TI 2015-034/V
Tinbergen Institute Discussion Paper

Thought for Food: Understanding Educational Disparities in Food Consumption

Hale Koç
Hans van Kippersluis

Erasmus School of Economics, Erasmus University Rotterdam, Tinbergen Institute, the Netherlands.

Tinbergen Institute is the graduate school and research institute in economics of Erasmus University Rotterdam, the University of Amsterdam and VU University Amsterdam.

More TI discussion papers can be downloaded at http://www.tinbergen.nl

Tinbergen Institute has two locations:

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 525 1600

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900
Fax: +31(0)10 408 9031

Duisenberg school of finance is a collaboration of the Dutch financial sector and universities, with the ambition to support innovative research and offer top quality academic education in core areas of finance.

DSF research papers can be downloaded at: http://www.dsf.nl/

Duisenberg school of finance
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 525 8579

Thought for Food: Understanding Educational Disparities in Food Consumption*

Hale Koç[1,2] and Hans van Kippersluis[1,2]

[1]Erasmus School of Economics, Erasmus University Rotterdam, The Netherlands
[2]Tinbergen Institute, The Netherlands

March 13, 2015

Abstract

Higher educated individuals are healthier and live longer than their lower educated peers. One reason is that lower educated individuals engage more in unhealthy behaviours including consumption of a poor diet, but it is not clear why they do so. In this paper we develop an economic theory of unhealthy food choice, and use a Discrete Choice Experiment to discriminate between the theoretical parameters. Differences in health knowledge appear to be responsible for the greatest part of the education disparity in diet. However, when faced with the most explicit health information regarding diet, lower educated individuals still state choices that imply a lower concern for negative health consequences. This is consistent with a theoretical prediction that part of the education differences across health behaviours is driven by the "marginal value of health" rising with education.

Keywords: Health, Education, Diet, Discrete Choice Experiment
JEL Codes : C25, I12, I24

*Van Kippersluis thanks the Netherlands Organization of Scientific Research (NWO Veni grant 016.145.082) and the National Institute on Aging of the National Institutes of Health (R01AG037398) for financial support. This paper makes use of data obtained through the LISS panel administered by CentERdata. Special thanks to Carlijn Kamphuis, Esther de Bekker-Grob and Frank van Lenthe for generously sharing their preliminary results, and we thank Michiel Bliemer, Esther de Bekker-Grob, Bas Donkers, Job van Exel, Patrick Hullegie, Owen O'Donnell, John Rose, Peter Savelyev, Elly Stolk, Darjusch Tafreschi, Tom Van Ourti, Arne Risa Hole, Liesbet van de Wetering, and seminar participants at ASHEcon Los Angeles 2014, the University of Duisberg-Essen, Shanghai University of Finance and Economics, and the Chinese University of Hong Kong, for helpful comments.

1 Introduction

The question "How can we induce people to look after their health?" was recently judged to be one of the 10 most pressing questions in the social sciences (Giles, 2011). Given the strong disparities in the prevalence of healthy behaviours (smoking, diet, exercise, preventive care, etc.) across education groups (e.g. Cutler and Lleras-Muney, 2010), the reasons why lower educated individuals behave unhealthily is of particular interest. In a recent review, however, Cutler et al. (2011) note that these reasons remain largely unclear.

In this paper our aim is to understand educational differences in one important aspect of health behaviour, namely unhealthy food choice. With obesity rapidly approaching smoking as the leading preventable cause-of-death, food choice is a vital aspect of health behaviour. We use economic theory to guide our design of a Discrete Choice Experiment (DCE), in which respondents make repeated choices between hypothetical meals that differ in taste, monetary price, preparation time, and health consequences. By randomly varying the information load that respondents face, our experimental design enables identifying the theoretical parameters and helps us understand why lower educated individuals adopt unhealthier diets: is it because they know less or because they care less about the health consequences?

Health behaviours have attracted a considerable amount of attention in the economics literature, and the education gradient in health behaviours is widely considered to contribute to the education gradient in health (Cawley and Ruhm, 2011). At first sight, one can be inclined to argue that the education gradient in health behaviours is simply due to higher educated individuals earning a higher income. Drewnowski and Specter (2004) argue that unhealthy diets composed of energy dense foods (such as refined grains, added fats and sugars) are more affordable than healthy diets, and the low cost of energy dense foods may partially explain the high prevalence of obesity among lower educated individuals. While an appealing argument, many other unhealthy habits that are more prevalent among the lower educated, like smoking and binge drinking, are costly, such that it is unlikely that income is the sole explanation.

Higher education is also associated with higher self-regulation (ability to defer an immediate reward for a future reward), internal locus of control (perceived control over one's life), and self-efficacy, all of which are needed to initiate and maintain healthy lifestyles (Leganger and Kraft, 2003; Saffer, 2014). More generally, Conti and Hansman (2013) conclude that non-cognitive skills contribute strongly to the association between education and health behaviours (see also Barsky et al., 1997; Picone et al., 2004), although the direction of causality is not well-established.[1]

Another explanation that is often stressed is health knowledge. Grossman (1972) and Meara

[1]Non-cognitive ability refers to a large set of personality traits including self-efficacy, self-esteem, internal locus of control, self-regulation, motivation, conscientiousness, openness, etc. For an excellent summary of the use of non-cognitive abilities (or personality) in the economics literature, see Almlund et al. (2011).

(2001) emphasize the "productive efficiency" hypothesis, where better educated individuals make more efficient use of existing knowledge, partly due to differences in cognitive ability (Bijwaard and Van Kippersluis, 2015). According to the alternative "allocative efficiency" hypothesis better educated individuals choose more efficient inputs into health investment (healthier lifestyles), typically thought to be caused by better health knowledge and a more receptive attitude towards new information. Kenkel (1991), Meara (2001) and Cutler and Lleras-Muney (2010) provide support for the allocative efficiency hypothesis by showing that higher educated individuals have superior knowledge on the health consequences of smoking, drinking and exercise; although these differences only account for a limited portion of education disparities.

In sum, the literature established that education is closely related to a large battery of health behaviours, but there is no consensus about the underlying reasons and their relative contributions to the association. Obtaining such knowledge is important from a policy perspective. If differences in possession of health knowledge are key to the observed disparities, then policy may want to focus on health promotion efforts on further distributing health information. However, if differences in education, cognitive or non-cognitive skills lead to a different valuation of health, then early childhood interventions aiming to reduce differentials in education, cognitive and non-cognitive abilities would be more effective.[2]

We argue that the progress and consensus on why higher educated individuals engage in healthier behaviour is at least partially hampered by economists' exclusive reliance on revealed preference data. This paper is, to the best of our knowledge, the first in the economics literature to use a Discrete Choice Experiment (DCE) to investigate educational disparities in dietary behaviour.[3]

Use of a stated preference DCE confers four main advantages over revealed preference data, namely (i) it enables controlling the amount of health information that individuals face, by randomly assigning them to different scenarios; (ii) it makes separating preferences for taste and health possible, by explicitly controlling for taste as a product attribute. In revealed preference data, even if we were to observe all objectively measured food attributes (price, preparation time, calories, fat, carbohydrates, etc.), and the higher educated would be buying healthier food, it is difficult to learn whether this is due to their preferences for healthier food, or simply due to a different idea of what is tasty; (iii) it defines, not assumes, the choice sets and food attributes that individuals face. In revealed preference data one typically assumes artificial choice sets on basis of other individuals' choices, but it is unclear whether these are

[2]From a more liberal perspective, any kind of intervention that goes beyond equalising opportunity would be deemed unnecessary as education differences result from free, albeit constrained, choices.

[3]The food demand literature employing discrete choice analysis has mainly focused on estimating the predicted demand for novel food attributes (Adamowicz and Swait, 2011). We are aware of only one similar study in public health that was independently developed around the same time (Kamphuis et al., 2015). Their aim is to document socioeconomic differences in food choices, but not to discriminate between the role of health knowledge and the value of health in driving these differences.

the actual choice sets, and whether the objective attributes in the artificial choice sets match the perceived attributes of the individual (Hensher et al., 2005, p. 223-224); and (iv) in contrast to revealed preference data, we are not restricted by products currently existing in the market (Hensher et al., 2005, p. 93).

Through the close linkage between the theoretical model and the DCE, and the flexibility of the DCE in controlling the information that respondents face, we are able to discriminate between the parameters of our theoretical model. In particular, we are able to disentangle the theoretical parameters related to the value of health and health knowledge. In this way, we are responding to a plea by Pampel et al. (2010) that *"...literature on SES disparities in health and health behaviours can do more to design studies that better test for the importance of the varied mechanisms."*

On top of the novel stated preference experimental design, which we view as complementary to more conventional revealed preference analyses, our study further contributes to the existing work on the effect of information provision on health behaviours. While the contribution of health information on smoking and drinking is widely investigated, fewer studies carry out a similar exercise for food choice. The results could well be different: consequences of smoking and alcohol abuse are common public knowledge – especially after all information campaigns, package labelling etc. – while knowledge about dietary risks is less widespread, more uncertain and differs by education.[4] Indeed, Downs et al. (2009) find that calorie consumption went down in hamburger restaurants in Brooklyn but not in Manhattan after posting calorie information became mandatory, suggesting that socioeconomically disadvantaged groups benefit more from provision of health information. Wisdom et al. (2010) and Bollinger et al. (2011) find that providing information on calorie content led to significantly lower calorie consumption, yet Elbel et al. (2009) and Finkelstein et al. (2011) find no effect of the menu labelling law on healthier food purchasing in fast-food chains.

We contribute to the menu labelling literature by choosing a non-fast-food restaurant setting and by investigating more health attributes like fat and sodium, apart from calories. Customers of fast-food chains may have a different profile, or mindset, than customers of normal restaurants or home cooks. Conditional on the choice to enter a fast-food restaurant, convenience and taste may be the priority rather than calories, or health consequences in general. Moreover, menu labelling studies have almost exclusively focused on calories (for exceptions see Mathios, 2000; Wansink and Chandon, 2006; Variyam, 2008), whereas overconsumption of sodium and saturated fat may be equally, or even more, harmful to health.

