the-art food frequency questionnaire with a choice-based preference elicitation module in a survey administered to a representative sample of the French adult population. To our knowledge, this is the first large-scale study to jointly measure overall diet quality and both risk and time preferences. Using both model-free and structurally estimated preference measures, we find that more impatient individuals exhibit diets of lower nutritional quality and higher energy intake, while more risk-seeking individuals display higher alcohol consumption, even after controlling for a rich set of sociodemographic characteristics. We obtain similar results when considering alternative diet quality indicators or structural assumptions, and address potential concerns related to measurement error or hypothetical incentives. We provide suggestive evidence on underlying behavioral channels, indicating that impatient individuals place less weight on the long-term health benefits of foods and are more likely to consume products that require minimal preparation time. Using variance decompositions, we show that risk and time preferences explain a substantial share of the heterogeneity in diet quality beyond sociodemographic factors. Despite their relevance for individual heterogeneity, behavioral preferences explain little of the nutritional inequalities across income and education observed in our data.

While economists studying food consumption often rely on field, experimental, or scanner data, these methods are generally unable to measure both at-home and out-of-home consumption or account for food waste. Therefore, nutritional epidemiologists often favor survey methods that measure the entire diet at the individual level and allow decomposition of intakes across many nutrients. This paper adopts the latter approach and uses a reduced food frequency questionnaire (Affret et al., 2018). By combining the individual consumption frequencies for the 28 food items and their nutrient compositions, we consider three complementary leading indicators of diet quality. First, we include the daily energy intake measured in calories. Second, we compute the nutritional quality index introduced by Vieux et al. (2013), which characterizes the nutritional adequacy relative to official recommendations. Third, we complement our evaluation of diet quality with alcohol intake, a key health driver unaccounted for in the nutritional quality index.

We design a module specifically adapted for estimating risk and time preferences in general population surveys. The module includes eight tasks, with four focusing on risk preferences and four on time preferences. Each task consists of a series of four 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 certainty (resp. sooner) equivalent. This preference module balances simplicity and theoretical consistency: the tasks are sufficiently simple for the general population to undertake and allow us to estimate structural risk aversion and time discounting using standard decision-theory models. While certainty and sooner equivalents can proxy for risk and time preferences, the benchmark discounted expected utility (DEU) model implies that sooner equivalents are shaped by both risk aversion and time discounting (Frederick et al., 2002). Collecting several certainty equivalents and sooner equivalents allows us to address this issue by jointly estimating individual risk aversion and impatience parameters. We do so using a hierarchical Bayes framework, which leverages the population distribution to estimate individual parameters, thereby improving accuracy and robustness compared to single-subject estimations (Murphy and ten Brincke, 2018).

We show that risk and time preferences explain diet quality across key aspects, using regressions that control for a wide range of sociodemographic factors. Our main result is that greater impatience is associated with higher daily energy intake and lower nutritional quality. We also find that more risk-seeking individuals consume more alcohol. These associations hold for both model-free equivalents and structural estimates under discounted expected utility. We show that alternative decision models deliver the same results. We also obtain consistent results when using alternative diet-quality indicators, food-item-specific regressions, or data from a lab experiment with real incentives. We further document that risk and time preferences have sizable explanatory power for dietary behavior. They explain a meaningful share of the variation in diet quality, energy intake, and alcohol consumption beyond standard sociodemographic characteristics, and capture dimensions of dietary behavior largely orthogonal to age, education, gender, and location. When adding our estimates of preferences to a regression with controls, the R2 increases by 6% for log energy intake, 21% for alcohol intake, and 29% for diet nutritional quality. Applying relative importance estimators following Grömping (2007), we show that impatience and risk preferences contribute as much as, and in some cases more than, several core demographic characteristics to explaining variation in key dietary outcomes. Finally, we explore whether risk and time preferences contribute to nutritional inequalities across income and education. Using the decomposition introduced by Gelbach (2016), we show that their respective contributions work in opposite directions. Behavioral preferences matter for diet nutritional quality, but they are not the primary drivers of nutritional inequalities across income and education.

These novel findings on the role of risk and time preferences contribute to the literature on the determinants of food preferences. While food demand has traditionally been explained by prices, income, and product characteristics, Dubois et al. (2014) show that preference heterogeneity is substantial and matters beyond these standard economic factors. An emerging strand of research documents the role of personality traits (Lunn et al., 2014), locus of control (Cobb-Clark et al., 2014), cultural factors (Atkin, 2016), impulsivity (Bénard et al., 2019), and social interactions (Bellet and Colson-Sihra, 2025). However, evidence linking general dietary habits to both risk and time preferences remains scarce. Several studies provide indirect evidence using the BMI (Ikeda et al., 2010; Sutter et al., 2013; Courtemanche et al., 2015), but recent evidence shows it cannot reliably assess diet nutritional quality nor identify unhealthy weight (Rubino et al., 2025). In particular, even obese individuals can lack essential nutrients (Kobylińska et al., 2022), and the adverse health effects of a high BMI can be mitigated by high-quality diets (Michaëlsson et al., 2020). Closer to our setting, several studies document links between food choices and behavioral preferences focusing either on a subset of the population or on one or a few product categories.[1] While single-category studies are valuable, particularly for marketing research, collecting data on overall diet is essential for analyzing its net health effects and accounting for cross-category synergies. We follow this approach and evaluate individual diet quality in a sample representative of the general adult population. Additionally, we elicit both risk and time preferences to distinguish their separate effects on diet quality, while accounting for potential correlations between them.

Our paper also contributes to the broader public health literature documenting the behavioral factors underlying hazardous health choices (Barsky et al., 1997; Khwaja et al., 2007; Norrgren, 2022). Most of this literature focuses on time preferences (Lawless et al., 2013), and only a handful of articles combine risk and time preferences (Sutter et al., 2013; Falk et al., 2018). As shown in our paper, measuring both risk and time preferences is key because they are correlated and influence health-related decisions in distinct ways. In particular, our result showing that alcohol consumption is more strongly associated with risk preferences than with impatience corroborates the results of Blondel et al. (2007), who found that substance users differ from nonusers in risk preferences, but not in time preferences.

Finally, we contribute to the literature that disentangles the gradients in health and health-related behaviors across education and income. Although these gradients are central to the design and public support of health policies, assessing the relative importance of the underlying causal and noncausal channels remains challenging (O'Donnell, 2025). A substantial literature has examined the role of confounding factors in the education–health behavior gradient (Cutler and Lleras-Muney, 2010; Bijwaard et al., 2015; Gensowski and Gørtz, 2024), while comparable decompositions of the income–health relationship remain scarcer. For example, Van Kippersluis et al. (2009) assess the contribution of age to the income gradient in self-assessed health. Closer to our setting, Allcott et al. (2019) show that nutritional knowledge and education explain an important share of the income gradient in diet nutritional quality in the US, although a substantial portion remains unexplained. We contribute to this literature by providing the first application of the decomposition proposed

[1] See for instance Anderson and Mellor (2008) on heavy drinking, De Marchi et al. (2016) on yogurt, Bradford et al. (2017) who focus on snacking and binge drinking, Samek et al. (2021) and List et al. (2022) who focus on children and adolescents, and Brownback et al. (2026) who focus on fruits and vegetables among low-income shoppers. Only Galizzi and Miraldo (2017) measure overall diet quality together with risk attitudes, over a sample of 120 students.

by Gelbach (2016) to jointly analyze income- and education-related gradients in diet quality.

The rest of the paper is organized as follows. Section 2 presents our survey and key indicators. In Section 3, we outline our empirical approach. Section 4 presents our baseline regression results using model-free estimates of preferences. In Section 5, we show that using structural estimates of risk and time preferences leads to similar results. Section 6 provides additional robustness checks and explores potential mechanisms. In Section 7, we document the explanatory power of risk and time preferences for diet indicators, and assess their respective contributions to nutritional inequality across income and education. Section 8 concludes.

2 Data and measurement

This section presents the survey modules, how we construct the relevant indicators, and descriptive statistics of the data.

2.1 Data source and sample

Our study uses data from a survey conducted in France in 2018 among participants in the ELIPSS panel. ELIPSS is a web-based longitudinal panel designed to be representative of the French adult population and operated by Sciences Po.[2] The target population consists of francophone residents of metropolitan France aged 18 to 79 living in ordinary households. Individuals were initially selected by the French National Institute of Statistics and Economic Studies (INSEE) using a stratified two-stage probability sampling design, drawing one respondent per household. An important feature of the ELIPSS panel is its high response rate. In exchange for participating in a monthly survey lasting about 30 minutes, panel members are provided with a touchscreen tablet and a mobile internet connection. This indirect monetary incentive results in response rates exceeding 80% in all survey waves. The representativeness of the panel has been largely documented in previous work (Blom et al., 2016). Table 2 shows that respondents to our survey closely match census shares along key sociodemographic dimensions.

Our analysis combines data from the 2018 annual ELIPSS survey with a dedicated questionnaire designed for this study, which elicits risk and time preferences and measures dietary behavior. The preference module consists of a series of binary choices allowing the estimation of individual risk and time preferences under alternative decision models. Dietary behavior is measured using a food frequency questionnaire from which we construct several diet indicators, including daily energy intake. The survey was administered between June 6 and July 26, 2018, to the 2,655 panel members who were still at that time. A total of 2,199 respondents completed the questionnaire, corresponding to a response rate of 83%. All analyses use survey weights correcting for differential nonresponse to ensure the representativeness of the French population.

[2] https://cdsp.sciences-po.fr/en/projects/elipss-panel/

2.2 Construction of key variables

This section describes how we construct our measures of diet quality and how we elicit individual risk and time preferences. We rely on survey-based instruments that capture habitual dietary behavior and structurally interpretable preference parameters, while balancing informational content and respondent burden in a large, representative general-population sample.

2.2.1 Measuring diet quality

Food Frequency Questionnaires (FFQs) are widely used in population-based studies due to their low cost, ease of administration, and ability to capture usual dietary patterns. An important alternative, the 24-hour recall, requires repeated collection days and trained interviewers and is therefore less suitable for large-scale surveys. Moreover, FFQs are designed to measure overall diet quality at the individual level, rather than short-run food choices. Validation studies generally find small differences between diet assessments based on FFQs and 24-hour recalls (Cui et al., 2023). We therefore adopt this approach to measuring diet quality.

In our survey, we use an FFQ based on Affret et al. (2018), which records frequencies of consumption and portion sizes for 28 food items grouped into seven food categories (see Appendix A). For each individual i and food item j, we compute average daily consumption Q_{ij} in grams per day by combining reported frequencies and portion sizes. Alcohol consumption is measured separately and used as an outcome variable in the analysis.

Reported food quantities are converted into daily nutrient intakes using standard nutrient composition tables. Specifically, daily intake of nutrient n by individual i is given by:

$$Intake_{in} = \sum_{j=1}^{28} Q_{ij} N_{jn}, \tag{1}$$

where N_{jn} denotes the nutrient content of food item j. Nutrient compositions are derived from the French INCA2 dietary survey and the CIQUAL food composition database. Details on the matching procedure are provided in Appendix A.1. Using these nutrient intakes, we construct several indicators summarizing dietary behavior. First, we compute the Daily Energy Intake (DEI), measured in kilocalories, as the sum of energy intake across all food items. This measure indicates the quantity of food ingested in caloric metric, but does not capture nutritional inadequacies to public health recommendations. We therefore complement this indicator with a measure of overall diet nutritional quality.

We measure overall diet nutritional quality using the index introduced in Vieux et al. (2013), which we refer to as the Whole Diet Index (WDI). The WDI aggregates three dimensions of nutritional quality: the Mean Adequacy Ratio (MAR), capturing adequacy relative to dietary reference intakes for key nutrients; the Mean Excess Ratio (MER), capturing excess intake of nutrients to be limited; and Energy Density (ED), the average caloric content of the diet per 100 grams. Higher MAR, lower MER, and lower ED indicate better diet quality. Formal definitions of the MAR and MER indicators are provided in Appendix A.2. For each individual, we construct the WDI as the sum of three indicators equal to one if MAR is above the gender-specific median, MER is below the gender-specific median, and ED is below the gender-specific median:

$$\mathrm{WDI}_i = 1_{\mathrm{MAR}_i > \mathrm{median(MAR)}} + 1_{\mathrm{MER}_i < \mathrm{median(MER)}} + 1_{\mathrm{ED}_i < \mathrm{median(ED)}}. \tag{2}$$

The resulting index takes values from 0 to 3, with higher values indicating better diet nutritional quality, and is deliberately constructed as a threshold-based measure that captures joint compliance with key nutritional recommendations rather than marginal variation in individual nutrients, thereby facilitating interpretation and limiting sensitivity to measurement error in dietary reporting. Construction details, including the computation of median cutoffs and the treatment of missing values, are reported in Appendix A. In Section 6, we show that our main findings are robust to the use of continuous nutrient-based indicators that preserve more cardinal information, as well as to a range of alternative diet quality measures.