The results indicate that the education disparity in diet derives mostly from superior health

[4]For example, in 1990, 96% of surveyed respondents knew that smoking is related to lung cancer (91% of high school dropouts vs. 97% of college graduates) (Cutler and Lleras-Muney, 2010). In contrast, in our survey 20 years later, only 66% of the diet related questions is answered correctly (63% among the lower educated vs. 73% among the higher educated).

knowledge among the higher educated. When faced with health information, better educated respondents do not change their valuation of health related product attributes, while lower educated respondents start to put a higher value on health attributes. This finding suggests that the lower educated are the main beneficiaries of health information, and the education gradient in unhealthy food choice becomes smaller upon provision of such information. Nonetheless, even after fully equalizing health information across education groups, the better educated tend to choose healthier diets. This suggests that higher educated respondents place a higher marginal value on their health – i.e. they care more about the health consequences of food. Auxiliary analyses suggest that at least part of these differences in the value of health derives from higher incomes and better health status among the higher educated.

The remainder of this paper is organized as follows. In section 2 we present our theoretical model and discuss its insights and predictions. In section 3 we discuss the DCE that enables us to discriminate between the theoretical parameters, and section 4 describes the LISS internet panel in which we implemented the DCE. Section 5 describes the empirical models that we estimate, of which results are presented in section 6. Section 7 presents several robustness checks, before section 8 summarizes and discusses the results.

2 A Theory of Food Consumption

2.1 Theoretical formulation

The theoretical model presented here is an adaptation of Galama and Van Kippersluis (2010), and builds on the human capital theory of the demand for health investment (Grossman, 1972). Individuals maximize the life-time utility function

$$\int_0^T U[C_h(t), C_u(t), H(t)]e^{-\rho t}dt, \tag{1}$$

where T denotes the life span, ρ is the rate of time preference and $U[C_h(t), C_u(t), H(t)]$ is a concave utility function in healthy consumption $C_h(t)$, unhealthy consumption $C_u(t)$, and health $H(t)$.

Healthy and unhealthy consumption $C_h(t)$ and $C_u(t)$ are produced by combining goods and services purchased in the market, $X_h(t)$ and $X_u(t)$, and own time inputs, $\tau_{C_h}(t)$ and $\tau_{C_u}(t)$, respectively.

$$C_h(t) \equiv C_h[X_h(t), \tau_{C_h}(t)], \tag{2}$$

$$C_u(t) \equiv C_u[X_u(t), \tau_{C_u}(t)]. \tag{3}$$

The objective function (1) is maximized subject to three constraints. First, health deteriorates at an aging rate $d(t)$ that is partly biological, but also depends endogenously on healthy consumption $C_h(t)$ and unhealthy consumption $C_u(t)$. Healthy consumption slows down biological aging ($\partial d/\partial C_h \leq 0$), while unhealthy consumption aggravates biological aging ($\partial d/\partial C_u > 0$).

The aging rate also depends in a flexible way on the health stock.

$$\frac{\partial H}{\partial t} \quad = \quad -\Big(\lambda(E) \times d[t; C_h(t), C_u(t), H(t)]\Big), \tag{4}$$

In practice there is uncertainty about the influence of biology and behaviour on health deterioration (e.g. Ippolito, 1981). Individuals take into account their own subjective assessment of health deterioration rather than the objective health deterioration (Johansson-Stenman, 2011). We model this through the parameter $\lambda(E)$, which is a function of education since the lower educated generally have worse health knowledge than the higher educated (Kenkel, 1991; Cutler and Lleras-Muney, 2010), due to differential efficiency in processing information (Schultz, 1975), monetary and time costs of obtaining information, and differences in the valuation of health (Ippolito and Mathios, 1990). $\lambda(E)$ takes the value of 1 in case individuals have perfect knowledge about health deterioration, and if unequal to 1, individuals either over- or underestimate the effect of biology and behaviour on health decline.

The second constraint that individuals face is a time constraint, where the total time available in any period Ω is divided between work $\tau_w(t)$, time inputs into healthy consumption $\tau_{C_h}(t)$, time inputs into unhealthy consumption $\tau_{C_u}(t)$, and some time is lost due to sickness, $s[H(t)]$, with $\partial s/\partial H < 0$.

$$\Omega = \tau_w(t) + \tau_{C_h}(t) + \tau_{C_u}(t) + s[H(t)], \tag{5}$$

Finally, individuals face a budget constraint. Assets $A(t)$ provide a return r, increase with earnings, and decrease with purchases of healthy consumption goods $X_h(t)$ and unhealthy consumption goods $X_u(t)$, at prices $p_{C_h}(t)$ and $p_{C_u}(t)$, respectively. Earnings are the multiplication of the wage rate $w(t; E)$ and the time spent working $\tau_w(t)$, with education E increasing the wage rate, and health $H(t)$ increasing the time available working through reduced sick time (see 5).

$$\frac{\partial A}{\partial t} \quad = \quad rA(t) + w(t; E)\tau_w(t) - p_{C_h}(t)X_h(t) - p_{C_u}(t)X_u(t), \tag{6}$$

The Hamiltonian of this problem is:

$$\Im \quad = \quad U(t)e^{-\rho t} + q_H(t)\frac{\partial H}{\partial t} + q_A(t)\frac{\partial A}{\partial t}, \tag{7}$$

where $q_H(t)$ is the marginal value of health $H(t)$ and $q_A(t)$ is the marginal value of assets $A(t)$. The marginal value of health $q_H(t)$ represents the marginal value of remaining life-time utility (from t onward) derived from additional health capital $H(t)$, and reflects both the consumption benefits $(\partial U/\partial H)$ and the production benefits $(w(E)\,[-\partial s/\partial H])$ of health $H(t)$:[5]

$$\begin{aligned} q_H(t) \quad = \quad & \int_t^T e^{-\int_t^x \lambda(E)\frac{\partial d}{\partial H}du}\left(\frac{\partial U}{\partial H}e^{-\rho x} + q_A(0)w(x; E)\left[-\frac{\partial s}{\partial H}\right]e^{-rx}\right)dx \\ & + q_H(T)e^{-\int_t^x \lambda(E)\frac{\partial d}{\partial H}dx} \end{aligned} \tag{8}$$

[5] The analytical expression is obtained by solving the differential equation delivered by the co-state equation (see Appendix A):

$$\frac{\partial q_H(t)}{\partial t} = q_H(t)\lambda(E)\frac{\partial d}{\partial H} - \frac{\partial U}{\partial H}e^{-\rho t} - q_A(0)w(t; E)\left[-\frac{\partial s}{\partial H}\right]e^{-rt},$$

and using the terminal condition that $H(T) = H_{min}$, such that $q_H(T) \neq 0$.

The marginal value of assets represents the marginal value of remaining life-time utility (from t onward) derived from additional assets $A(t)$, and follows the dynamic equation $q_A(t) = q_A(0)e^{-rt}$.

Initial and end conditions are given by $A(0) = A_0$, $H(0) = H_0$, $A(T) = A_T$, and $H(T) = H_{\min}$. The latter implies that individuals die when the health stock falls below the minimum health stock $H_{\min}$, where length-of-life is assumed exogenous for simplicity.

2.2 Equilibrium conditions

The first-order condition for healthy consumption is (see Appendix A for derivations):

$$\frac{\partial U}{\partial C_h}e^{-\rho t} + q_H(t)\lambda(E)\left[-\frac{\partial d}{\partial C_h}\right] \quad = \quad q_A(t)\pi_{C_h}(t), \tag{9}$$

The left-hand side describes the marginal benefits of healthy consumption, which consists of (i) discounted marginal utility and (ii) the marginal health benefit of healthy consumption. The marginal health benefit is the product of $q_H(t)$, the marginal value ("shadow price") of health, and the subjective assessment of amount of health "saved", $\lambda(E)\,[\partial d/\partial C_h]$.

The right-hand side presents the marginal monetary cost of healthy consumption

$$\pi_{C_h}(t) \equiv \frac{p_{X_h}(t)}{\partial C_h/\partial X_h} = \frac{w(t)}{\partial C_h/\partial \tau_{C_h}}, \tag{10}$$

The monetary cost is a function of the price of healthy consumption goods and services $p_{X_h}(t)$ and the opportunity cost of time $w(t)$, and is multiplied by the marginal value of wealth, $q_A(t)$. Hence, the optimality condition requires the marginal benefit of consumption (discounted marginal utility + the marginal health benefit) to equal the marginal cost of consumption (the marginal value of wealth $q_A(t)$ times the marginal reduction in wealth, i.e. the marginal cost of consumption $\pi_{C_h}(t)$).

The first-order condition for unhealthy consumption is

$$\frac{\partial U}{\partial C_u}e^{-\rho t} \quad = \quad q_A(t)\pi_{C_u}(t) + q_H(t)\lambda(E)\frac{\partial d}{\partial C_u}, \tag{11}$$

where $\pi_{C_u}(t)$ is the monetary cost of unhealthy consumption

$$\pi_{C_u}(t) \equiv \frac{p_{X_u}(t)}{\partial C_u/\partial X_u} = \frac{w(t;E)}{\partial C_u/\partial \tau_{C_u}}, \tag{12}$$

and $q_H(t)\lambda(E)\,[\partial d/\partial C_u]$ is the perceived health cost of unhealthy consumption.

Similar to healthy consumption, the left hand side (LHS) of the first-order condition (11) captures the discounted marginal utility individuals derive from unhealthy consumption goods. The first part on the right hand side (RHS) represents the *monetary cost* individuals face, which is a function of the marginal value of wealth, $q_A(t)$, the monetary price $p_{C_u}(t)$ and the opportunity cost of time, $w(t)$. The second term on the RHS is the perceived *health cost* of unhealthy consumption. It is the product of the marginal value people attach to health, $q_H(t)$, and the subjective assessment of the "unhealthiness" of the good, $\lambda(E)\,[\partial d/\partial C_u]$.