Lastly, because alcohol consumption is not included in the WDI despite its important health implications, we analyze total alcohol intake as a separate outcome. A well-established literature documents the association between alcohol consumption and individual risk attitudes in adult populations (Barsky et al., 1997; Anderson and Mellor, 2008), while Sutter et al. (2013) study the joint relationship between alcohol use, risk attitudes, and time preferences in an adolescent sample using incentivized experimental measures. We include alcohol consumption as a benchmark outcome and assess whether our preference measures exhibit the expected associations with alcohol use in a representative adult population.

2.2.2 Eliciting risk and time preferences

There is a long tradition in experimental economics of eliciting risk and time preferences using choice-based measures (Somerville and O'Donoghue, forthcoming; Cohen et al., 2020). These methods allow the identification of theoretically grounded preference parameters and are therefore well-suited for welfare and policy analysis. Their use in general population surveys remains limited due to implementation costs and concerns about noise and respondent burden. Building on this literature, we use choice-based elicitation to recover structurally interpretable measures of individual risk and time preferences, accounting for noisy responses (see Section 3.2). We use a parsimonious preference module adapted from laboratory elicitation methods and implemented in a large-scale online survey. The module is short (approximately 5–10 minutes), sufficiently simple for the general population, and relies on repeated binary choices rather than self-reported attitudes.

Preferences are elicited through sequences of binary choices in which respondents compare a given prospect to a certain or sooner amount. Rather than eliciting point values, this procedure identifies, for each prospect, an interval containing the individual's certainty or sooner equivalent. For risky prospects, the certainty equivalent is the sure amount that makes the respondent indifferent between receiving it with certainty and facing the risky prospect. For intertemporal prospects, the sooner equivalent is the amount received at date t that makes the respondent indifferent between receiving that amount at date t and receiving a larger amount at a later date $t+\tau$. Eliciting sooner rather than later equivalents has at least advantages: it yields equivalents that are always bounded upwards, and it allows for homogeneously scanning the entire range of the impatience parameter.

Because individual responses to risk and time preference elicitation tasks are likely noisy, obtaining reliable estimates of underlying preferences requires collecting responses to several tasks per respondent. However, including too many tasks may generate cognitive fatigue and attrition. The number of prospects included in the questionnaire therefore reflects a trade-off between statistical precision and feasibility in a general population survey. Balancing these constraints, the module includes four risk prospects and four time prospects as shown in Table 1. In the risk part of the questionnaire, respondents face four risky prospects with immediate outcomes that vary in stakes and probabilities. In the time part, respondents face four delayed but certain prospects that vary in both the delay τ and the timing of the sooner option t. The order of prospects is randomized across respondents and within each part of the questionnaire.

Risk				**Time**			
	x	y	p		x	t	τ
R1	80	0	0.50	T1	80	1 day	3 months
R2	80	0	0.25	T2	80	1 day	6 months
R3	80	0	0.75	T3	80	1 day	12 months
R4	100	20	0.50	T4	80	6 months	6 months

Table 1: Risk and time prospects used to elicit certainty and sooner equivalents

Note: For risk, p is the probability of receiving x. For time, t denotes the delay before the sooner outcome and τ the additional delay before receiving x.

Our elicitation tasks are similar to the "staircase" procedure of Falk et al. (2018). For each of the eight prospects, the corresponding equivalent is elicited through four successive binary choices using a bisection algorithm that progressively narrows the interval containing the respondent's certainty or sooner equivalent. For instance, for task R1, we first ask whether the respondent would accept €40 against the risky prospect of €80 with 0.5 probability. If she accepts, her equivalent is lower than €40. We then ask the same question with €20 instead of €40, dividing the length of the interval containing the equivalent by two. This bisection algorithm is repeated four times to obtain intervals of length €5. More details on the elicitation method can be found in Berlin et al. (2026), who focus on the role of incentives using the same tasks.

All outcomes are expressed in euros. Our paper thus focuses on the external validity of risk and time preferences elicited with monetary outcomes for diet quality. Attema et al. (2019) document that domain-specific risk preferences assessments are positively correlated. Fredslund et al. (2018) provide corroborating evidence for time preferences. Dohmen et al. (2011) also find that domain-specific preferences are most correlated with the corresponding domain behavior, suggesting that considering health outcomes rather than monetary outcomes would yield stronger associations.

2.3 Descriptive statistics

This section documents the representativeness of our sample for the target general population and presents descriptive statistics for dietary outcomes and elicited preferences.

2.3.1 Sample representativeness and dietary outcomes

Table 2 reports summary statistics for the main sociodemographic characteristics of the respondents and the corresponding dietary outcomes. sociodemographic variables include gender, age, education, region, and nationality. These variables are drawn from administrative records used to construct the survey weights and are therefore not subject to misreporting.

Table 2: Demographics and diet quality

Variable	Census	Full sample			Sample after trimming*				
	Share	N	Share	Weight	N	Weight	DEI	WDI	Alcohol
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gender									
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
Age									
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
Education									
No high school	27.8%	292	13.3%	27.8%	268	27.1%	2,038	1.50	6.07
Some high school	23.4%	497	22.6%	23.3%	468	23.4%	2,125	1.40	6.44
High school	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) presents the shares for the target population from the 2014 Census. Columns (4) and (6) give the weighted shares. The values in Columns (7-9) are weighted averages. The daily energy intake "DEI" is expressed in calories 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.

Column (1) reports population shares from the 2014 Census for the target population at the time of panel recruitment, namely francophone residents of metropolitan France aged 18–79 living in ordinary households. Columns (2)–(4) show the corresponding distributions in the full sample. The weighted sample closely matches census shares across all key dimensions, confirming the representativeness of the panel. Columns (5)–(9) report statistics for the estimation sample, obtained after excluding respondents who failed to complete all risk or time preference tasks and trimming the 5% tails of the daily energy intake distribution to correct for obvious misreporting. The resulting sample includes 2,086 individuals and remains highly representative after weighting. We keep only individuals between the 2.5th (753 kcal/day) and 97.5th (4,505 kcal/day) weighted quantiles of the daily energy intake distribution. Consistent with the INCA3 French national dietary survey, men exhibit higher daily energy intake and alcohol consumption, while younger individuals consume slightly more calories and less alcohol on average. Diet nutritional quality, measured by the WDI, increases with age and education and is mechanically balanced across genders by construction.

2.3.2 Certainty and sooner equivalents

Table 3 reports descriptive statistics for the certainty and sooner equivalents elicited in the preference module. As described in Section 2.2.2, preferences are elicited through repeated binary choices that identify, for each prospect, an interval containing the individual's equivalent. For descriptive purposes, we summarize these interval-censored observations using the midpoint of each interval.

Table 3: Certainty and sooner equivalents in euros

Prospect				Average	Median	S.d.	# Answers	
							4/4	0/4
Risk	$(x; y)$	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
Time	x	t	τ					
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	6 months	53.0	57.5	20.0	2,167	25

Note: For the risk prospect R1, the answers yield intervals which middles have an average of €28.3 across respondents, 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. These values are not weighted and computed with the raw data (N=2,199).

The ranking of average certainty equivalents across risk prospects is consistent with the experimental design: equivalents increase with both the stake and the probability of receiving the high outcome. Median certainty equivalents are systematically below the expected value of the corresponding lotteries, indicating risk aversion on average. For time prospects, average sooner equivalents decrease with the delay τ and increase with the timing of the sooner option t, as expected. We also find positive but moderate correlations between certainty and sooner equivalents, ranging between 0.1 and 0.2 (see Table C.1 in the Appendix), highlighting the importance of jointly accounting for risk and time preferences to identify their respective associations with economic behavior.

The last two columns show the number of individuals who answered all or none of the 4 binary choices in the bisection for each task. Most respondents completed all preference tasks. A small number of individuals failed to answer any risk tasks, any time tasks, or both. As these respondents provide no information on their underlying preferences, they are excluded from the subsequent analysis, yielding the final analysis sample of 2,086 individuals described in the previous section.

3 Empirical analysis

Our empirical strategy links dietary outcomes to experimentally elicited measures of risk and time preferences. We proceed in two steps. First, we document associations using model-free summaries of the elicited certainty and sooner equivalents. Second, we estimate structural preference parameters within a joint decision model that explicitly accounts for interval-censored elicitation data and respondent-level measurement error. Throughout the analysis, we focus on the three outcomes described in Section 2.2.1: the daily caloric intake (DEI), the overall diet nutritional quality (WDI), and the daily alcohol intake. We interpret our estimates as descriptive associations conditional on a rich set of observed controls, rather than as causal effects. We nonetheless conduct extensive robustness checks to assess the sensitivity of these associations to alternative specifications and to address concerns related to measurement error in preference elicitation. All specifications use survey weights and control for the baseline sociodemographic covariates described in Section 2.3.1. The estimation sample excludes respondents with no information on preferences and trims the tails of the DEI distribution, as described in Section 2.3.

3.1 Baseline regressions

For a given diet indicator y_i, we estimate the generic equation:

$$y_i = g\big(\beta_r r_i + \beta_t t_i + X_i' \theta + \varepsilon_i\big) \,, \tag{3}$$

where r_i and t_i are individual-level preference indices and X_i is a vector of sociodemographic controls, including gender, age, education, nationality, and living area. The parameters of interest are β_r and β_t, which capture the associations between y_i and risk-seeking and impatience, respectively. The function $g(\cdot)$ maps the latent behavioral index into the observed outcome and depends on the measurement scale of the dietary indicator. For energy intake DEI_i, $g(\cdot)$ is the exponential function, yielding a log-linear specification estimated by OLS. For diet quality, WDI_i is an ordered categorical variable taking values in $\{0, 1, 2, 3\}$, and $g(\cdot)$ is the threshold-crossing function with a logistic error distribution leading to the ordered logit model. The third outcome Alcohol_i contains null values, so we take $g(\cdot)$ as the identity function and estimate the model by OLS.

Our baseline estimates of r_i and t_i are model-free metrics of risk-seeking and impatience derived from the certainty and sooner equivalents. For each respondent and each risk (resp. time) prospect, the elicitation procedure yields an interval bounding the individual's certainty (resp. sooner) equivalent. As a model-free summary, we use the midpoint of the elicited interval as a point estimate of the equivalent. To aggregate information across tasks, we compute, for each individual, the average of midpoints across the four risk prospects and across the four time prospects. We then transform these averages into within-sample ranks, ranging from 0 to 1. This rescaling facilitates interpretation, reduces sensitivity to extreme values, and yields measures that are comparable across specifications. Higher values of the ranked certainty-equivalent measure indicate greater risk-seeking behavior. For time prospects, higher sooner equivalents correspond to greater patience. We reverse the rank so that higher values correspond to greater impatience in all baseline regressions. These regressions using model-free equivalents are presented in Section 4.

Because single measures of risk and time preferences are noisy, we evaluate the sensitivity of model-free results to the particular prospect used. We run baseline regressions for all 4×4 combinations of one certainty equivalent and one sooner equivalent (16 pairs) and summarize how often the estimated associations are statistically significant and have the expected sign. This exercise quantifies the reliability gain from aggregating information across multiple tasks. We also address the concern that controlling for multiple measures with correlated noise may deliver spuriously significant associations, and implement the IV strategy proposed by Gillen et al. (2019).

3.2 Structural estimation of risk and time preferences

The baseline measures of risk and time preferences may inaccurately capture true preferences, and thus lead to biased estimates of β_r and β_t, for at least two reasons.

First, responses to elicitation tasks are noisy and sometimes appear inconsistent across prospects. Although averaging across equivalents is a parsimonious metric, it does not optimally separate the signal from the noise in the answers. Only a structural decision model provides a principled mapping from observed equivalents to latent preference parameters, while explicitly allowing for respondent-level response noise. This improves precision and delivers individual-specific measures of response reliability.

Second, under the normative benchmark of DEU, sooner equivalents reflect both time discounting and utility curvature. As highlighted in the time-preference literature (Frederick et al., 2002; Abdellaoui et al., 2010), concave utility mechanically affects intertemporal trade-offs. Empirically, ignoring curvature can substantially bias estimated discount rates. In our setting, this implies that model-free impatience measures based on sooner equivalents may partly capture risk attitudes. Econometrically, this measurement issue can bias the OLS estimates of β_r in Equation (3). Consider, for instance, that the model-free measure of impatience is a proxy $t_i^* = t_i + u_i$ of true impatience t_i, with the measurement error correlated with r_i. In that case, the measurement error would be captured by the residual term, leading to an endogeneity issue with r_i, similar to the case treated by Gillen et al. (2019). Using structural estimates of risk and time preferences as regressors, rather than the equivalent, addresses this confounding.