2.3 Theoretical insights

The theoretical model helps us understand how individuals make food choices. The first order conditions for healthy and unhealthy consumption in (9) and (11) suggest that consumption choices are mainly governed by four product attributes: (i) taste, as reflected in the marginal utilities of consumption, $\partial U/\partial C_h$ and $\partial U/\partial C_u$, (ii) the monetary price, $p_{C_h}(t)$ and $p_{C_u}(t)$, (iii) the opportunity cost of time, $w(t)$, and (iv) the health consequences, $\partial d/\partial C_h$ and $\partial d/\partial C_u$. How much value individuals attach to these attributes is determined by the time preference rate and the parameters of the utility function (for taste), the marginal value of wealth, $q_A(t)$ (for the monetary price and opportunity cost of time), and the product of the marginal value of health and health knowledge, $q_H(t)\lambda(E)$ (for the health consequences).

The model additionally reveals potential causes for education disparities in consumption choices. Due to differences in budget and time constraints (e.g. Cutler et al., 2003; Drewnowski and Specter, 2004), differences in the efficiency of using market inputs and own time in production (Michael and Becker, 1973), and differences in preferences (Drewnowski, 1997), higher educated individuals may have different valuations of the product attributes price, time, and taste. The first order condition for unhealthy consumption (11) illustrates that the valuation of health consequences depends on the product of $q_H(t)$ and $\lambda(E)$. By assumption $\lambda(E)$ is a function of education. Equation (8) illustrates that the marginal value of health is also a function of education. Higher educated individual earn higher wages, and better health enables them to generate more earnings by reducing sick time and increasing the time spent working (i.e. higher educated have higher production benefits of health). As a result, it can be easily derived from (8) that $\partial q_H(t)/\partial E > 0$.

In the empirical analysis, we seek to discriminate between the theoretical parameters $\lambda(E)$ and $q_H(t)$, which are potentially causing education disparities in unhealthy diets. Our main question is: Are education disparities in healthy food choice mainly caused by disparities in health knowledge (i.e. driven by $\lambda(E)$), or do they simply reflect disparities in the marginal value of health ($q_H(t)$)? A secondary question is to what extent any potential differences in the marginal value of health are driven by education, and to what extent by health, the marginal value of wealth, and time preference.[6]

Answering these questions is not straightforward and puts huge requirements on the data. In particular, equation (8) shows that $q_H(t)$ and $\lambda(E)$ are not separately identified, since the marginal value of health depends in a highly non-linear way on the health knowledge the individ-

[6]The theory suggests that the marginal value of health additionally depends on the health stock $H(t)$, life-time wealth $q_A(0)$, and the rate of time preference ρ (see 8):

$$q_H(t) = f\left[E, H(t), q_A(0), \rho\right] \tag{13}$$

Since all of these variables are likely to be correlated to education, education disparities in the marginal value of health may partially derive from differences in the marginal value of wealth, health status, and time preferences.

ual possesses. Only in the special case that $\lambda(E) = 1$, we can separately identify the marginal value of health. Since consumer demand theory does not provide any credible instrumental variables (Etilé, 2011), we rely on experimental variation in health information to set $\lambda(E) = 1$ in order to separately identify $q_H(t)$.

3 Discrete Choice Experiment

A Discrete Choice Experiment (DCE) is a stated preference technique aimed at eliciting individual preferences for attributes of a certain (consumption) good. DCEs are strongly grounded in Random Utility Theory (Louviere et al., 2010). In a DCE, multiple choice sets are presented to respondents, and in each choice set respondents make a choice between two or more alternatives. An alternative is described by a number of attributes, each of which can take several levels. The fundamental idea is that utility is derived from the bundles of attributes that make up the consumption goods, and not the consumption goods per se (Lancaster, 1966).

3.1 Setting of the design

The setting of our DCE is the choice for a dinner meal. In terms of food choice, dinner seems to be the most relevant setting as it contains the largest fraction of calories (36%), fat (42%), salt (36%), and fiber (36%) in Dutch diet (Van Rossum et al., 2011), with similar findings for the US (Cutler et al., 2003, p. 101). Moreover, the largest disparities in healthy diets across education groups seem to derive from regular meals rather than snacks, candies and other refreshments: in our sample, 38% of the higher educated eat candies and snacks at least once a week, compared with only 32% of the lower educated.

The question we present to respondents is “Which of the following two meals would you eat regularly (at least twice a week)?”.[7] By asking a general question about which of the two meals they would prefer, we intend to avoid the dependence of the choice on the respondent’s recent food choices that day, or over the past week. Arguably, the alternative question asking “which of the two meals would you prefer to eat now?” would depend more on whether they just ate something, and their eating behaviour over the past few days.

An example choice set of the experimental design is given by Table 1. The design is an unlabeled design with a forced choice between the two meals. That is, we make respondents choose between “Meal A” and “Meal B”, and do not allow them to choose neither of the two. In a labeled design (e.g. “pizza” vs. “mashed potatoes”), individuals will have intrinsic preferences for, and associations with, the specific alternatives, and this will contaminate the estimation of the attribute importance (Hensher et al., 2005, p. 113). Moreover, we decided not to include an opt-out option as we are mainly interested in the trade-off between the attributes, and opt-out choices do not convey any information on attribute importance (Hensher et al., 2005, p. 176).

[7] See Appendix B.3 for the full introductory text.

3.2 Attributes and levels

The theoretical model developed in section 2 determines our selection of attributes. The four attributes of consumption goods that the theory postulates are (i) the taste, (ii) the monetary cost, (iii) the time (or opportunity) cost, and (iv) the health consequence. Reassuringly, the four attributes derived from the theory coincide with the seminal Food Choice Questionnaire developed by Steptoe et al. (1995).[8] Moreover, in a conducted pilot study among 87 respondents, no other attribute was mentioned consistently to be important by more than 5% of the respondents, suggesting that these four attributes are salient and well-established. Nonetheless, to err on the side of prudence, we additionally added the sentence "Assume all other characteristics of the meals are the same, e.g. they are equally filling, contain an equal amount of carbohydrates and proteins, are equally biological and fair-trade, etc." to avoid that respondents make assumptions about possibly omitted attributes.

While the attributes taste, monetary cost, and time cost all seem relatively easily interpretable, the attribute health consequences is more difficult to operationalize. We choose to operationalize this attribute by dividing it into three separate attributes which we call *health attributes*: calories, saturated fat, and sodium. We restricted health consequences to three attributes in order to reduce the cognitive difficulty of completing a DCE, and to avoid that participants apply a simple decision rule on basis of a subset of attributes (Mangham et al., 2009).

The three health attributes are chosen on basis of three criteria. First, Dietary Guidelines for Americans state that all three are associated with health consequences (U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010). Overconsumption of calories is associated with overweight, obesity, and diabetes; overconsumption of sodium is related to high blood pressure and stroke; and overconsumption of saturated fat is associated with high cholesterol and cardiovascular disease.[9] Second, listing the amounts for these three attributes is compulsory on the package of consumption goods.[10] Third, official guidelines prescribe a daily recommended intake for these three attributes (U.S. Department of Agriculture and U.S. Department of Health and Human Services, 2010). This in contrast to for example sugar, for which the daily recommended intake is not agreed upon.

[8]While nine factors emerged in the Steptoe et al. study as being important, the authors claim that *"sensory appeal, health, convenience and price are the most important factors on average, with the five other factors being typically endorsed less strongly."* (Steptoe et al., 1995, p. 282).

[9]Admittedly, there is a certain amount of uncertainty surrounding the health consequences of some food components. For calories and sodium, this is not the case, but we are aware of recent studies that challenge the association between saturated fat and cardiovascular disease (e.g. Malhotra, 2013; Chowdhury et al., 2014). Nonetheless, we decided to follow the Dietary Guidelines for Americans, 2010 which deploys the message that saturated fat is linked to cardiovascular disease.

[10]See Regulation (EC) No. 1924/2006 of the European Parliament and the Council, 20 December 2006, for details.

The proposed levels for the attributes are (refer to appendix B.1 for a detailed motivation of the levels):

- **Price** - 2 Euro, 6 Euro, 10 Euro
- **Time** - 10 minutes, 30 minutes, 50 minutes
- **Taste** - OK, Good, Very Good[11,12]
- **Calories** - 800 calories, 1100 calories, 1400 calories
- **Saturated Fat** - 10 gram, 20 gram, 30 gram
- **Sodium** - 900 milligram, 1200 milligram, 1500 milligram

3.3 Experimental design

Design size We choose to present 18 choice sets to each individual, which is seen as a practical limit before boredom sets in (Hanson et al., 2005). Using 5 blocks of 18 choice sets ensures that the total number of choice sets generated is 90, which gives a comfortable buffer to identify all main effects and two-way interactions of the attribute levels.[13] The blocking of the design is performed such that the levels of each attribute are evenly divided over blocks.

Generating an efficient design As the example choice set in Table 1 illustrates, there are an awfully lot of different combinations possible to generate 90 choice sets with two alternatives out of all combinations of the attribute levels. We choose to generate an "efficient design" that chooses the 90 most informative choice sets, for a given set of prior values. We do so by minimizing the median "D-Error", which is the determinant of the asymptotic variance-covariance (AVC) matrix of the parameters (Huber and Zwerina, 1996; Hensher et al., 2005, p. 153).[14] Apart from statistical efficiency, an important advantage is that efficient designs avoid

[11] Kamphuis et al. (2015) ran pilots in which the levels of "Taste" included descriptions such as "tasteless" or even tasting "bad". It turns out that respondents never chose a meal that was tasting bad, such that we choose to start from a taste that is "OK".

[12] A robustness check has shown that replacing the attribute name *taste* with *sensory appeal*, which additionally includes smell and visual appearance besides taste, does not make a difference for our results, and if anything makes individuals care less about the attribute.

[13] The number of choice sets directly determines the number of parameters that are identified. With 6 attributes, each with 3 levels, the full factorial including main effects and all interactions amounts to $3^6 = 729$ parameters. Since three-way and higher-order interactions are unlikely to be of importance (e.g. Hensher et al., 2005, p. 113; Lancsar and Louviere, 2008), 90 choice sets allows identifying at least the 12 main effects and 60 two-way interactions.

[14] The AVC matrix only depends on the assumed model and the parameters, and not on the actual choices (McFadden, 1973). Hence upon assuming prior values for the parameters in a given model, the AVC matrix can be computed. The experimental design is generated in the software program Ngene version 1.1.1 (ChoiceMetrics, 2012).

so-called dominant alternatives – uninformative choice sets where one of the meals is superior in all respects (a meal that is tastier, cheaper, quicker, and healthier than the other meal).