We consider the DEU baseline decision model. Let a sure gain x yield utility $u_i(x) = x^{\alpha_i}$, where α_i governs utility curvature. A utility u received at time t is discounted in the present by $D_i(t) = \exp(-\delta_i t)$, where δ_i governs discounting. Consider a risk prospect $R = (x, p, y)$ delivering x with probability p and y otherwise. Under DEU, the theoretical certainty equivalent of individual i for R verifies $u_i(c_{iR}^*) = p\, u_i(x) + (1-p)\, u_i(y)$. The theoretical sooner equivalent for time prospect T (sooner amount in t equivalent to x in $t+\tau$) verifies $D_i(t)u_i(c_{iT}^*) = D_i(t+\tau)u_i(x)$. Our functional forms imply:

$$c_{iR}^* = \left[px^{\alpha_i} + (1-p)y^{\alpha_i}\right]^{1/\alpha_i}, \tag{4}$$

and:

$$c^*_{iT} = \exp\left(-\frac{\delta_i}{\alpha_i}\tau\right)x, \tag{5}$$

where $\alpha_i > 0$ governs risk attitudes and $\delta_i > 0$ is the monthly discount rate. The elicitation procedure does not directly deliver the equivalents, but rather provides intervals that contain the respondent's equivalents. We interpret apparent inconsistencies across tasks as arising from noisy representations of equivalents rather than violations of monotonic preferences. Specifically, we assume additive noise at the equivalent level:

$$\begin{aligned} c_{iR} &= c^*_{iR} + \varepsilon_{iR}, \qquad \varepsilon_{iR} \sim \mathcal{N}\big(0, (\sigma^r_i)^2\big), \quad R \in \{\text{R1}, \ldots, \text{R4}\}, \\ c_{iT} &= c^*_{iT} + \varepsilon_{iT}, \qquad \varepsilon_{iT} \sim \mathcal{N}\big(0, (\sigma^t_i)^2\big), \quad T \in \{\text{T1}, \ldots, \text{T4}\}. \end{aligned} \tag{6}$$

The parameters σ^r_i and σ^t_i measure respondent-level response noise for risk and time tasks, respectively. We estimate risk and time parameters jointly using a hierarchical Bayesian approach that leverages the full set of observations across the eight elicitation tasks. Individual parameters are assumed to be drawn from population-level distributions that are estimated simultaneously with individual-level parameters. Posterior means of (α_i, δ_i) provide individual measures of risk attitudes and impatience, while posterior inference on (σ^r_i, σ^t_i) delivers respondent-specific measures of response noise. This Bayesian approach has proven effective compared to single-subject estimations (Murphy and ten Brincke, 2018). Estimation details (likelihood construction under interval censoring, priors, and computation) are provided in Appendix B. We replicate all regressions from the previous section, replacing the mean certainty and sooner equivalents with the corresponding structural estimates of risk and time preferences. These results are presented in Section 5.

3.3 Robustness checks and interpretation

A secondary outcome of the structural estimation of risk and time preferences is the individual's metric of noise variance for risk and time tasks. In a robustness check, we use these measures to identify highly inconsistent respondents and verify that the baseline associations are not driven by them. Specifically, we re-estimate the baseline regressions after excluding respondents in the upper tail of the estimated noise distributions. A drawback of the structural estimation is that it requires the assumption of a decision model for respondents. If the baseline DEU framework does not apply, our estimates of risk and time preferences, and their associations with diet quality indicators, may be biased. To assess whether the main findings are sensitive to the DEU assumptions, we consider a specification with linear utility for both risk and time prospects and allow for probability weighting.

We also examine the role of incentives by contrasting results from the population survey with those from a companion incentivized study that uses the same elicitation tasks and diet module. We assess the robustness of the results to alternative definitions of diet quality by considering continuous nutrient-based indicators that combine adequacy and excess components. Finally, we show that our main results hold when we include income as a control, although this addition substantially reduces the sample.

3.4 Explanatory power of preferences

Beyond statistical significance, we assess the explanatory power of risk and time preferences for dietary behavior. This analysis examines whether preference measures explain economically significant variation in diet outcomes beyond standard sociodemographic characteristics, and how they contribute to socioeconomic gradients in diet quality. These results are presented in Section 7.

First, we quantify the incremental variance explained by preferences by comparing goodness-of-fit measures across specifications. Specifically, we compute the increase in R^2 when adding risk and time preferences to regressions that include only sociodemographic controls, and compare it to the explanatory power of preferences alone. This exercise evaluates whether preferences capture dimensions of dietary behavior that are orthogonal to observable characteristics.

Second, we assess the relative contributions of preferences and key sociodemographic variables using variance decomposition methods. We rely on the LMG decomposition described in Grömping (2007), which distributes a regression model's R2 across predictors by averaging each covariate's marginal contribution over all possible orderings of the regressors. This approach provides an ordering-invariant measure of relative importance, allowing us to compare the explanatory power of impatience and risk-seeking with that of age, education, location, and nationality in accounting for variation in diet outcomes.

Third, we assess how risk and time preferences contribute to gradients in diet nutritional quality across income and education using the method of Gelbach (2016). Let Y_i and S_i denote scalar measures of diet nutritional quality and socioeconomic position, where S_i is alternatively measured by income or educational attainment. We compare the slope λ of regressions of Y_i on S_i with or without controlling for other variables (X_{iv}), including sociodemographic and risk and time preferences. Let $\hat{\lambda}_{\text{base}}$ be the coefficient on S_i in a baseline regression of Y_i on S_i only, and $\hat{\lambda}_{\text{full}}$ the corresponding coefficient when controlling for all variables (X_{iv}). Gelbach (2016) shows that:

$$\hat{\lambda}_{\text{base}} - \hat{\lambda}_{\text{full}} = \sum_{v \in V} \hat{\pi}_v, \qquad \text{with} \qquad \hat{\pi}_v = \hat{\phi}_{v,\text{full}}\, \hat{\psi}_{v,\text{aux}},$$

where $\hat{\phi}_{v,\text{full}}$ is the coefficient on X_{iv} in the full regression and $\hat{\psi}_{v,\text{aux}}$ is the coefficient on S_i from an auxiliary regression of X_{iv} on S_i. To align with this derivation, we run these regressions without survey weights. For each variable v, we report $\hat{\pi}_v/\hat{\lambda}_{\text{base}}$ to express each contribution as a share of the baseline gradient. A positive (negative) contribution means that the corresponding variable accounts for a decrease (increase) in the socioeconomic gradient λ when moving from the baseline to the fully controlled specification (i.e., from $\hat{\lambda}_{\text{base}}$ to $\hat{\lambda}_{\text{full}}$), indicating that nutritional inequalities are smaller (larger) net of this variable.

4 Model-free results

In this section, we provide evidence of the real-life relevance of risk and time preferences for dietary behavior, showing that elicited preferences are significantly associated with dietary indicators in the general population. Before turning to the results, we briefly recall the construction of the model-free preference measures used throughout this section.

For each respondent and each risk (resp. time) prospect, the elicitation procedure yields an interval bounding the individual's certainty (resp. sooner) equivalent. We summarize each interval by its midpoint and aggregate information across tasks by averaging midpoints over the four risk prospects and over the four time prospects. These averages are then transformed into within-sample ranks between 0 and 1. For time preferences, ranks are reversed so that higher values uniformly correspond to greater impatience. These measures are model-free in the sense that they do not impose functional-form assumptions on utility curvature or discounting.

4.1 Illustrative binscatter plots

Figure 1 depicts the averages of our main dietary indicators by decile of the model-free measures of risk and time preferences. Average energy intake and diet nutritional quality decrease slightly with risk-seeking behavior and more sharply with impatience. Mean alcohol consumption is higher among deciles corresponding to more risk-seeking and impatient individuals, with a more pronounced gradient for risk preferences.

4.2 Regressions with sociodemographic controls

We next examine whether the associations documented above persist after controlling for sociodemographic characteristics. Following the empirical strategy described in Section 3, we estimate three outcome-specific models. In the top panel of Table 4, we regress each dietary indicator on the ranked averages of the model-free measures of risk-seeking and impatience. Overall, we find that the rescaled structural parameters significantly explain different aspects of dietary behavior. Impatience is primarily associated with the energy content and overall quality of the diet, whereas risk-seeking attitudes are most strongly related to alcohol consumption.

We find that greater impatience is significantly associated with higher daily energy intake and lower overall diet nutritional quality, even after controlling for risk attitudes and sociodemographic characteristics. The estimate in column (2) indicates that the most impatient individuals (those at the top of the impatience ranking) consume on average 11% more calories per day than the most patient individuals, holding constant gender, age, education, nationality, and location. Similarly, column (4) shows that the odds of adopting a higher-quality diet (as measured by the WDI) are 33% lower for the most impatient individuals than for the most patient ones, conditional on the same set of controls. These findings corroborate existing evidence from experimental and quasi-experimental studies linking impatience to unhealthy consumption patterns (De Marchi et al., 2016; Samek et al., 2021; List et al., 2022), as well as evidence from specific product categories (Bradford et al., 2017; Brownback et al., 2026). Similarly, we find that the model-free measure of risk-seeking is negatively associated with diet nutritional quality, with a magnitude comparable to that for impatience.

In contrast, alcohol consumption exhibits a markedly different pattern. We find a strong and positive association between risk-seeking attitudes and daily alcohol intake, consistent with earlier

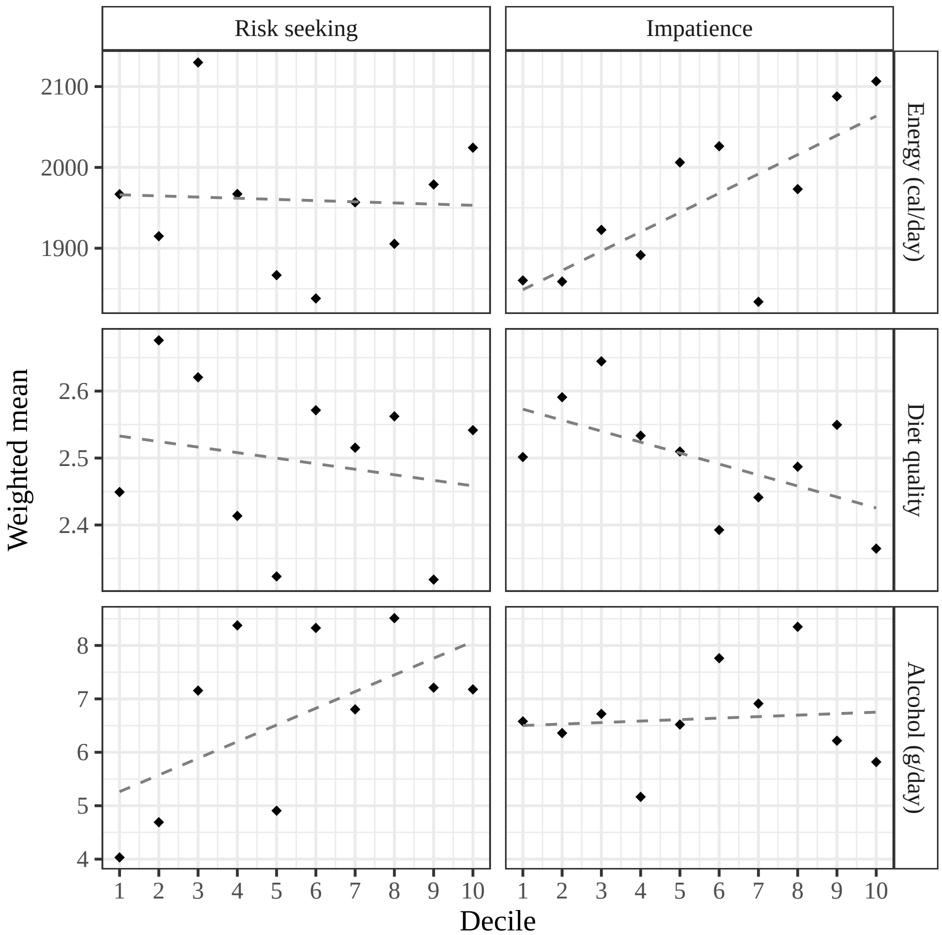


Figure 1: Main nutritional indicators by decile of model-free risk and time preference measures
Note: The diamonds represent weighted averages by decile using survey weights. The dashed lines correspond to slopes from weighted linear regressions of the decile averages. Deciles of the time-preference measure are reversed so that higher values reflect greater impatience.

findings in the literature (Barsky et al., 1997; Anderson and Mellor, 2008). The magnitude of this association is economically meaningful: the estimates imply that the most risk-seeking individuals consume, on average, around 3 grams more pure alcohol per day than the most risk-averse individuals. This corresponds to approximately two additional standard drinks per week (with one standard drink containing 10 grams of pure alcohol in France). The association between alcohol consumption and time preferences is weaker. It is only marginally statistically significant (at the 10% level) once sociodemographic controls are included and is not significant in unconditional specifications. This pattern reflects the fact that, in the general population, alcohol consumption is strongly correlated with age, gender, and education, which themselves are also correlated with patience (see Table 2). Conditioning on these characteristics reveals a modest positive relationship between impatience and alcohol intake, but the dominant behavioral margin for alcohol consumption appears to be risk preferences rather than time preferences.

Table 4: Regressions using model-free preference measures

Dependent variable	Energy intake		Diet quality		Alcohol intake	
Model	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Model-free measures: averages across prospects					
Ranked averages						
Rank of mean $\hat{c}_{iR}$	0.022	0.061	-0.258 **	-0.302 **	3.280 ***	3.628 ***
	(0.042)	(0.042)	(0.104)	(0.101)	(1.073)	(1.046)
Rank of mean -$\hat{c}_{iT}$	0.109 ***	0.105 **	-0.366 ***	-0.333 ***	0.778	1.904 *
	(0.041)	(0.042)	(0.090)	(0.097)	(1.034)	(1.019)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086
	Number of significant estimates across 16 task pairs					
Ranked averages						
Rank of $\hat{c}_{iR}$	+ 0 ; - 0	+ 4 ; - 0	+ 0 ; - 8	+ 0 ; - 8	+ 16 ; - 0	+ 16 ; - 0
Rank of -$\hat{c}_{iT}$	+ 11 ; - 0	+ 10 ; - 0	+ 0 ; - 16	+ 0 ; - 15	+ 0 ; - 0	+ 4 ; - 0

Note: For ordered logit models, coefficients are reported as odds ratios minus one, i.e., $\exp(\hat{\beta}) - 1$. Standard errors are shown in parentheses. Linear models are estimated by OLS with robust standard errors; ordered logit models are estimated by maximum likelihood. Controls include gender, age (6 categories), education (4), nationality (3), and living area (8). All estimations use survey weights. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our regressions yield four key statistically significant associations: between impatience and daily energy intake, impatience and diet quality, risk-seeking and diet quality, and risk-seeking and alcohol consumption. All four remain significant after correcting for multiple hypothesis testing using the sequential procedure of Holm (1979). Together, these results indicate that risk and time preferences correlate with distinct and meaningful dimensions of dietary behavior in the general population. To illustrate how these aggregate associations map to specific food categories, Figure C.1 in the Appendix reports regressions that explain the logarithm of consumption for each food item separately. We use the ranked averages of the model-free preference measures as proxies for risk-seeking and impatience and order coefficients from most positive to most negative. While individual estimates are often imprecise and not always statistically significant, the overall pattern closely mirrors that obtained with aggregated diet indicators. Unhealthy food items (such as alcoholic beverages, processed meats, fried foods, sweet desserts, and pizzas) tend to be positively associated with risk-seeking and impatience, whereas healthier food items (such as fruits and vegetables) are negatively associated.

In the bottom panel of Table 4, we assess the advantage of collecting multiple preference measures. We separately consider each of the 4×4 possible pairings of one certainty and one sooner equivalent, and estimate the same regression for each pairing. This yields 16 estimates for each coefficient. For each coefficient, we report the number of estimates that are significantly positive and significantly negative. We find that for many pairings, the sign and statistical significance differ from the baseline results. For example, in column (2), the association between energy intake and risk-seeking (resp. impatience) is statistically significant with controls for 4 (resp. 10) pairings, corresponding to a false-positive rate of 25% (resp. false-negative rate of 37.5%). This exercise highlights the value of aggregating information across multiple tasks to improve the reliability of model-free preference measures and reduce the likelihood of low-powered null results. Finally, we test whether correlated measurement errors across risk and time tasks influence our results. We conduct the instrumental-variables estimation of Gillen et al. (2019) that exploits multiple equivalents as repeated noisy measures of the same latent preferences, and find that the association between impatience and diet nutritional quality, and between risk-seeking and alcohol consumption, remains qualitatively unchanged. The full regression results are reported in Appendix C.

5 Structural results

This section estimates risk and time preferences within a structural framework and relates the resulting parameters to dietary outcomes. Relative to the model-free analysis, the structural approach (i) aggregates information from all elicitation tasks while accounting for interval censoring and response noise, and (ii) disentangles risk and time preferences in intertemporal choices when utility is nonlinear. We present baseline estimates under DEU, assess robustness to respondent-level inconsistency, and consider an alternative specification with linear utility and probability weighting.

5.1 Structural estimates under DEU distributions

The structural estimation reveals substantial heterogeneity in both risk and time preferences. Table C.3 in the Appendix reports summary statistics for the estimated distributions of the risk attitude parameter $\hat{\alpha}_i$ and the monthly discount rate $\hat{\delta}_i$. The average estimated risk attitude parameter is 0.71, with a median of 0.57, implying that a large majority of respondents are risk averse (84%). These values are in line with estimates reported in other large-scale studies using choice-based elicitation methods (Bradford et al., 2017; Meissner et al., 2023). The median estimated monthly discount rate is 0.037, which implies that one euro received in one month has a present value of approximately €0.94 at median utility curvature. This level of impatience lies toward the upper range of estimates reported in the survey by Frederick et al. (2002), a pattern that likely reflects the relatively short delays and modest monetary stakes used in our elicitation tasks (Cohen et al., 2020).

In the top panel of Table 5, we replicate the regressions reported in the top panel of Table 4, substituting structural estimates to model-free estimates of risk seeking and impatience. We find qualitatively similar associations to those obtained with model-free metrics, except for the association between risk seeking and diet nutritional quality, which becomes small and no longer statistically significant when using structural estimates. This may reflect the endogeneity bias mentioned in Section 3.2, caused by sooner equivalents being influenced by the utility curvature under DEU.

Table 5: Joint association between structural preferences and dietary outcomes

Dependent variable	Energy intake		Diet quality		Alcohol intake	
Model	Log-linear		Ordered logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Estimates under DEU					
Risk seeking: rank($\hat{\alpha}_i$)	-0.053	-0.010	-0.024	-0.115	2.957 ***	2.594 **
	(0.046)	(0.048)	(0.145)	(0.137)	(1.072)	(1.038)
Impatience: rank($\hat{\delta}_i$)	0.132 ***	0.127 ***	-0.408 ***	-0.362 ***	0.545	1.992 *
	(0.044)	(0.044)	(0.089)	(0.100)	(1.073)	(1.048)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086
	Estimates under DEU excluding respondents with outlying error variance					
Risk seeking: rank($\hat{\alpha}_i$)	-0.027	0.012	-0.245 *	-0.323 **	2.584 **	2.191 *
	(0.049)	(0.052)	(0.123)	(0.114)	(1.188)	(1.137)
Impatience: rank($\hat{\delta}_i$)	0.106 **	0.101 **	-0.455 ***	-0.420 ***	1.494	2.962 **
	(0.048)	(0.047)	(0.090)	(0.099)	(1.232)	(1.187)
Controls		✓		✓		✓
Observations	1,916	1,916	1,916	1,916	1,916	1,916
	Estimates under Yaari-type linear utility and probability weighting					
Risk seeking: rank($\hat{\gamma}_i$)	-0.062	-0.015	-0.343 ***	-0.441 ***	3.264 ***	3.391 ***
	(0.047)	(0.049)	(0.098)	(0.087)	(1.050)	(1.053)
Impatience: rank($\hat{\delta}_i$)	0.099 **	0.103 **	-0.384 ***	-0.358 ***	0.812	2.065 **
	(0.043)	(0.043)	(0.092)	(0.099)	(1.056)	(1.040)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,086	2,086

Note: For ordered logit models, coefficients are reported as odds ratios minus one, i.e., $\exp(\hat{\beta})-1$. Standard errors are shown in parentheses. Linear models are estimated by OLS with robust standard errors; ordered logit models are estimated by maximum likelihood. Controls include gender, age (6 categories), education (4), nationality (3), and living area (8). All estimations use survey weights. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Outliers for noise variance

A key advantage of the structural framework is that it delivers respondent-level noise parameters $(\hat{\sigma}_i^r, \hat{\sigma}_i^t)$ summarizing the propensity to provide inconsistent answers across elicitation tasks. Extremely noisy respondents may attenuate estimated relationships by reducing the precision with which underlying preferences are measured. Rather than excluding respondents based on violations of preference monotonicity (see, e.g., Bradford et al. 2017), which implicitly treats inconsistencies as irrational behavior and can mechanically discard a substantial share of the sample, our approach interprets such inconsistencies as arising from stochastic response noise. We therefore re-estimate the baseline regressions after excluding the 5% of individuals with the highest estimated error variance in either the risk or the time tasks.

The results of these regressions are reported in the middle panel of Table 5. The main associations are preserved for energy intake and alcohol consumption. Moreover, the relationship between risk preferences and diet nutritional quality becomes statistically significant after excluding highly inconsistent respondents, suggesting that extreme response noise attenuates this association in the full sample. This strengthened relationship is consistent with the findings of Galizzi and Miraldo (2017), who report a significant link between risk aversion and diet quality in a student sample.

5.3 Alternative structural assumptions

We evaluate whether our results hold under alternative decision models. In particular, we consider an alternative model with linear utility for both risk and time prospects allowing for probability weighting to capture risk attitudes (Yaari, 1987). This Yaari-type specification mitigates the confounding between utility curvature and discounting by construction and is empirically motivated by experimental evidence suggesting near-linearity of utility for small monetary stakes (Abdellaoui et al., 2011). Specifically, preferences are structurally estimated under the assumption of linear utility, $u(x) = x$, for both risk and time prospects. Under rank-dependent utility, the certainty equivalent of a binary lottery $R = (x, p, y)$ satisfies $c^*_{iR} = w(p; \gamma_i)x + [1 - w(p; \gamma_i)]y$, so individual risk attitudes are summarized by the probability-weighting parameter γ_i. 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). Time preferences are captured by δ_i as in the DEU framework. Parameters (γ_i, δ_i) are estimated jointly using the same method as in the baseline specification. Appendix Table C.4 reports summary statistics for these estimates.

The bottom panel of Table 5 reports regressions substituting these estimates for the estimates under DEU. The results closely mirror those obtained under DEU when excluding respondents with outlying error variance. Impatience remains significantly associated with higher energy intake and lower diet nutritional quality, while risk-seeking behavior (captured through probability weighting) is strongly associated with alcohol consumption. These main results are robust to alternative assumptions about the shape of the utility function, while the association between diet nutritional quality and risk-seeking depends on the specification. For completeness, we also find consistent results with an extended Yaari-type model allowing for present bias using a two-parameter quasi-hyperbolic discounting function $D(t, \beta_i, \delta_i) = \beta_i e^{-\delta_i t}$ if $t > 1$ day and 1 otherwise. Appendix Table C.5 gives the corresponding statistics. The resulting estimates of δ_i and β_i are too correlated (0.94) to be jointly included in a regression (their respective variance inflation factors are 9.7 and 10.4), but we include them separately in Appendix Table C.6 and find virtually identical results to those under DEU.

6 Other robustness checks and interpretation

This section provides additional robustness checks using alternative diet quality indicators and other control variables, a lab experiment with real incentives, and explores potential mechanisms that explain our results.

6.1 Alternative diet quality indicators

We examine whether our findings depend on the specific measure of diet quality used in the baseline analysis. We consider three alternative continuous indicators. First, we use a numeric version of the WDI and estimate linear regressions rather than ordered logit models. Second, we construct a nutrient-based indicator defined as NRDe = MAR - MER, which assigns equal weight to nutrient adequacy and excess and is closely related to the Nutrient Rich Diet family of indices. Third, we compute a proxy for the Healthy Eating Index 2015 (HEI).[3] All indicators are standardized to unit variance to facilitate comparison across specifications.

Table 6 reports the results. Across all three indicators, impatience is consistently and significantly associated with lower diet quality, with comparable magnitudes across specifications. By contrast, the association between risk preferences and diet quality is weaker and less stable, although it becomes positive and statistically significant with the NRDe indicators. In the Appendix, Table C.7, we report corroborating results from regressions explaining BMI, consistent with the literature (Sutter et al., 2013; Golsteyn et al., 2014). Overall, these results confirm that the link between impatience and diet quality is stronger and more robust than the link between risk attitudes and diet quality, and that our conclusions do not hinge on a particular specification of dietary outcomes.