When generating an efficient design, prior values have to be assigned to the parameters. Given that all our attributes have a clear ordinal structure (e.g. a lower price always yields a higher utility than a higher price; fewer saturated fat yields more utility than more saturated fat for a given taste), the sign of the parameters is easily determined. The magnitude of the parameters is less well-established, and hence we use Bayesian priors with 1000 Halton draws from a Normal distribution to ensure robustness against misspecification (see Appendix B.2 for details).

Gradually adding health information The baseline design (from here scenario I or no health information scenario) identifies the product of the theoretical parameters $q_H(t)$ and $\lambda(E)$, and therefore cannot separately identify the effect of health knowledge $\lambda(E)$ and the value of health $q_H(t)$. For example, if the higher educated care more about calories and fat, is that because they know more about the possible dangers of overconsuming calories and fat, or is it because they care more about the health consequences of calories and fat? In order to tease this out, we generate two additional scenarios in which we gradually add health information to fix $\lambda(E)$ at 1.

Scenario II (or health information scenario) is identical to scenario I, except that the attribute descriptions are supplemented with some health information. In the introductory text for scenario II, not only the attributes calories, saturated fat, and sodium are introduced, but also the adverse health effects of overconsumption, and the recommended daily allowances for dinner are explicitly provided (see Appendix B.3 for the exact introduction texts). Moreover, in every choice set the respondent is reminded of the recommended intake with the sentence "The recommended intake for a dinner is 800 calories, 10 gram saturated fat, and 900 milligram sodium". An example choice set is given in Table 2.

The idea of scenario II is to see how education disparities in the value individuals attach to the health attributes change when health information is provided. Yet, while diminishing potential gaps in health information, in scenario II one still requires cognitive capabilities to internalize the given health information. Therefore, in scenario III (or explicit health information scenario) we make the health information even more explicit in an attempt to equalize it across education groups (i.e. fixing $\lambda(E)$ at 1). We replace the three health attributes, calories, saturated fat, sodium, with the single attribute

- **Health consequences** - healthy (associated with reduced risk of disease), (ii) health neutral, and (iii) unhealthy (associated with increased risk of disease).

While compromising on the realism of the choice that individuals face, scenario III makes sure that all respondents are on the same page in terms of health information. Hence, we interpret any potential differences in the valuation of the attribute health consequences in scenario III as being due to the marginal value of health $q_H(t)$, rather than differences in health knowledge $\lambda(E)$. An example choice set is given in Table 3.

4 Data and descriptive statistics

4.1 Data

Our DCE is implemented in the LISS (Longitudinal Internet Studies for the Social Sciences) panel administered by CentERdata (Tilburg University, The Netherlands). The LISS panel is a monthly internet panel that runs since October 2007 consisting of 5000 households, comprising 8000 individuals, who are paid upon completing a questionnaire. The panel is based on a true probability sample of households drawn from the population register by Statistics Netherlands, and households that could not otherwise participate are provided with a computer and internet connection.

A representative sample of 4,377 panel members was randomly selected for the DCE in the first wave, which took place in April 2014. We restricted the sample to 18+ individuals as younger ones often live with their parents, typically do not cook, and do not have much choice over what they eat for dinner. Each respondent is first randomly assigned to one of the three scenarios, and then to one of the five blocks within a scenario (see section 3.3 for more detail on the scenarios and blocks). Within a block, each respondent is presented with 18 randomly ordered choice sets, with randomly ordered attributes (Kjær et al., 2006). Table 4 provides descriptive statistics for the sample. Our respondents are between 18 and 91, with an average age of 51, and roughly equally divided between men and women. Randomization of individuals to the different scenarios worked properly, as the means of the variables do not differ across scenarios.[15]

In a second wave, in May 2014, we have collected information about the respondents' time preferences, health knowledge (both objective and self-assessed), health valuation, and dietary habits.[16] Wave 2 is administered only among respondents who participated in the DCE in wave

[15]Due to chance, there are a couple of exceptions. The respondents in scenario II eat more often in a restaurant (p-value=0.049), and the respondents in scenarios II and III consume vegetables more frequently than the respondents of scenario I (p-values are 0.047 and 0.091 respectively). The respondents of scenario III have a lower level of education than the respondents of scenario I (p-value=0.001). This does not pose any problems because we either compare respondents with different levels of education *within* scenarios, or respondents with the same level of education *across* scenarios.

[16]We asked the additional questions in a separate wave, one month later than the DCE, in order to avoid any priming and/or learning effects. It is likely that asking questions about health knowledge before the start of the DCE will make health attribute(s) salient compared to other product attributes in the DCE, resulting in an overestimation of the relative importance of the health attribute(s). Asking health knowledge questions immediately after the DCE may result in an overestimation of health knowledge among scenario II respondents, as they were provided with health information. Interestingly, when we compare the number of correct answers

1. After accounting for non-response (18.2% in the first wave and 10.5% in the second wave), we have 3,157 individuals who responded both to wave 1 and wave 2. After dropping respondents with missing values for variables used in the analysis, we end up with a final sample size of 2,869.[17]

4.2 Variables

The main variables used in the analysis are defined below. Note that all these variables are fixed for a given respondent across choice sets, and hence cannot be controlled for in the empirical estimation (see section 5 for details). The variables do differ across respondents, however, and we will exploit this variation by estimating the models for different subgroups. To limit the number of subgroups, we choose to dichotomize all respondent characteristics defined below.

Education We measure education by the highest level completed with a diploma.[18] We dichotomize education into Lower Education (67% of the sample), including individuals having completed primary education, secondary school, or lower vocational education. Higher Education (33% of the sample) is defined as having completed higher vocational education or university.

Self-reported Health Self-reported health is measured by the question "How would you describe your health, generally speaking?", with possible answers Excellent, Very Good, Good, Moderate, or Poor. We classify the first two categories as "Good Health", while the latter three as "Poor Health".

Health Knowledge Respondents' health knowledge with respect to diet is measured via 12 yes/no questions, including a "I don't know" option (see Table 6). Half of the questions is about calories, saturated fat, and sodium as these are the food components that we focus in our DCE. The other half of the questions ask about other dietary components in order to get an idea about the level of general knowledge the respondent has. Respondents know the least about daily recommended amounts of sodium and saturated fat. Hence, choice behaviour may be different when we provide (scenario II) or withhold (scenario I) information about dietary guidelines, as such information is apparently not widespread among respondents.

given to health knowledge questions among respondents from scenario I and scenario II, we observe no difference, suggesting that answering questions in scenario II did not result in a lasting accumulation of health knowledge.

[17]According to Lancsar and Louviere (2008) one rarely needs more than 20 respondents per parameter to estimate reliable models. We have 24 main effects to estimate in scenarios I and II, and 8 main effects in scenario III. Therefore our sample size gives us a very comfortable buffer to identify all main effects reliably, and even permits estimating two-way interactions if deemed necessary.

[18]Respondents between age 18 and 25 may still be attending school or university. However, when restricting to individuals aged 25 and above, our results are unaffected.

We construct a dietary knowledge index by counting the number of correct answers for 12 questions. We follow a 'strict' scoring procedure in the sense that we count "don't know" responses also as incorrect, as both incorrect and "don't know" responses indicate a lack of knowledge. Then we construct a binary knowledge variable where a person is considered to have High Health Knowledge if his/her knowledge index is above the median, and Low Health Knowledge otherwise.

Income The theory shows that behaviour is driven by $q_A(0)$, i.e. the marginal value of wealth, typically operationalized as permanent income. Here, we use current income instead as a proxy for permanent income, and note that in the presence of credit constraints, current income does determine the individual's budget constraint. Income is measured continuously as net monthly household income in Euros. We recoded this variable into a binary one, where High (Low) Income corresponds to income levels which are above (below) the median level of income in the sample.

Future orientation Following Oreopoulos and Salvanes (2011), we asked respondents to rate their agreement ([1] Strongly disagree [2] Disagree [3] Neutral [4] Agree [5] Strongly agree) with the statement "Nowadays, a person has to live pretty much for today and let tomorrow take care of itself". We treat responses to this statement as a proxy for future orientation (or time preference) where a higher degree of agreement implies a higher level of orientation to the future. A person is defined as having High Future Orientation if his/her response is (strongly) disagree, and Low Future Orientation otherwise. While simplistic, we still prefer to use this measure over more conventional ones, as it is simple for respondents to understand and respond to. Indeed, the non-response and irrational response rate for classical measures of time preference via *money now versus money later* type of comparisons is very large in our sample (around 30 percent).[19]

Diet We asked respondents whether they follow any diet, with possible dietary restrictions for salt, cholesterol, calories, or other diets. We classify Diet as 1 if the respondent follows any kind of diet, and 0 otherwise.

Dietary habits We asked respondents how often they consume the following goods, on a scale from 1 (Never) to 6 (Every day): fruit, vegetables, candy, sodas and energy drinks, and general snacks. Further, we asked respondents, using the same scale, how often they (i) cook

[19] Our future orientation measure is strongly correlated to the classic time preference question "If offered 100 euros now or X euros in 6 months, what would be the smallest amount of money (X euros) you would accept rather than the immediately available 100 euros?". After omitting irrational responses, i.e. $X <= 100$ (leaving N=1778), those who are future oriented have on average discount rates that are 30 percentage points lower (p-value < 0.01).

at home on basis of raw ingredients, (ii) cook processed meals at home, (iii) have a take-away or home-delivered meal, and (iv) eat out in a restaurant.

4.3 Descriptive evidence of disparities across education groups

Table 5 summarizes differences in dietary habits across the two education groups. In line with previous evidence (e.g. De Irala-Estevez et al., 2000; Cutler and Lleras-Muney, 2010), we find higher educated individuals to consume fruit and vegetables more frequently (p-values 0.000 and 0.004, respectively), and to drink sodas less frequently (p-value=0.028). Interestingly, the higher educated seem slightly more likely to eat candies (p-value=0.003).

The table additionally documents educational disparities in health knowledge. Overall health knowledge clearly is better among the higher educated (p-value=0.000). According to Table 6, the share of respondents giving a correct answer is statistically higher at a 1% significance level among the higher educated for 9 out of 12 questions. Higher educated respondents are more knowledgeable about the recommended amounts of calories and saturated fat; about the health consequences of overconsuming calories, saturated fat and sodium; and more generally about what constitutes a healthy diet and diet-disease connections.