6.2 Income as a confounding factor

The controls in the regression above 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).

To address this concern, we use the income reported by the panelists in the April 2018 annual survey as a proxy for their income at the time of our survey. The respondents state their monthly

[3] Some HEI-2015 components cannot be implemented exactly with our FFQ and nutrient variables. We cannot separate whole fruit from fruit juice, so "whole fruit" is proxied by total fruit. "Greens and beans" is approximated using pulses only (no measure of dark-green vegetables). "Seafood and plant proteins" captures fish and pulses only (no nuts/seeds/soy). Whole vs. refined grains rely on a single self-reported whole-grain proportion applied to bread, pasta/rice, and breakfast cereals. Finally, intakes in grams are converted into cups and ounce equivalents.

Table 6: Comparison across standardized numeric diet quality indicators

Dependent variable	Numeric WDI		NRDe		HEI	
Model	Linear		Linear		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Model-free measures: average across prospects					
Rank of mean $\hat{c}_{iR}$	-0.134	-0.180	0.161	0.167	-0.144	-0.111
	(0.114)	(0.114)	(0.127)	(0.131)	(0.108)	(0.110)
Rank of mean -$\hat{c}_{iT}$	-0.230 **	-0.213 *	-0.284 **	-0.239 *	-0.176 *	-0.174 *
	(0.112)	(0.111)	(0.128)	(0.129)	(0.105)	(0.105)
	Estimates under DEU					
Risk seeking: rank($\hat{\alpha}_i$)	0.005	-0.055	0.388 **	0.353 **	-0.007	0.019
	(0.116)	(0.120)	(0.153)	(0.153)	(0.126)	(0.128)
Impatience: rank($\hat{\delta}_i$)	-0.273 **	-0.239 **	-0.358 ***	-0.286 **	-0.224 **	-0.202 *
	(0.113)	(0.114)	(0.136)	(0.132)	(0.111)	(0.112)
	Estimates under Yaari-type linear utility and probability weighting					
Risk seeking: rank($\hat{\gamma}_i$)	0.180	0.217 *	-0.095	-0.117	0.173	0.124
	(0.119)	(0.120)	(0.130)	(0.134)	(0.110)	(0.113)
Impatience: rank($\hat{\delta}_i$)	-0.228 **	-0.199 *	-0.314 **	-0.245 *	-0.211 **	-0.191 *
	(0.113)	(0.112)	(0.135)	(0.132)	(0.106)	(0.106)
Controls		✓		✓		✓
Observations	2,086	2,086	2,086	2,086	2,039	2,039

Note: All diet quality indicators are standardized to unit variance. Standard errors of models are robust. Controls include gender, age (6 categories), education (4), nationality (3), and living area (8). All estimations use survey weights. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Main regressions controlling for income

Dependent variable	Energy intake		Diet quality		Alcohol intake	
Model	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Equivalents					
Rank of mean $\hat{c}_{iR}$	0.027	0.052	-0.548 ***	-0.571 ***	3.134 ***	3.978 ***
	(0.047)	(0.049)	(0.076)	(0.076)	(1.213)	(1.181)
Rank of mean -$\hat{c}_{iT}$	0.056	0.060	-0.397 ***	-0.403 ***	2.057	2.583 **
	(0.046)	(0.047)	(0.103)	(0.104)	(1.332)	(1.273)
Log Income per unit	-0.066 **	-0.048	0.272 ***	0.173 *	0.351	-1.070
	(0.026)	(0.030)	(0.109)	(0.113)	(0.672)	(0.693)
	DEU estimates					
Risk seeking: rank($\hat{\alpha}_i$)	-0.002	0.023	-0.416 ***	-0.438 ***	1.773	2.314 *
	(0.054)	(0.057)	(0.109)	(0.110)	(1.272)	(1.218)
Impatience: rank($\hat{\delta}_i$)	0.065	0.066	-0.421 ***	-0.433 ***	2.230	2.869 **
	(0.050)	(0.049)	(0.108)	(0.108)	(1.380)	(1.302)
Log Income per unit	-0.066 **	-0.049 *	0.274 ***	0.181 *	0.380	-1.057
	(0.026)	(0.029)	(0.109)	(0.114)	(0.665)	(0.693)
Controls		✓		✓		✓
Observations	1,627	1,627	1,627	1,627	1,627	1,627

Note: All estimations exclude individuals with outlying error variance. The estimations, formats, and control variables are the same as in Table 5. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

income by unit of consumption, after social security contributions and before income tax, 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. 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, (ii) unlike the sociodemographic 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. We present in Table 7 the same regression as in Table 5, controlling for income. We find that our main results are qualitatively unaffected when controlling for income.

6.3 Real incentives

While incentivized choices are standard in laboratory experiments, their use in large general population surveys remains limited. Implementing real incentives substantially increases the cost of large-scale surveys and requires time-consuming and cognitively demanding procedures. In particular, incentive-compatible designs often involve detailed explanations prior to the tasks, which may increase respondent fatigue, response noise, and attrition. The empirical evidence on hypothetical bias in eliciting risk and time preferences is mixed. A recent meta-analysis by Lipman and Attema (2024) concludes that discount rates elicited under hypothetical choices are broadly comparable to those obtained with real incentives. Similarly, Hackethal et al. (2023) show, in a large and high-powered study, that incentives play a limited role in shaping measured risk attitudes.

There are reasons a priori to believe that hypothetical bias is unlikely to threaten our main conclusions. First, a constant bias would not affect the estimated relationships between preferences and diet. Second, additional normal noise would tend to attenuate estimates toward zero. Our structural framework explicitly allows for stochastic response noise, mitigating this concern. Besides, there is no incentive-compatible method for food frequency questionnaires, so dietary outcomes necessarily rely on self-reported consumption (see Section 2). For consistency across modules and for the reasons outlined above, the preference elicitation relies on hypothetical choices. The high level of internal consistency observed across tasks suggests that respondents engaged seriously with the questionnaire.

We nonetheless assess the role of incentives by comparing our population-based results with those obtained in an incentivized laboratory experiment described in Berlin et al. (2026), a companion study that tests alternative incentive schemes. The experiment uses the same preference-elicitation tasks and food questionnaire, allowing us to construct identical dietary indicators. For the 230 participants assigned to the incentivized treatments, we estimate the same regressions as in the main analysis. Figure 2 compares the key estimates from the population survey to those obtained in the incentivized experiment, together with their confidence intervals. Given the smaller

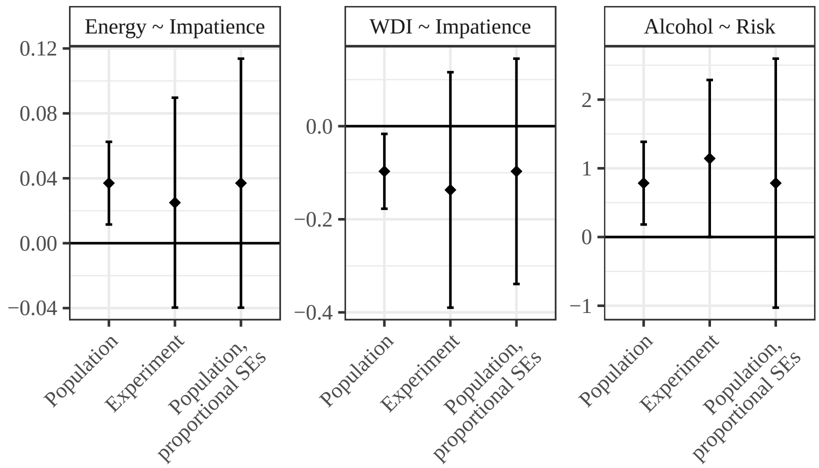


Figure 2: Comparison of population and incentivized experiment results

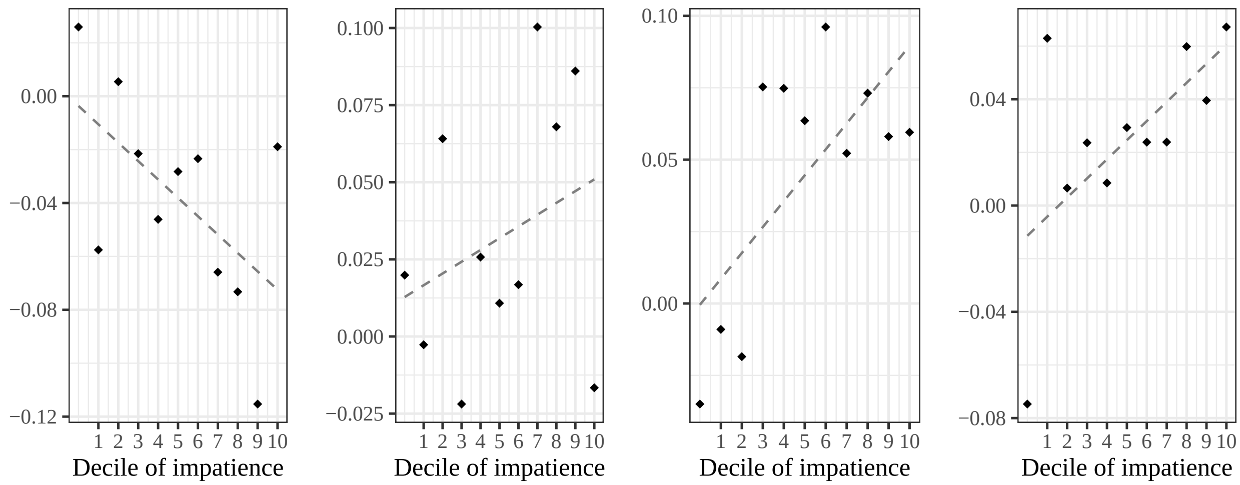
Note: The figure compares confidence intervals from the incentivized experiment and the general population survey. Standard errors for the population estimates are rescaled by $\sqrt{2086/230}$ to account for differences in sample size. The left panel reports the coefficient on log impatience in a regression explaining caloric intake; the middle panel reports the corresponding odds ratio (minus one) in an ordinal logit model explaining diet quality; the right panel reports the coefficient on log risk-seeking in a regression explaining alcohol intake. All estimates use the log specification with sociodemographic controls.

sample size in the experiment (230 versus 2,086 in the population survey), we expect lower statistical precision. To facilitate comparison, we also display counterfactual confidence intervals for the population estimates with standard errors rescaled by $\sqrt{2086/230}$. Across outcomes, point estimates are remarkably similar, and differences in precision are consistent with differences in sample size, supporting the generalizability of our results to incentivized settings.

6.4 Potential mechanisms

This section discusses potential mechanisms for the associations we estimate. Our main result shows that impatience is associated with both higher energy intake and lower nutritional quality of the diet. One potential channel consistent with our findings is that more patient individuals are more sensitive to future health hazards and, therefore, more likely to adopt healthier diets. This mechanism may explain both the effects on the energy intake and the nutritional quality of the diet. Furthermore, impatience is expected to increase the opportunity cost of time, which suggests a second potential causal mechanism. More impatient individuals may spend less time on food production, which may lower diet quality. Using data from the survey "Lifestyles and Environment" administered to the same sample in 2017, we provide correlational evidence consistent with both mechanisms in Figure 3.

The survey includes a yes/no question on health motivations for food purchases and questions about the frequency of consumption of canned food, frozen food, and ready meals. Although these categories are not necessarily unhealthy from a nutritional perspective, they are quick to prepare and thus are expected to appeal more to more impatient individuals, granted the second causal



(a) Health motive (b) Canned food (c) Frozen food (d) Ready meals

Figure 3: Illustrative evidence of causal mechanisms

Note: Health motive is a dummy indicating that a respondent mentioned that health is a criterion for purchase. The frequencies of canned food, frozen food, and ready meal consumption are measured with a dummy indicating weekly or more frequent consumption. All panels show the impatience decile-specific average partial residuals from a regression on impatience and all covariates from Table 5.

mechanism applies. Figure 3 plots the partial residuals from regressions controlling for all covariates included in the main regressions. First, impatient individuals are less likely to report health as a purchase motive, consistent with the first mechanism. Second, impatient individuals are also more likely to consume canned foods, frozen foods, and ready meals every week, arguably to decrease their cooking time. Altogether, these figures are consistent with the second mechanism according to which impatient individuals have a lower diet quality because they allocate less time to home food production.

7 Explanatory power

This section evaluates the explanatory power of the risk and time equivalents introduced above in relation to individual dietary behavior. We document the additional variance in diet outcomes explained by behavioral preferences, compare their explanatory power to that of standard sociodemographic characteristics, and determine whether they help explain well-documented socioeconomic gradients in diet quality. For clarity, we focus on the model-free metric for risk and time preferences in this section. Results using alternative specifications yield qualitatively identical results.