In the next section we will describe our empirical approach to estimate the contribution of health knowledge to the reported disparities in healthy diets across education groups.

5 Empirical estimation

5.1 From theory to empirical estimation

The equilibrium conditions for healthy and unhealthy consumption in (9) and (11) suggest that the utility individuals derive from consumption goods is a function of (i) the taste, (ii) the price, (iii) the preparation time, and (iv) the health consequences. Translated into a Random Utility Framework this implies that the utility that individual i derives from meal j can be written as

$$U_{ij} = \mathbf{x'_{ij}}\beta_{\mathbf{i}} + \varepsilon_{ij} \tag{14}$$

where $\mathbf{x_{ij}}$ is the matrix of product attributes taste, price, time, health consequences, β_i is the vector of individual specific coefficients/valuations of the attributes $x_k, k =$ *taste, price, time, health consequences*, and ε_{ij} is an error term.

The β_i coefficients are the empirical analogues of the structural theoretical parameters. In particular, the coefficients for the health attributes in scenario I identify the product of the marginal value of health q_H and the health knowledge parameter $\lambda(E)$. Scenario II and III gradually fix the parameter $\lambda(E)$ to 1, and therefore we interpret the coefficient for health consequences in Scenario III as the empirical translation of q_H, the marginal value of health. Estimating the exact theoretical parameters $\lambda(E)$ and q_H would however require rather stringent functional form assumptions that we do not want to impose.

If we assume that the error term follows a type I extreme value distribution, equation (14) leads to a standard logit specification. The theory however suggests that the valuations (coefficients) β_i for the product attributes are heterogeneous. For example, the value of health consequences depends on education, the health stock, the marginal value of wealth, and time preference (cf. 13). Therefore, we specify a mixed logit (also known as random parameters logit) model, which allows for taste heterogeneity by letting each individual have an individual-specific valuation (i.e., coefficient) for every attribute.

5.2 Panel Mixed Logit

Model specification Generalizing the standard logit model, mixed logit specifies an *individual specific* vector of coefficients β_i as in equation (14). β_i follows the density $f(\beta_i|\theta)$, which describes the variation in tastes in the population with θ representing the parameter set.

As in the regular logit model, the respondent compares the utility of choosing alternative $j = 0$ with the utility of choosing alternative $j = 1$, and chooses the alternative with greater utility. What we observe is the outcome, $y_i = \{0, 1\}$, of these latent utility comparisons. The mixed logit model defines the unconditional probability of individual i choosing alternative j in a given choice set as

$$P^u_{ij}(\theta) = \int \left(\frac{e^{x_{ij}\beta_i}}{1 + e^{x_{ij}\beta_i}} \right) f(\beta_i|\theta) d\beta_i \tag{15}$$

Hence, the unconditional probability in the mixed logit model is simply a weighted average of standard logit probabilities for different values of β_i. Respective weights for each β_i value are provided by the density $f(\beta_i|\theta)$. Thus, the regular logit model is a special case of the mixed logit model where β_i takes a single value b for everyone and $f(\beta) = 1$ for $\beta = b$.

The unconditional likelihood of individual i making the observed series of choices, $(y_{i1}, y_{i2}, ..., y_{i18})$, can be derived from his/her unconditional probabilities for every choice situation t, and is given by

$$L^u_i(\theta^*) = \int \prod_{t=1}^{18} \left(\frac{e^{x_{ijt}\beta_i}}{1 + e^{x_{ijt}\beta_i}} \right) f(\beta_i|\theta) d\beta_i \tag{16}$$

where the inner part is the conditional likelihood given the parameter values

$$L^c_i(\beta_i) = \prod_{t=1}^{18} \frac{e^{x_{ijt}\beta_i}}{1 + e^{x_{ijt}\beta_i}} \tag{17}$$

and the log-likelihood function for the model is $LL(\theta) = \sum_i \ln\, L^u_i(\theta)$.

Since the loglikelihood function depends on unknown parameters, and involves an integral (see equation 16) that cannot be solved analytically, exact maximum likelihood estimation is not possible. Instead a distribution is specified for the density $f(\beta_i|\theta)$ with given values of the parameter set θ. We choose to specify a normal distribution. A value of β_i is drawn from the normal density and in turn standard logit probabilities are calculated for each choice set. The product of the standard logit probabilities are used to calculate the conditional likelihood given in (17). This process is repeated for many draws and the average of the resulting conditional likelihoods is used to approximate the unconditional likelihood:

$$SL_i^u(\theta) = (1/R) \sum_{r=1,\ldots,R} L_i^c(\beta_i^r|\theta) \tag{18}$$

where R is the number of draws, $\beta_i^r|\theta$ is the r^{th} draw from $f(\beta_i|\theta)$, and $SL_i^u(\theta)$ is the simulated likelihood of individual i's sequence of choices.

The simulated log-likelihood function is constructed as $SLL(\theta) = \sum_i \ln SL_i^u(\theta)$ and is maximized to find a consistent estimator of the true parameter vector θ (see Train (2009) for a complete discussion).

Extracting individual-level coefficients In the mixed logit model the coefficients are heterogeneous across the population, and follow a given, random distribution, $f(\beta_i|\theta)$. Revelt and Train (2000) show that using the observed choices of the respondents in the DCE, y, one can construct estimates of individual-specific preferences $h(\beta_i|y;\theta)$ (see also Greene et al., 2005; Hensher et al., 2005, p. 608-610). Effectively, using the respondent's choices one can localize the individual's position in the random distribution of the parameter using Bayes' rule:

$$h\left(\beta_i|y;\theta\right) = \frac{P\left(y_i|\beta_i;\theta\right) f\left(\beta_i|\theta\right)}{P\left(y_i|\theta\right)} \tag{19}$$

where $P\left(y_i|\theta\right) = \int_{\beta_i} P\left(y_i|\beta_i;\theta\right) d\beta_i$ is the choice probability integrated over all possible value of β_i. Since, this integral does not have an analytical solution, again we resort to simulation and for each individual compute the mean of the individual-specific distribution $h\left(\beta_i|y;\theta\right)$.

In particular, we are interested in the individual-specific preferences for the health consequences in scenario III, which can be interpreted as the empirical analogue of the marginal value of health. This allows us to gauge the validity of the stated preference data, by comparing the individual specific stated preferences for health with the reported food choices respondents make (see section 6.2). It also allows us to explore heterogeneity in the marginal value of health, i.e. to what extent do education disparities in the marginal value of health reflect differences in income, time preference, and health (see section 6.4)?

6 Results

6.1 Results on the full sample

Table A4 in the Appendix presents the parameter estimates, estimated separately for each scenario. All attributes have a statistically significant impact on food choice with the expected sign. A higher price and longer preparation time make an alternative less likely to be chosen. On the other hand, tastier and healthier alternatives are more likely to be chosen. The estimated standard deviations are highly significant for the majority of attributes, indicating that there is a considerable amount of heterogeneity in the valuation of these attributes across respondents. In the following sections, we will have a closer look at the sources of this heterogeneity, in particular with respect to educational attainment.

Because coefficients from a mixed logit model are not directly interpretable, we report average marginal effects of each attribute on the choice probability under each scenario in Table 7.[20] For example, when the price of a certain meal is increased from 2 Euros to 10 Euros, the probability of choosing that alternative is reduced by 17 to 24 percentage points, ceteris paribus. Likewise, when calories increase from 800 to 1400, ceteris paribus, the probability of choosing that meal decreases by 16 to 18 percentage points. The price, taste, and calories seem to be the most important food attributes in the baseline scenario I, yet one should be careful with comparing the relative importance of different attributes since the variation in attribute levels is hard to compare (e.g. "Taste" varies from OK to Very Good, while "Price" varies from 2 to 10 Euros).

Comparing across columns, the average marginal effects of the health attributes are higher in absolute terms under scenario II compared to scenario I. Given that scenario II is identical to scenario I except that it contains supplemental health information, it seems that respondents place a higher value on the health attributes when faced with health information. Interestingly, respondents in scenario II place a relatively lower value on the price and taste compared to their peers in scenario I. This suggests that when faced with new health information, individuals are willing to trade off part of the taste and price, but not time, for a healthier meal.

6.2 Assessing the predictive validity of stated preferences

In the mixed logit model all coefficients of the attributes follow a normal distribution, of which the mean and standard deviation are reported in Table A4. As explained in section 5.2, it is possible to localize individuals within this coefficient distribution by applying Bayes' rule (see 19). As such, we can obtain an estimate of the individual-specific coefficient for all attributes. Of particular interest is the individual-level coefficient for "health consequences" in scenario III, which can be interpreted as the individual-specific stated preference for a "Healthy" compared to an "Unhealthy" meal.

As part of wave II, we surveyed the same respondents on their habits with respect to food choices (see section 4). This small food choice questionnaire is a common way to measure dietary intake (Thompson and Subar, 2008, p. 11), and it is established to be predictive for actual food intake (e.g. Willett et al., 1985). Hence, for every individual we observe (i) their stated preferences with respect to healthy meals, and (ii) their reported actual food choices,

[20] An alternative way of transforming the logit coefficients into meaningful quantities is to compute the willingness-to-pay (WTP) for each attribute. Table A5 presents the results. Similar findings appear as when using the average marginal effects: calories and taste seem important attributes in scenario I, and health information raises the WTP for a healthier meal when comparing scenario I and II.

such that we can assess the predictive validity of the stated preference for the reported food choices.

Table 8 shows that the stated preference for hypothetical healthy food options is highly correlated with actual healthy food choices. Those with a higher stated preference for healthy alternatives tend to eat more fruit and vegetables, eat less candies and snacks, and drink less high-sugar sodas. Moreover, those with a higher stated preference for healthy options also eat less processed foods and take-away meals. This evidence builds confidence that the stated preference data has external validity for actual choices that people make (revealed preferences).