7.1 Added explained variance

Figure 4 gives the R^2 of regressions of our indicators on certainty and sooner equivalents with and without controls. We find that equivalents add substantial explained variance even when controlling for the sociodemographics. When adding equivalents to a regression with controls, the R^2 increases by 6% for log energy intake, 21% for alcohol intake, and 29% for diet quality as proxied by numeric WDI. Remarkably, the net increase in explained variance when adding equivalents to controls is similar to the explained variance by equivalents alone. This suggests that these metrics explain variation in diet that is mostly orthogonal to the generally observed demographics.

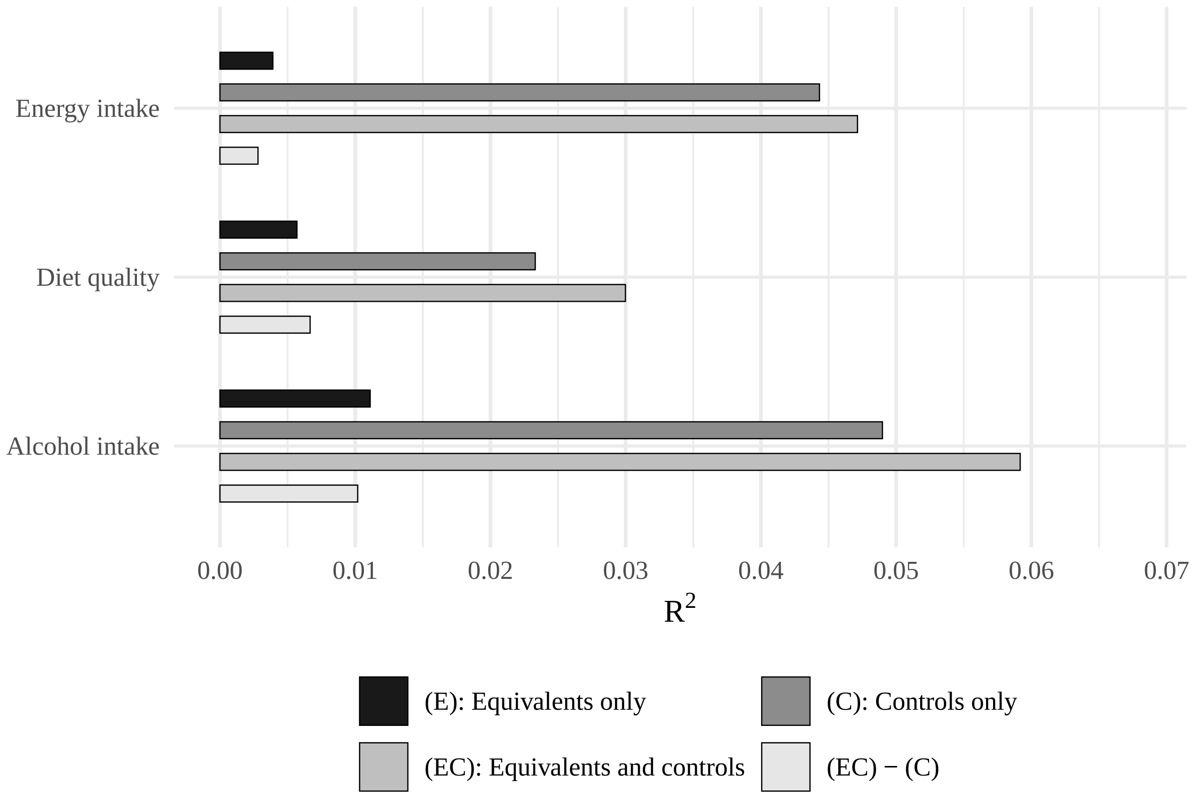


Figure 4: Variance explained by equivalents

Note: "Equivalents" refer to the ranked means of certainty and sooner equivalents. "Controls" refer to all demographics used as controls in the regressions. Diet quality is the numeric WDI. Energy intake is rescaled by log.

7.2 Variance decomposition

To assess how the shares of variance explained by each equivalent compare with those explained by key demographics, we conduct the LMG variance decomposition described in Grömping (2007). For comparable dimensionality, we now consider age in years, education in years of formal education, location with log city size, and nationality as a dummy equal to one for native citizens. Figure 5 shows that, for all considered dimensions of diet quality, the equivalents explain more variance than at least some key demographics. Specifically, risk-seeking explains more variance in alcohol intake than education. Impatience explains more variance in energy intake than age, and more variance in diet quality than location.

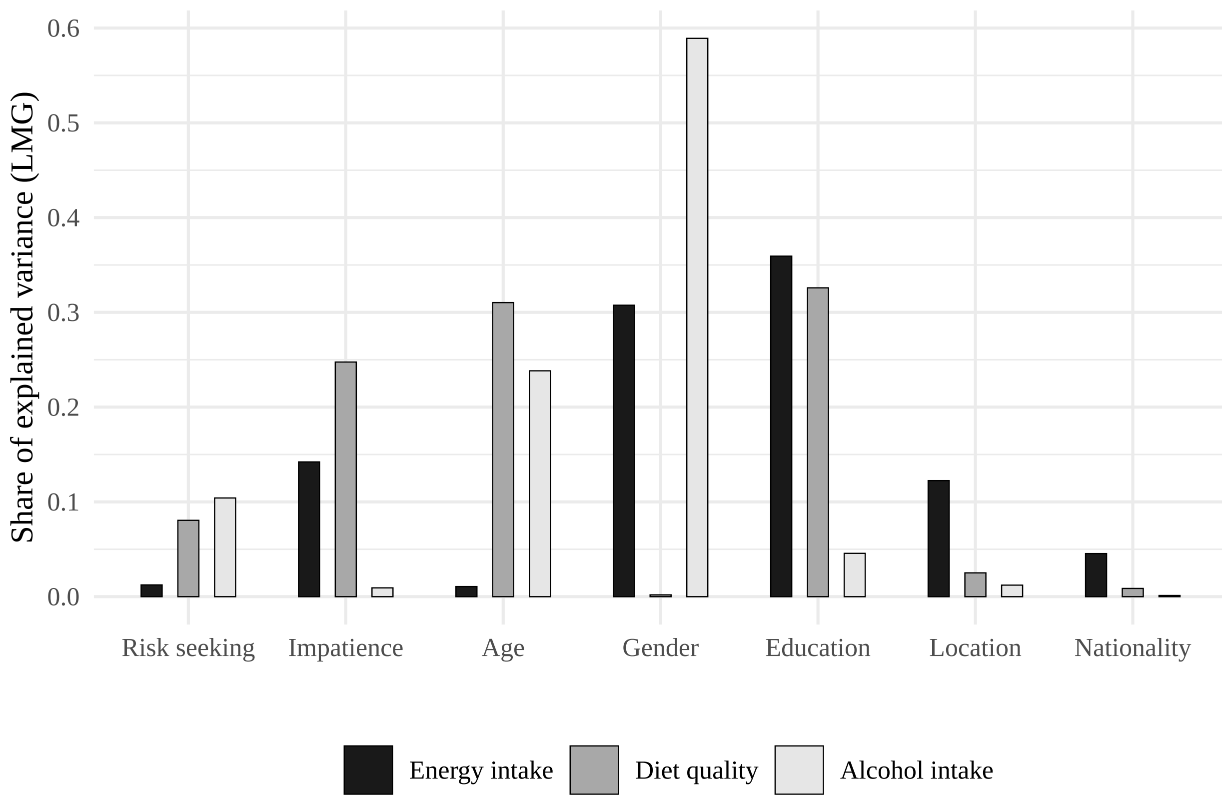


Figure 5: Variance decomposition

Note: The shares sum to one for each diet indicator. Diet quality is the numeric WDI, which is gender-neutral by construction. Energy intake is in log.

7.3 Explaining socioeconomic gradients

Our final analysis examines how risk and time preferences contribute to the well-documented positive socioeconomic gradient in diet quality in industrialized countries, whereby more educated and higher-income individuals tend to adopt higher-quality diets (Darmon and Drewnowski, 2008). Following Allcott et al. (2019), who study nutritional inequalities across income groups, we quantify the respective contributions of factors potentially driving these gradients using the decomposition method proposed by Gelbach (2016). We conduct the analysis for both the income–diet-quality and education–diet-quality gradients. The latter has received comparatively less attention in the food domain, but parallels recent evidence on the broader relationship between education and health (Gensowski and Gørtz, 2024). As in previous sections, diet nutritional quality is measured using the numeric WDI indicator, and risk and time preferences are proxied by equivalent measures. Using other diet indicators or structural preference estimates yields similar results. Figure 6 reports the contributions of each factor to nutritional inequalities across income and education. All estimates from the necessary regressions are given in the Appendix Table C.8.

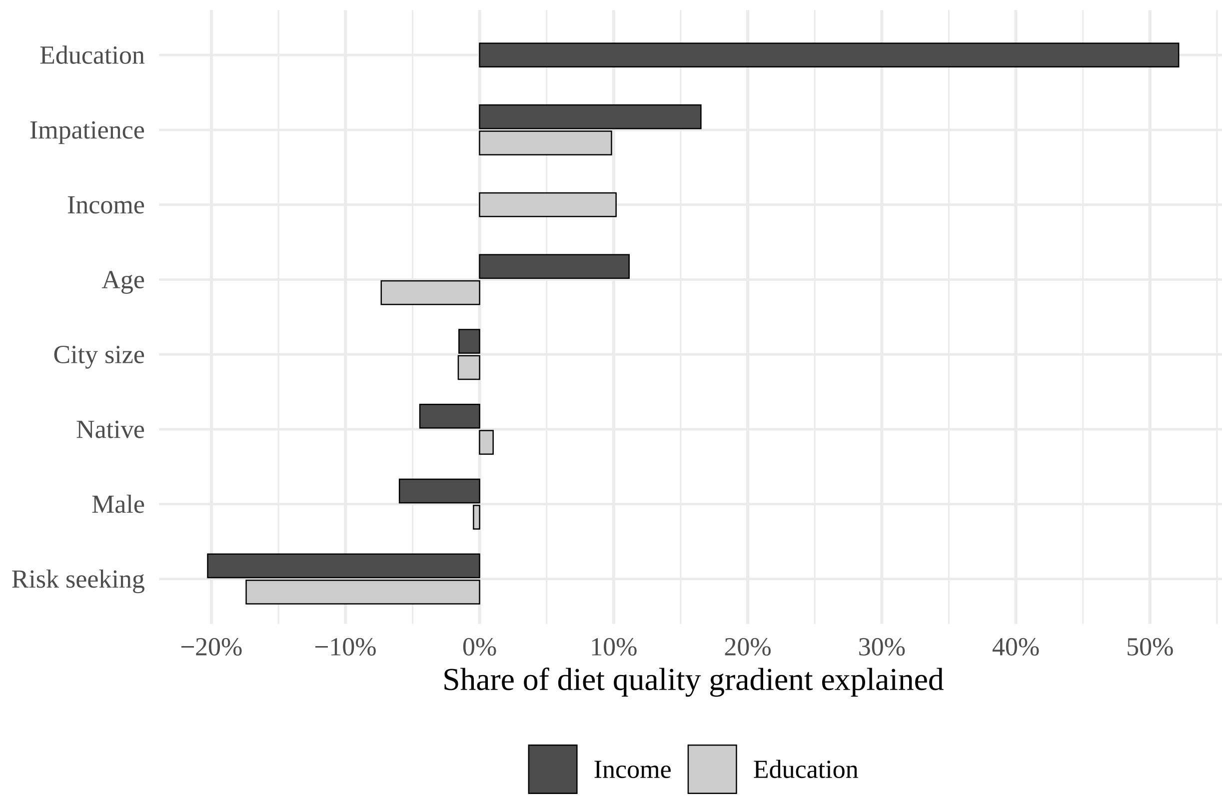


Figure 6: Explaining the gradient between diet quality and socioeconomic status

Note: Education is in log years of formal education. Health benefits focus

Consistent with Allcott et al. (2019), education explains a large share of the income–diet-quality gradient, while a substantial fraction of the gradient remains unexplained by observable characteristics. However, income reciprocally explains only a limited share of the education-diet-quality gradient. Overall, controls and equivalents explain respectively 48% of the income-diet-quality gradient, but contribute slightly negatively (-6%) to the education-diet-quality gradient. Demographic controls account for only 51% and 2% of the income- and education-diet-quality gradients, respectively. Risk and time preferences contribute in opposite directions to both gradients. Impatience contributes positively, while risk preferences contribute negatively to both the income– and education–diet-quality gradients. This negative contribution arises because higher-income and more educated individuals tend to be more risk-seeking, whereas risk-seeking behavior is negatively correlated with diet quality in our data. Taken together, risk and time preference negatively contribute to both gradients, as the negative contribution of risk attitudes dominates the positive contribution of time preferences. These results suggest that higher-income individuals with more years of formal education exhibit better diet quality despite, rather than because of, their risk and time preferences. Behavioral preferences matter for diet quality, but they do not help rationalize why more educated and higher-income individuals adopt healthier diets.