The second panel of Table 8 shows that the predictive power does not vary greatly across education groups, suggesting that stated preferences are equally predictive for actual choices irrespective of educational attainment.[21] While we are wary of many potential biases that remain in terms of the exact size of the coefficients from stated preference data (e.g. WTP is notoriously overstated in SP data due to hypothetical bias – Loomis, 2011), this bias is unlikely to differ systematically by educational attainment. Therefore, we conclude that the sign, and the relative magnitude across education groups, of stated preference coefficients represents useful and reliable information.

6.3 Disparities across education groups and the role of health knowledge

In this section we explore heterogeneity in individuals' evaluation of health attributes by level of education. The first three columns of Table 9 provide the average marginal effects, estimated separately for lower educated (first column) and higher educated (second column) individuals.[22] The third column presents the difference between the two marginal effects. In the baseline scenario (scenario I), without any health information, higher educated individuals take the health attributes more into account while making food choices. Differences are statistically significant at 5% level for calorie level 1400, for both levels of saturated fat, and for sodium equal to 1200 mg.[23] Hence, in the absence of health information higher educated individuals care more about the health consequences of a dinner meal.

Now we turn to the question whether higher educated make healthier food choices because they know more about the consequences of unhealthy consumption. The experimental design permits investigating this by comparing the education disparities among respondents randomly assigned to scenario I (without health information) and the education disparities among respon-

[21] Only for fruit, vegetables, and ready-cooked meals, the differences in predictive validity across education groups are statistically significant. However, for fruit and vegetables the predictive validity is greater among the higher educated, while for ready-cooked meals the predictive validity is greater among the lower educated. Hence, no systematic patterns are discernible.

[22] Please refer to Table A6 in Appendix D for the full set of results including the price, taste, and time attributes.

[23] Overconsumption of calories is relative to calorie need. Since lower educated individuals more often have physically demanding job tasks (60% of lower educated compared with only 30% of higher educated in our sample), differences in calorie need may partially explain preferences for calories across educational groups.

dents randomly assigned to scenario II (with health information).

The results show that upon provision of information on recommended daily intake levels and health consequences (scenario II), all differences across educational groups become statistically insignificant. The higher educated hardly change their valuation of health attributes (compare column 2 to column 5). In sharp contrast, we see that the lower educated start to care significantly more about calories, saturated fat and sodium when exposed to health information (compare column 1 to column 4). For example, among lower educated respondents, increasing the sodium content from 900 mg. to 1200 mg. reduces the choice probability by 8.3 percentage points under scenario II, while only with 4.6 percentage points under scenario I. This shows that lower educated respondents are the main beneficiaries of health information, and that education disparities become smaller, and even turn statistically insignificant, when health information is supplied.

6.4 What explains the remaining differences across education groups?

In scenario III we give respondents the most explicit health information available, that is, we tell them whether a meal is "healthy", "health neutral", or "unhealthy". This equalizes all health information across respondents, such that potential education disparities in the value of the "health consequences" attribute are entirely due to a different marginal value of health. The final three columns of Table 9 show that, when exposed to the most explicit health information available, the education disparities in the value of "health consequences" are small and statistically insignificant.[24] This is consistent with our earlier findings that a large part of education disparities in diet are driven by health knowledge.

The results in Table 9 however represent simple differences across educational groups in the value of health. In our final analysis we extract the individual level coefficients for the attribute level "Health consequences = healthy" (see section 5.2), and use this coefficient as the dependent variable in a cross-sectional regression among respondents of scenario III. This allows to further investigate the educational disparities in the value of health, and see how the value of health varies with income, time preference and the level of health.

Table 10 shows that, in contrast to the simple difference of Table 9, conditioning on a standard set of control variables like age, age-squared, gender, and whether on a diet, higher educated individuals do have a significant higher value of health, with corresponding p-value of 0.069. This suggests that, conditional on a standard set of demographic variables, higher educated individuals place a higher value on their health in line with the theoretical prediction. In other words, even with the most explicit health information available, part of the disparities across educational groups seems to remain. Since the standard deviation of the dependent variable is 0.93, moving from lower to higher education represents a 0.13 standard deviation

[24]See Table A6 in Appendix D for the marginal effects of the other product attributes.

increase in the marginal value of health. Table 10 further shows that women place a higher value on health, and the linear and quadratic age coefficients suggest an increasing value of health up to the age of 60, after which it decreases.

Moving across columns shows that while adding a proxy for time preference does not significantly change the coefficient of education, the addition of self-reported health status, and particularly income, renders the coefficient of education insignificant. This suggests that at least part of the education disparities in the value of health derives from increased income and better health status among the higher educated.

7 Robustness Checks

Despite the evidence for the importance of health information from section 6.3, one could argue that individuals start to care more about health attributes when faced with health information only because provision of such information makes health attributes salient, i.e. draws attention to these attributes. In order to investigate this possibility, we generated an additional three-scenario DCE and implemented this among 892 respondents residing in the U.S. via Amazon Mechanical Turk (MTurk).[25] The first two scenarios are identical to the original DCE where we provide respondents with no information and health information. In the third scenario, the choice sets are identical to the first two scenarios, yet we make the time attribute more salient by adding the uninformative sentence "If you spend t minutes on preparing food, you cannot do anything else in those t minutes". Since individuals are randomly assigned to the scenarios, and the information provided is completely useless, any difference between scenario I (no information) and scenario III (time information) in the importance of the time attribute would be due to salience.[26]

Table 11 presents average marginal effects from mixed logit models estimated for each scenario. Column 3 compares the health related attributes under the health information scenario (column 2) with the ones under the no information scenario (column 1). In line with our previous results, respondents attach a higher value to the health attributes when faced with health information. The differences are statistically significant for both 1100 cals. and 1400 cals. levels; and for saturated fat, at 30 gr. level. Importantly, comparing the time information scenario (column 5) with the no information scenario (column 4), the importance of the time attributes does not change significantly (column 6). These results corroborate our main finding from section 6.3 that individuals start to care more about health attributes when given health information, and that the information content itself matters and it is not simply salience that is driving behaviour.

[25] MTurk is an online survey instrument. See Appendix C for details on the exact implementation.

[26] The randomization worked properly, with no differences being significant at 5% in terms of age, gender, race, household size, education, and income across scenarios.

While the mixed logit model provides a flexible way of accounting for unobserved heterogeneity, one may be worried that the results are driven by the distributional assumption for the coefficients. In the baseline analyses we have chosen a Normal distribution. All average marginal effects are however very similar when using either a Log-Normal distribution for the coefficients in a mixed logit setting, or a fixed effects logit model, in which the coefficients are assumed to be fixed (results available upon request). This suggests that distributional assumptions are not driving our results in any way.

The randomization of the order in which the choice sets and the attributes within the choice sets are presented makes it very unlikely that there is any systematic bias in the answers of respondents. Still, there could be a so-called "left-right bias", if respondents systematically prefer the left option (i.e. Meal A). We included an intercept in our Mixed Logit models to analyze this, and the constant term turned out to be insignificant in all three scenario's (results available upon request), suggesting that left-right bias is not present.

Finally, the results may be different across demographic variables such as gender, age, and the size of the household. We find that men, younger individuals, and those living on their own generally care less about the health consequences, and that educational disparities are larger within those population groups. Nonetheless, also among women, individuals above 50, and among those living in larger households we observe educational disparities that become considerably smaller upon the provision of health information. This suggests that while demographic characteristics are important determinants of food choice, our main results hold irrespective of the population subgroup (results available upon request).

8 Discussion

While it is established that health behaviours such as diet contribute to the gap in health and life expectancy across education groups, *why* the higher educated eat healthier diets is unclear (Cutler and Lleras-Muney, 2010). To the best of our knowledge, this is the first attempt to adopt a stated preference Discrete Choice Experiment to understand education disparities in (un)healthy food choices. While somewhat unconventional, and potentially subject to hypothetical response bias, we argue that stated preference data can be complementary to revealed preference data in revealing mechanisms.

We have two main messages. First, a large of part of education disparities in diet derives from differences in health knowledge. Higher educated individuals have superior knowledge on the adverse health consequences of overconsuming salt, fat and calories, and therefore value the health consequences of food more than lower educated individuals. When confronted with health information regarding the health consequences of the health attributes and the recommended allowance, higher educated individuals hardly changed their valuation of the attributes, while lower educated individuals strongly responded. Providing health information substantially reduced the disparities in the valuation of the health attributes, and suggests that health information/health knowledge is a key contributor to education disparities in diet.

The second message that derives from our results is that, even conditional on the most explicit health information (that is, individuals know exactly which meal is healthy and which one is unhealthy), and conditional on the price and time inputs in meal preparation, higher educated individual still have a higher valuation of the health consequences. In other words, conditional on health knowledge, higher educated individuals simply care more about their health. This result is consistent with theory, which also shows a positive dependence of the marginal value of health on educational attainment. Auxiliary analyses suggest that at least part of these differences in the marginal value of health derive from higher incomes and better health status among the higher educated.

One major concern of stated preference data is hypothetical response bias (Loomis, 2011; Hausman, 2012). While this is an unavoidable limitation of any stated preference approach, we argue that the specific criticism applies mostly to the exact size of the estimated coefficients, and does not interfere with our aim of understanding education disparities in diet. Firstly, the mixed logit model we apply in our estimations allows extracting the individual-level stated preferences for healthy food attributes. Correlating these individual stated preferences to actual healthy food choices shows strong predictive power: stated preferences are predictive for revealed preferences. Second, we are careful not to interpret the actual size of the coefficients and implied WTP values, as these are likely to be biased. We do compare the relative magnitudes of the coefficients, which is less problematic since there is no evidence for systematic differences in hypothetical biases across education groups.

The food choice setting we investigate is the choice for a dinner meal. Arguably, the time lapse between the choice and actual consumption of dinner is sufficiently long for our rational decision framework to be applicable. In contrast, for snacks and in fast food contexts, it is established that impulses, self-control, and craving play an important role (e.g. Shiv and Fedorikhin, 1999). In these contexts, our rational model could serve as the 'long-run self' or 'cool state', while an additional 'short-run self' or 'hot state' (Bernheim and Rangel, 2004; Fudenberg and Levine, 2006) would have to be added in order to accommodate the temptations associated with the consumption of snacks and other fast food.

We do not attempt to estimate the causal effect of education on diet. Hence, the education disparities in diet, and variations in health knowledge and the value of health, are likely to reflect variables correlated to educational attainment, such as cognitive and non-cognitive abilities (e.g. Conti et al., 2010). Instead, the analysis in this paper reveals mechanisms through which education, and its correlates, impact on food choices, which is an essential input into any policy discussion on encouraging healthy diets.

The implications of our results are threefold. First, with the caveat that the point estimates should be interpreted with caution, the results allow for some counterfactual simulations to gauge what it requires to make the lower educated eat healthier diets. There exists a widespread notion that healthy meals are expensive, inconvenient, and usually not very tasty. In contrast, unhealthy meals are generally cheap, tasty and convenient. One interesting counterfactual is what the tax should be on a unhealthy, tasty, and convenient meal in order to make lower educated individuals switch to a healthy and inconvenient meal that is not so tasty. Our results suggest that the price of the unhealthy alternative should be at least 6 Euros, representing an enormous 200% additional tax compared with the baseline price of 2 Euros. If healthy meals were more convenient (that is, reducing the preparation time from 50 to 10 minutes), the indifference price would still have to be 4 Euros, which implies a 100% tax. Therefore, our results suggest that while taxes on unhealthy food and the availability of convenient healthy food would make healthier options more attractive for lower educated individuals, the required taxes and time gains would have to be implausibly large to make these options equally attractive as a tasty, cheap, quick and unhealthy meal.

Second, the provision of health information significantly increased the marginal value attached to the health consequences of food, especially among lower educated individuals. The assumption of perfect information is clearly rejected by the data. This is line with the results of Downs et al. (2009), Roberto et al. (2010), Wisdom et al. (2010) and Bollinger et al. (2011), who all find that calorie labelling reduced the amount of calories ordered and consumed. Arguably, disparities in diet that result from lack of information, jointly with the large external medical costs of obesity (Cawley and Meyerhoefer, 2012), and potential self-control issues (Hoch and Loewenstein, 1991), could give a justification for policy intervention. The first movements in this regard are already made (e.g. Guidingstars.com). The findings of this study suggest that health warnings may be a more promising alternative than the introduction of taxes to promote healthy diets among the lower educated, not just in terms of calories, but also in terms of salt and fat, and outside of fast-food settings.

A third implication is that, even with the most explicit health information possible, education disparities in food choices will remain. The empirical finding that conditional on health information, and a standard set of demographic characteristics, higher educated individuals value health consequences more is consistent with the theoretical prediction that the marginal value of health is positively influenced by educational attainment. The disparities in food choice, as well as more general health behaviour, that derive from disparities in the marginal value of health are the result of free, albeit constrained, choices. For the part of disparities that results from disparities in the marginal value of health, policy intervention is unlikely to be successful. In fact, it may even be welfare reducing, unless the deeper causes of variation in the marginal value of health are tackled, which seems a heroic task.

References

Adamowicz, Vic W.L. and Jofre D. Swait (2011), "Discrete choice theory and modeling." In *The Oxford Handbook of the Economics of Food Consumption and Policy* (J.L. Lusk, J. Roosen, and J.F. Shogren, eds.), 119–151, Oxford University Press.

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz (2011), "Personality psychology and economics." *Handbook of the economics of education*, 4.

Barsky, Robert B, Miles S Kimball, F Thomas Juster, and Matthew D Shapiro (1997), "Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement survey." Technical report, National Bureau of Economic Research.

Bernheim, B Douglas and Antonio Rangel (2004), "Addiction and cue-triggered decision processes." *American Economic Review*, 94, 1558–1590.

Bijwaard, Govert and Hans Van Kippersluis (2015), "Efficiency of health investment: Education or intellingence?" Working Paper TI-15-004/V, Tinbergen Institute.

Bliemer, Michiel CJ and John M Rose (2010), "Construction of experimental designs for mixed logit models allowing for correlation across choice observations." *Transportation Research Part B: Methodological*, 44, 720–734.

Bollinger, Bryan, Phillip Leslie, and Alan Sorensen (2011), "Calorie posting in chain restaurants." *American Economic Journal: Economic Policy*, 3, 91–128.

Cawley, John (2004), "An economic framework for understanding physical activity and eating behaviors." *American journal of preventive medicine*, 27, 117–125.

Cawley, John and Chad Meyerhoefer (2012), "The medical care costs of obesity: An instrumental variables approach." *Journal of health economics*, 31, 219–230.

Cawley, John and Christopher J. Ruhm (2011), "The economics of risky health behaviors." In *Handbook of Health Economics* (Thomas G. Mcguire Mark V. Pauly and Pedro P. Barros, eds.), volume 2 of *Handbook of Health Economics*, 95 – 199, Elsevier.

ChoiceMetrics (2012), "Ngene 1.1.1 user manual and reference guide." *Download from: http://www.choice-metrics.com/index.html.*

Chowdhury, Rajiv, Samantha Warnakula, Setor Kunutsor, Francesca Crowe, Heather A. Ward, Laura Johnson, Oscar H. Franco, Adam S. Butterworth, Nita G. Forouhi, Simon G. Thompson, Kay-Tee Khaw, Dariush Mozaffarian, John Danesh, and Emanuele Di Angelantonio (2014), "Association of dietary, circulating, and supplement fatty acids with coronary risk: A systematic review and meta-analysis." *Annals of Internal Medicine*, 160, 398–406.

Conti, Gabriella and Christopher Hansman (2013), "Personality and the education–health gradient: A note on "understanding differences in health behaviors by education"." *Journal of Health Economics*, 32, 480 – 485.

Conti, Gabriella, James Heckman, and Sergio Urzua (2010), "The education-health gradient." *American Economic Review*, 100, 234–38.

Cutler, David M., Edward L. Glaeser, and Jesse M. Shapiro (2003), "Why have Americans become more obese?" *The Journal of Economic Perspectives*, 17, 93–118.

Cutler, David M. and Adriana Lleras-Muney (2010), "Understanding differences in health behaviors by education." *Journal of Health Economics*, 29, 1 – 28.

Cutler, David M., Adriana Lleras-Muney, and Tom Vogl (2011), "Socioeconomic status and health: Dimensions and mechanisms." In *Oxford Handbook of Health Economics* (Sherry Glied and Peter C. Smith, eds.), Oxford University Press.

De Irala-Estevez, Jokin, Margit Groth, Lats Johansson, U Oltersdorf, R Prattala, and Miguel Angel Martínez-González (2000), "A systematic review of socio-economic differences in food habits in europe: consumption of fruit and vegetables." *European Journal of Clinical Nutrition*, 54, 706–714.

Downs, Julie S., George Loewenstein, and Jessica Wisdom (2009), "Strategies for promoting healthier food choices." *The American Economic Review*, 99, pp. 159–164.

Drewnowski, A. (1997), "Taste preferences and food intake." *Annual Review of Nutrition*, 17, 237–253. PMID: 9240927.

Drewnowski, Adam and SE Specter (2004), "Poverty and obesity: The role of energy density and energy costs." *The American Journal of Clinical Nutrition*, 79, 6–16.

Elbel, Brian, Rogan Kersh, Victoria L Brescoll, and L Beth Dixon (2009), "Calorie labeling and food choices: a first look at the effects on low-income people in new york city." *Health Affairs*, 28, w1110–w1121.

Etilé, Fabrice (2011), "Food consumption and health." In *The Oxford Handbook of the Economics of Food Consumption and Policy* (J.L. Lusk, J. Roosen, and J.F. Shogren, eds.), 317–346, Oxford University Press.

FDA (2012), "Sodium in your diet." *Foodfacts from the U.S. Food and Drug Administration.*

Finkelstein, Eric A, Kiersten L Strombotne, Nadine L Chan, and James Krieger (2011), "Mandatory menu labeling in one fast-food chain in king county, washington." *American journal of preventive medicine*, 40, 122–127.

Fudenberg, Drew and David K Levine (2006), “A dual-self model of impulse control.” *The American Economic Review*, 96, 1449–1476.

Galama, Titus and Hans Van Kippersluis (2010), “A theory of socioeconomic disparities in health over the life cycle.” *RAND Working Paper no. 773*.

Giles, Jim (2011), “Social science lines up its biggest challenges.” *Nature*, 470, 18–19.

Greene, William H., David A. Hensher, and John M. Rose (2005), “Using classical simulation-based estimators to estimate individual wtp values.” In *Applications of Simulation Methods in Environmental and Resource Economics* (Riccardo Scarpa and Anna Alberini, eds.), volume 6 of *The Economics of Non-Market Goods and Resources*, 17–33, Springer Netherlands.

Grossman, Michael (1972), “On the concept of health capital and the demand for health.” *Journal of Political Economy*, 80, pp. 223–255.

Hanson, Kara, Barbara McPake, Pamela Nakamba, and Luke Archard (2005), “Preferences for hospital quality in Zambia: Results from a discrete choice experiment.” *Health Economics*, 14, 687–701.

Hausman, Jerry (2012), “Contingent valuation: From dubious to hopeless.” *The Journal of Economic Perspectives*, 26, pp. 43–56.

Hensher, David A. (2006), “How do respondents process stated choice experiments? Attribute consideration under varying information load.” *Journal of Applied Econometrics*, 21, 861–878.

Hensher, David A, John M Rose, and William H Greene (2005), *Applied choice analysis: A primer*. Cambridge University Press.

Hoch, Stephen J. and George F. Loewenstein (1991), “Time-inconsistent preferences and consumer self-control.” *Journal of Consumer Research*, 17, pp. 492–507.

Huber, Joel and Klaus Zwerina (1996), “The importance of utility balance in efficient choice designs.” *Journal of Marketing Research*, 33, pp. 307–317.

Ippolito, Pauline M. (1981), “Information and the life cycle consumption of hazardous goods.” *Economic Inquiry*, 19, 529–558.

Ippolito, Pauline M. and Alan D. Mathios (1990), “The regulation of science-based claims in advertising.” *Journal of Consumer Policy*, 13, 413–445.

Johansson-Stenman, Olof (2011), “Health investments under risk and ambiguity.” In *The Oxford Handbook of the Economics of Food Consumption and Policy* (J.L. Lusk, J. Roosen, and J.F. Shogren, eds.), 438–471, Oxford University Press.