8 Conclusion

This paper examines the relationship between diet quality and individuals' risk and time preferences in the general population. We combine state-of-the-art methods from nutritional epidemiology and behavioral economics to elicit both overall diet quality and behavioral preferences in a survey conducted on a representative sample of the French population. Dietary behavior is measured at the individual level using a food frequency questionnaire, a standard instrument in nutritional epidemiology. Our behavioral module allows us to elicit risk and time preferences and to jointly estimate individual-specific behavioral parameters within a structural framework.

Our results document robust associations between risk and time preferences and key dietary outcomes. Greater impatience is associated with higher energy intake and lower nutritional quality, while more risk-seeking individuals exhibit higher alcohol consumption. These patterns are robust across a variety of model-free and structural specifications. We also find evidence of an association between risk attitudes and nutritional quality, but its statistical significance is specification-dependent. We conduct a variance decomposition analysis that shows that risk and time preferences capture dimensions of dietary behavior that are largely orthogonal to standard sociodemographic characteristics such as age, education, gender, and location. Despite their relevance for individual heterogeneity, these preferences explain little of the observed socioeconomic gradients in diet quality. Although an ideal research design would randomly assign risk and time preferences to identify causal effects, such experimental manipulation is not feasible. As a result, observational studies such as ours remain a primary empirical approach for examining how preferences relate to real-life health behaviors.

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CRediT authorship contribution statement

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

Declaration of generative AI in the writing process:

During the preparation of this manuscript, the authors used ChatGPT-5.2 (and previous versions) to assist with language editing of several sentences. All content generated with the help of this tool was subsequently reviewed and edited by the authors, who take full responsibility for the final version of the manuscript.

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Appendix

A Construction of diet quality indicators

Figure A.1 gives a screenshot of a question from the food frequency questionnaire. For each food item j, the frequency of consumption was estimated through a two-stage procedure. On the left panel, 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 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. On the right panel, respondents were asked to select their average portion size from several pictures 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?".

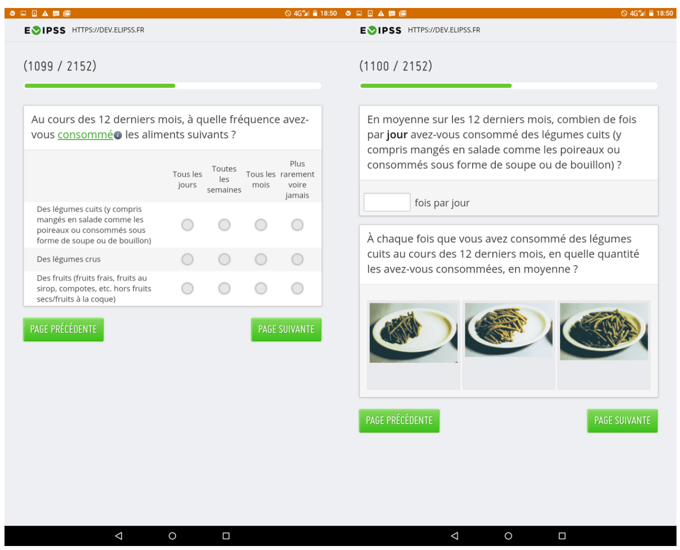

Figure A.1: Example question from the food frequency questionnaire

The 28 items are Cooked vegetables, Raw vegetables, Fruit, Bread, Pasta/Rice, Breakfast cereals, Potatoes, Poultry, Meat, Eggs, Fish, Pulses, Milk, Yogurt, Cheese, and Fries. Pizza/Quiches/Lasagna, Breaded meat or fish, Savory snacks, Sweet snacks, Sweetened desserts, Cured meat, Vegetable oils, Other fats, Water, Hot Beverages, Other beverages, and Alcohol. We combine respondents' responses for each item to infer their average daily consumption. The declared consumption frequencies expressed per month (resp. per week) were converted to per-day frequencies by dividing them by 30 (resp. 7). Portion sizes were either quantified from the FFQ itself (when quantity was available) or with the help of the SUVIMAX book[4], which provides the conversion between pictures of portion sizes and the exact volumes for 244 food items generally consumed in France.

[4]Hercberg, Deheeger, Preziosi, and Suvimax (2002). *Portions alimentaires–Manuel photos pour l'estimation des quantités*. Paris: Editions Polytechnica.

A.1 Construction of nutrient composition for FFQ food items

Nutrient compositions for the 28 food items included in the food frequency questionnaire (FFQ) were constructed using data from the French food composition database CIQUAL and the INCA2 national dietary survey. Each FFQ food item corresponds to a broad food category that aggregates several individual food products. To assign a nutrient composition to each FFQ item, we relied on the list of 1,183 individual food products consumed by adults in the INCA2 survey. Each of these foods was uniquely matched to one of the 28 FFQ items, ensuring full coverage of respondents' diets as measured by the questionnaire. Let $j \in \{1, \ldots, 28\}$ index FFQ food items and let $k \in \mathcal{K}_j$ denote the set of INCA2 food products mapped to FFQ item j. The nutrient content per gram of FFQ item j for nutrient n, denoted N_{jn}, is computed as a consumption-weighted average of the nutrient contents of the associated INCA2 foods:

$$N_{jn} = \sum_{k \in \mathcal{K}_j} w_k \, N_{kn}, \tag{7}$$

where N_{kn} is the nutrient content per gram of INCA2 food k and w_k is the share of total adult consumption accounted for by food k in the INCA2 survey, with $\sum_{k \in \mathcal{K}_j} w_k = 1$. This weighting scheme reflects actual consumption patterns in the French adult population and prevents infrequently consumed foods from disproportionately influencing the nutrient composition of aggregated FFQ items. For example, within the FFQ category "Fruit," foods that are consumed in larger quantities by adults (e.g., apples or raspberries) receive greater weight than less frequently consumed items (e.g., blueberries). This procedure yields a nutritionally representative composition for each FFQ food item while maintaining consistency with national dietary data and ensuring comparability with other studies using CIQUAL and INCA-based nutrient matching.

A.2 Construction of nutrient adequacy and excess indicators

This Appendix details the construction of the nutrient-based indicators used to summarize individual diet quality: the Mean Adequacy Ratio (MAR) and the Mean Excess Ratio (MER). These indicators are standard in nutritional epidemiology and capture complementary dimensions of dietary quality, namely nutrient adequacy and nutrient excess.

Mean Adequacy Ratio (MAR) Let $Intake_{in}$ denote the average daily intake of nutrient n by individual i, expressed in physical units (e.g., g/day or mg/day). Let DRI_n denote the age- and gender-specific Dietary Reference Intake for nutrient n. The Mean Adequacy Ratio (MAR) for individual i is defined as:

$$\text{MAR}_i = \frac{1}{N_A} \sum_{n=1}^{N_A} \min\left\{ \frac{Intake_{in}}{\text{DRI}_n}, 1 \right\}, \tag{8}$$

where $N_A = 20$ is the number of nutrients included in the indicator.
By construction, $\text{MAR}_i \in [0, 1]$. A value of one indicates that the individual meets or exceeds the recommended intake for all nutrients considered. Truncation at one prevents excessive intake of a given nutrient from compensating for deficiencies in others.

Mean Excess Ratio (MER) To capture excessive intake of nutrients for which overconsumption is associated with adverse health outcomes, we compute the Mean Excess Ratio (MER). Let MRV_n denote the

Maximum Recommended Value for nutrient n. The MER for individual i is defined as:

$$\text{MER}_i = \frac{1}{N_E} \sum_{n=1}^{N_E} \left(\max \left\{ \frac{Intake_{in}}{\text{MRV}_n}, 1 \right\} - 1 \right), \tag{9}$$

where $N_E = 3$ corresponds to saturated fats, salt, and free sugars.
The MER is bounded below by zero. A value of zero indicates that none of the maximum recommended values are exceeded, while higher values reflect increasing degrees of nutrient excess.
Together, MAR and MER provide complementary measures of nutritional adequacy and excess and form two of the three components of the WDI used in the main analysis.

A.3 Distribution of dietary indicators

Table A.1 reports the gender-specific quantiles used to construct the WDI. Table A.2 describes the distribution of nutritional indicators. The first panel reports average intake by food item across WDI categories. Individuals with higher diet quality consume more fruits and vegetables and pulses, and less high-fat, sugar, and salt foods. The second panel reports the distribution of DEI, MAR, MER, and ED across WDI categories. Average DEI is higher for the two lowest diet quality categories.

Table A.1: Quantiles by gender

	MAR	MER	ED
Female	83.10	4.19	155.39
Male	82.99	8.13	168.23

Note: MAR is expressed in percentage points (i.e., 100× MAR). MER is unbounded above and equals zero when no maximum recommended value is exceeded. The reported values correspond to gender-specific medians computed over the full sample (N = 2,199).

A.4 Treatment of missing values in the FFQ

Among the 2,199 individuals who completed the preference module, 314 (14%) failed to answer at least one question in the diet module. Among these respondents, 137 missed only one question for a single item, and 253 missed five questions or fewer across the 84 questions covering the 28 items. For these individuals, the available information covers most of their diet and allows us to approximate overall diet quality reasonably. To retain these individuals in the main analysis, missing values are imputed as follows. First, if the frequency of consumption for a given item is missing, we impute a frequency of zero. Second, if the frequency is reported but the number of consumption occasions is missing, we impute one occasion per reported periodicity unit. Third, if frequency and number of occasions are reported but portion size is missing, we impute the average portion size computed over non-missing observations.[5] Overall, missing values concern a limited number of items and respondents. Our main results hold when removing these individuals.

[5] For several food categories, respondents were asked to report the subcategory they consume most often to refine nutrient composition (e.g., sweetened vs. light beverages). For these questions, missing values are imputed using consumption-weighted averages across observed responses.

Table A.2: Distribution of nutritional indicators

	Whole Diet Index			
	0:Low	1:Intermediate -	2:Intermediate +	3:High
Intake by food item (g/day)	Average within WDI group			
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
Nutritional quality indicators				
Daily Energy Intake (DEI, kcal/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, kcal/100g)	202	188	139	123
Observations (share)	207 (9.9%)	810 (38.8%)	869 (41.7%)	214 (10.3%)

Note: These statistics are computed without weights for transparency; weighted versions yield very similar patterns.

B Hierarchical Bayesian estimation

This Appendix describes the estimation approach used to infer individual-level preference parameters and response-noise parameters from interval-censored elicitation data. Conditional on $\theta_i = (\alpha_i, \delta_i, \sigma_i^r, \sigma_i^t)$, the probability that a latent equivalent c_{ij} for task j and individual i falls within the observed interval is

$$\Pr\big(c_{ij}^- \le c_{ij} \le c_{ij}^+ \mid \theta_i\big) = \Phi\left(\frac{c_{ij}^+ - c_{ij}^*(\theta_i)}{\sigma_i^{d(i,j)}}\right) - \Phi\left(\frac{c_{ij}^- - c_{ij}^*(\theta_i)}{\sigma_i^{d(i,j)}}\right), \tag{10}$$

where $\Phi(\cdot)$ is the standard normal CDF and $\sigma_i^{d(i,j)}$ equals σ_i^r for risk tasks and σ_i^t for time tasks. Let $\mathcal{J}_i$ denote the set of elicitation tasks completed by respondent i and (c_{ij}^-, c_{ij}^+) the observed interval for task j. Under conditional independence across tasks given θ_i, the individual likelihood of the choices of individuals i is

$$\mathcal{L}_i(\theta_i) = \prod_{j \in \mathcal{J}_i} \left[\Phi\left(\frac{c_{ij}^+ - c_{ij}^*(\theta_i)}{\sigma_i^{d(i,j)}}\right) - \Phi\left(\frac{c_{ij}^- - c_{ij}^*(\theta_i)}{\sigma_i^{d(i,j)}}\right)\right]. \tag{11}$$

The sample likelihood is $\prod_i \mathcal{L}_i(\theta_i)$. We assume that individual parameters are drawn from population distributions. A convenient choice is to work on the log scale for strictly positive parameters. For example,

$$\begin{aligned}
\log \alpha_i &\sim \mathcal{N}(\mu_\alpha, \tau_\alpha^2),\\
\log \delta_i &\sim \mathcal{N}(\mu_\delta, \tau_\delta^2),\\
\log \sigma_i^r &\sim \mathcal{N}(\mu_{\sigma r}, \tau_{\sigma r}^2),\\
\log \sigma_i^t &\sim \mathcal{N}(\mu_{\sigma t}, \tau_{\sigma t}^2),
\end{aligned} \tag{12}$$

with weakly informative hyperpriors on means and standard deviations. The exact hyperprior choices and computational implementation can be adapted to the estimation software used. Our estimates of respondent-level preferences are the posterior means of $(\alpha_i, \delta_i, \sigma_i^r, \sigma_i^t)$. These summaries are used as regressors or diagnostics in the empirical results.

C Supplementary tables and figures

Table C.1: Correlation across equivalents

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

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

Table C.2: IV estimation à la Gillen et al. (2019)

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

Note: We verify that our model-free results are not driven by the bias highlighted by Gillen et al. (2019), which can arise when multiple preference measures are noisy and the underlying true parameters are correlated. This concern is relevant in our setting, as both risk and time preferences are elicited through choice-based tasks and therefore measured with error. Our survey design provides multiple measures within each domain (four certainty equivalents for risk and four sooner equivalents for time preferences) which can be interpreted as repeated noisy measurements of the same latent preferences. We exploit this structure by implementing the IV strategy proposed by Gillen et al. (2019), stacking all $4{\times}4$ combinations of risk and time measures and instrumenting each focal measure with the remaining measures from the same domain. This approach isolates the common latent preference component while purging domain-specific measurement error, and we estimate IV regressions of dietary outcomes on the instrumented preference measures with the same set of controls as in the baseline specifications. In these regressions, diet quality is measured by a dummy indicating a WDI of 2 or higher. All regressions control for gender, age (6 categories), education (4), nationality (3), and living area (8), and use survey weights. Standard errors are clustered at the individual level. The estimation sample includes only respondents who completed all risk and time elicitation tasks. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

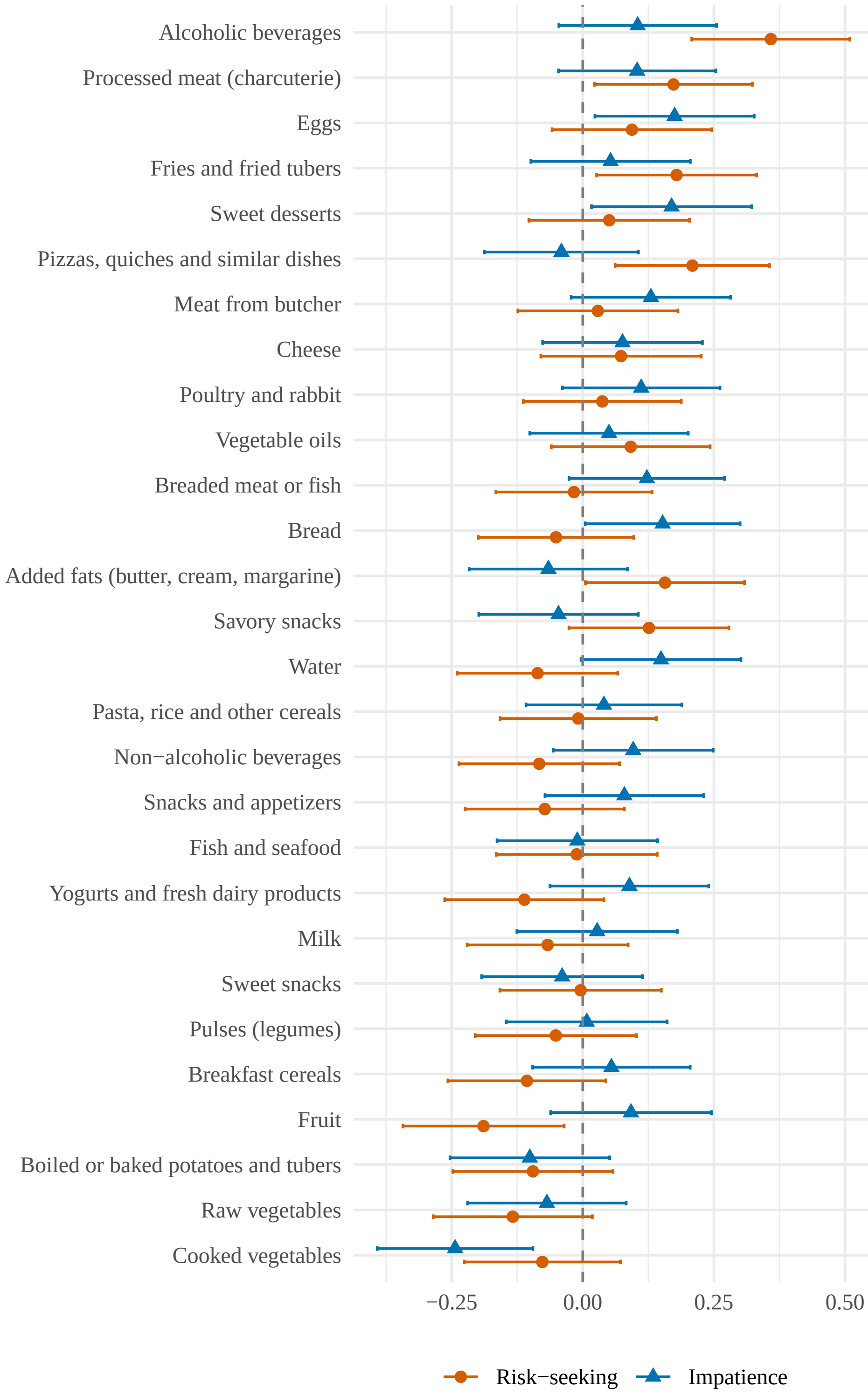

Figure C.1: Regression estimates for each food category

Note: For each food item, the interval give the estimate and confidence interval of the coefficients for risk-seeking and impatience in regressions explaining the standardized quantity consumed, controlling for the same set of covariates as in baseline regressions. Standard errors are robust.

Table C.3: Estimates of the individual parameters

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

Note: These summary statistics describe the distribution of the estimated individual parameters in the benchmark DEU model.

Table C.4: Individual parameters in the linear utility with probability weighting model

	Min	Q25	Median	Mean	Q75	Max	Std. dev.
Risk							
$\hat{\gamma}_i$	0.05	0.14	0.24	0.28	0.35	1.64	0.18
$\hat{\sigma}_i^r$	7.9	13.6	16.3	17.4	20.9	35.2	4.9
Time							
$\hat{\delta}_i$	0.004	0.027	0.067	0.099	0.132	0.532	0.100
$\hat{\sigma}_i^t$	1.8	5.8	10.4	10.9	14.9	39.2	6.4

Note: These summary statistics describe the distribution of the estimated individual parameters in the linear utility model for risk and time with probability weighting.

Table C.5: Individual parameters in the linear utility with probability weighting model and hyperbolic discounting

	Min	Q25	Median	Mean	Q75	Max	Std. dev.
Risk							
$\hat{\gamma}_i$	0.05	0.14	0.24	0.28	0.35	1.62	0.19
$\hat{\sigma}_i^r$	7.7	13.5	16.2	17.3	20.9	35.4	4.9
Time							
$\hat{\delta}_i$	0.003	0.017	0.050	0.083	0.103	0.496	0.099
$\hat{\beta}_i$	0.76	0.82	0.86	0.87	0.92	1.01	0.07
$\hat{\sigma}_i^t$	2.0	5.2	9.1	9.4	12.6	37.3	5.2

Note: These summary statistics describe the distribution of the estimated individual parameters in the linear utility model for risk and time with probability weighting.

Table C.6: Additional regressions using Yaari-type estimates allowing for present bias

Dependent variable	Energy		Diet quality		Alcohol	
Model	Log-Linear		Ordinal Logit		Linear	
	(1)	(2)	(3)	(4)	(5)	(6)
	Using $\hat{\gamma}_i$ and $\hat{\delta}_i$ estimates					
Risk seeking: rank($\hat{\gamma}_i$)	-0.060	-0.012	-0.344 ***	-0.441 ***	3.202 ***	3.338 ***
	(0.047)	(0.049)	(0.097)	(0.087)	(1.058)	(1.063)
Impatience: rank($\hat{\delta}_i$)	0.102 **	0.108 **	-0.396 ***	-0.371 ***	0.802	2.038 *
	(0.043)	(0.044)	(0.090)	(0.096)	(1.068)	(1.048)
	Using $\hat{\gamma}_i$ and $\hat{\beta}_i$ estimates					
Risk seeking: rank($\hat{\gamma}_i$)	-0.077 *	-0.031	-0.300 **	-0.409 ***	3.149 ***	3.082 ***
	(0.046)	(0.049)	(0.100)	(0.089)	(1.016)	(1.025)
Present bias: rank(-$\hat{\beta}_i$)	0.079 *	0.079 *	-0.383 ***	-0.365 ***	1.033	2.014 **
	(0.043)	(0.042)	(0.089)	(0.094)	(1.022)	(0.997)

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 logit 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, age (6 categories), education (4), nationality (3), and living area (8). All estimations use weights.

Table C.7: Results for BMI

Dependent variable	BMI	
Model	Ordinal Logit	
	(1)	(2)
	Model-free measures	
Rank of mean $\hat{c}_{iR}$	-0.109	0.269
	(0.141)	(0.213)
Rank of mean -$\hat{c}_{iT}$	0.523 ***	0.554 **
	(0.248)	(0.268)
	DEU estimates	
Risk seeking: rank($\hat{\alpha}_i$)	-0.278 *	0.025
	(0.124)	(0.188)
Impatience: rank($\hat{\delta}_i$)	0.500 **	0.494 **
	(0.264)	(0.278)
Controls		✓
Observations	1,815	1,814

Note: BMI data come from the ELIPSS general survey and were merged with our survey. BMI is computed from self-reported height and weight. Because 13% of respondents had missing BMI values in 2018, we use 2017 ELIPSS wave BMI for these individuals to preserve statistical power, when possible. This results in 1,815 BMI observations after excluding individuals with outlying error variance. For confidentiality reasons, BMI values are truncated below 18.5 and above 35. Individuals are classified into WHO BMI categories: underweight (<18.5), normal weight (18.5–25), overweight (25–30), and obese (≥30). Lagged BMI is a strong predictor of current BMI. We also include a five-category measure of physical activity frequency observed for 1,903 individuals. Since physical activity may confound the relationship between BMI and preferences, we include physical activity indicators as controls in BMI regressions. Consistent with the results on diet quality, we find that more impatient individuals are more likely to have a higher BMI, even after controlling for physical activity. Controls include gender, age (6 categories), education (4), nationality (3), living area (8), and physical activity (4). All estimations use weights. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: Gelbach Decomposition: Base, Full, and Auxiliary Regressions

	Income Gradient			Education Gradient		
	Base	Full	Aux	Base	Full	Aux
Income	0.069 **	0.036			0.036	0.803 ***
	(0.034)	(0.038)			(0.038)	(0.058)
Education		0.303 ***	0.119 ***	0.286 ***	0.303 ***	
		(0.104)	(0.008)	(0.091)	(0.104)	
Risk seeking		-0.215 ***	0.065 ***		-0.215 ***	0.232 ***
		(0.069)	(0.013)		(0.069)	(0.033)
Impatience		-0.120 *	-0.095 ***		-0.120 *	-0.235 ***
		(0.069)	(0.013)		(0.069)	(0.032)
Male		-0.099 **	0.042 *		-0.099 **	0.013
		(0.039)	(0.022)		(0.039)	(0.057)
Native		-0.108	0.029 **		-0.108	-0.027
		(0.077)	(0.012)		(0.077)	(0.030)
Age		0.001	5.171 ***		0.001	-14.062 ***
		(0.002)	(0.573)		(0.002)	(1.517)
City size		-0.001	1.100 ***		-0.001	4.708 ***
		(0.004)	(0.235)		(0.004)	(0.592)
N	1,763	1,763	1,763	1,763	1,763	1,763

Note: This table reports the regressions underlying the Gelbach (2016) decomposition of socioeconomic gradients in diet quality. For each gradient, the "Base" column reports a bivariate regression of diet quality on the variable of interest. The "Full" columns report the same multivariate regression including all preference parameters and sociodemographic controls. Both base and full specifications are estimated on the same sample, defined by complete cases for the full model. The "Aux" column reports the auxiliary regressions required for the decomposition. Specifically, each covariate added in the full specification is regressed on the variable of interest using the same sample – each estimate is from a separate regression. The contribution of a given variable to a given gradient is the product of the corresponding estimates from the full and auxiliary regressions, divided by the one from the base regression. Age is measured in years, education in years of formal education, and city size in log population size. All models are estimated by ordinary least squares. Robust standard errors are reported in parentheses. To align with the original derivation, these regressions do not use sampling weights. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.