Kamphuis, Carlijn BM, Esther W de Bekker-Grob, and Frank J van Lenthe (2015), "Factors affecting food choices of older adults from high and low socioeconomic groups: a discrete choice experiment." *The American Journal of Clinical Nutrition*.

Kenkel, Donald S. (1991), "Health behavior, health knowledge, and schooling." *Journal of Political Economy*, 99, pp. 287–305.

Kjær, Trine, Mickael Bech, Dorte Gyrd-Hansen, and Kristian Hart-Hansen (2006), "Ordering effect and price sensitivity in discrete choice experiments: Need we worry?" *Health economics*, 15, 1217–1228.

Lakdawalla, Darius and Tomas Philipson (2009), "The growth of obesity and technological change." *Economics & Human Biology*, 7, 283–293.

Lancaster, Kelvin J. (1966), "A new approach to consumer theory." *Journal of Political Economy*, 74, pp. 132–157.

Lancsar, Emily and Jordan Louviere (2008), "Conducting discrete choice experiments to inform healthcare decision making." *PharmacoEconomics*, 26, 661–677.

Leganger, Anette and Pal Kraft (2003), "Control constructs: Do they mediate the relation between educational attainment and health behaviour?" *Journal of Health Psychology*, 8, 361–372.

Loomis, John (2011), "What's to know about hypothetical bias in stated preference valuation studies?" *Journal of Economic Surveys*, 25, 363–370.

Louviere, Jordan J, Terry N Flynn, and Richard T Carson (2010), "Discrete choice experiments are not conjoint analysis." *Journal of Choice Modelling*, 3, 57 – 72.

Malhotra, Aseem (2013), "Saturated fat is not the major issue." *British Medical Journal*, 347.

Mangham, Lindsay J., Kara Hanson, and Barbara McPake (2009), "How to do (or not to do) – designing a discrete choice experiment for application in a low-income country." *Health Policy and Planning*, 24, 151–158.

Mathios, Alan D (2000), "The impact of mandatory disclosure laws on product choices: An analysis of the salad dressing market." *The Journal of Law and Economics*, 43, 651–678.

McFadden, Daniel L. (1973), "Conditional logit analysis of qualitative choice behavior." *Frontiers in Econometrics*, P. Zarembka (ed.), pp. 105–142.

Meara, Ellen (2001), "Why is health related to socioeconomic status?" Technical report, National Bureau of Economic Research.

Michael, Robert T and Gary S Becker (1973), "On the new theory of consumer behavior." *The Swedish Journal of Economics*, 378–396.

NIBUD (2014), "Wat geeft u uit aan voeding?" *Extracted from http://www.nibud.nl/uitgaven/huishouden/voeding.html*.

Oreopoulos, Philip and Kjell G Salvanes (2011), "Priceless: The nonpecuniary benefits of schooling." *The Journal of Economic Perspectives*, 159–184.

Pampel, Fred C., Patrick M. Krueger, and Justin T. Denney (2010), "Socioeconomic disparities in health behaviors." *Annual Review of Sociology*, 36, 349–370.

Picone, Gabriel, Frank Sloan, and Jr. Taylor, Donald (2004), "Effects of risk and time preference and expected longevity on demand for medical tests." *Journal of Risk and Uncertainty*, 28, 39–53.

Revelt, David and Kenneth Train (2000), "Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier." *Department of Economics, UCB*.

Roberto, Christina A, Peter D Larsen, Henry Agnew, Jenny Baik, and Kelly D Brownell (2010), "Evaluating the impact of menu labeling on food choices and intake." *American Journal of Public Health*, 100, 312.

Rose, John M. and Michiel C.J. Bliemer (2013), "Sample size requirements for stated choice experiments." *Transportation*, 40, 1021–1041.

Saffer, Henry (2014), "Self-regulation and health." Working Paper 20483, National Bureau of Economic Research.

Schultz, Theodore W. (1975), "The value of the ability to deal with disequilibria." *Journal of Economic Literature*, 13, pp. 827–846.

Shiv, Baba and Alexander Fedorikhin (1999), "Heart and mind in conflict: The interplay of affect and cognition in consumer decision making." *Journal of Consumer Research*, 26, pp. 278–292.

Steptoe, Andrew, Tessa M. Pollard, and Jane Wardle (1995), "Development of a measure of the motives underlying the selection of food: The food choice questionnaire." *Appetite*, 25, 267 – 284.

Thompson, Frances E and Amy F Subar (2008), "Dietary assessment methodology." In *Nutrition in the Prevention and Treatment of Disease* (Ann M. Coulston, Carol J. Boushey, and Mario G. Ferruzzi, eds.), volume 3 of *Nutrition in the Prevention and Treatment of Disease*, 3–39, Elsevier.

Thompson, Tommy G and Ann M Veneman (2005), "Dietary guidelines for Americans 2005." *United States Department of Health and Human Services and United States Department of Agriculture.*

Train, Kenneth E (2009), *Discrete choice methods with simulation*. Cambridge university press.

U.S. Department of Agriculture and U.S. Department of Health and Human Services (2010), *Dietary Guidelines for Americans*, 7th edition, Washington, DC edition. U.S. Government Printing Office.

Van Rossum, C.T.M., H.P. Fransen, J. Verkaik-Kloosterman, E.J.M Buurma-Rethans, and M.C. Ocke (2011), "Dutch national food consumption survey 2007-2010 : Diet of children and adults aged 7 to 69 years."

Variyam, Jayachandran N (2008), "Do nutrition labels improve dietary outcomes?" *Health Economics*, 17, 695–708.

Wansink, Brian and Pierre Chandon (2006), "Can "low-fat" nutrition labels lead to obesity?" *Journal of marketing research*, 43, 605–617.

Willett, Walter C., Laura Sampson, Meir J. Stamper, Bernard Rosner, Christopher Bain, Jelia Witschi, Charles H. Hennekens, and Frank E. Speizer (1985), "Reproducibility and validity of a semiquantitative food frequency questionnaire." *American Journal of Epidemiology*, 122, 51–65.

Wisdom, Jessica, Julie S. Downs, and George Loewenstein (2010), "Promoting healthy choices: Information versus convenience." *American Economic Journal: Applied Economics*, 2, pp. 164–178.

Tables

Table 1: Example choice set Scenario I (no health info.)

	Meal A	Meal B
Price	2 Euro	6 Euro
Time	10 min	30 min
Taste	OK	Very good
Calories	1400 calories	800 calories
Saturated Fat	10 gram	30 gram
Sodium	1200 mg	900 mg

Table 2: Example choice set Scenario II (health info.)

	Meal A	Meal B
Price	2 Euro	6 Euro
Time	10 min	30 min
Taste	OK	Very Good
Calories	1400 calories	800 calories
Saturated Fat	10 gram	30 gram
Sodium	1200 mg	900 mg

The recommended intake for a dinner is 800 calories, 10 gram saturated fat, and 900 milligram sodium.

Table 3: Example choice set Scenario III (explicit health info.)

	Meal A	Meal B
Price	6 Euro	10 Euro
Time	50 min	30 min
Taste	Very Good	Good
Health consequences	Unhealthy	Health Neutral

Table 4: Distribution of respondent characteristics across scenarios

	Scenario I		Scenario II		Scenario III	
Respondent characteristics	No. of resp.	Mean	No. of resp.	Mean	No. of resp.	Mean
Age	974	51.25	917	50.94	978	51.89
Male	974	47.5%	917	47.7%	978	46.9%
Education=High	974	36.6%	917	33.5%	978	29.7%
Health=Good	736	23.7%	683	22.4%	725	20.4%
Health knowledge=High	974	44.8%	917	46.3%	978	44.3%
Income=High	974	50.2%	917	51.9%	978	47.2%
Future orientation=High	974	41.5%	917	44.4%	978	42.9%
Currently on (any kind of) diet	974	15.3%	917	16.2%	978	13.9%
Frequently go to a restaurant	974	0.31%	917	0.98%	978	0.41%
Frequently eat fruits	974	81.93%	917	81.35%	978	80.98%
Frequently eat vegetables	974	94.35%	917	95.97%	978	96.22%
Frequently eat candy	974	35.32%	917	33.26%	978	34.25%
Frequently drink soda	974	31.11%	917	28.03%	978	29.35%
Frequently snack	974	16.12%	917	15.16%	978	13.50%

Notes: High education is having completed higher vocational education or university with a diploma. Good health is self reported health as very good or excellent (measured in a separate wave, hence fewer observations). High health knowledge is having answered more health knowledge questions correctly than the median respondent. High income is having an income level above the median in the sample. High future orientation indicates (strong) disagreement with the statement "Nowadays, a person has to live pretty much for today and let tomorrow take care of itself". Frequently is defined as at least 3-4 times per week.

Table 5: Dietary habits and health knowledge by educational attainment

	Low educated	High educated
Dietary habits		
Frequently eat fruits	79.33%	85.62%
Frequently eat vegetables	94.73%	97.06%
Frequently eat candy	32.46%	37.99%
Frequently drink soda	30.85%	26.86%
Frequently snack	14.30%	16.16%
Health knowledge		
Health knowledge=High	38.83%	57.71%
Mean number of correct answers to health questions	7.54	8.61
No. of respondents	1,916	953

Note: We define frequently as at least 3-4 times per week. High health knowledge is having answered more than the median number of questions correctly.

Table 6: Health and dietary knowledge items: Percentage of respondents reporting the correct answer

	Low educated	High educated
Even in the absence of overweight, poor diet is associated with cardiovascular disease, hypertension, and type 2 diabetes. (True)	89.35%	91.50%
There are health benefits of limiting those foods which contain high levels of added sugar such as soft drinks, cordial and biscuits. (True)	87.42%	92.24%
Overconsumption of sodium can lead to hypertension and heart diseases. (True)	77.09%	87.09%
Depending on age and physical activity level, experts recommend that an adult male should consume around 2500 calories, and an adult female should consume around 2000 calories, per day. (True)	68.89%	78.80%
Consumption of fruits and vegetables is associated with reduced risk of many chronic diseases. (True)	68.68%	79.01%
Sodium is a form of sugar. (False)	64.41%	81.43%
Meat, chicken, fish and eggs should make up the largest part of our diet. (False)	64.87%	79.01%
Experts advise to eat a variety of vegetables, especially dark green, red and orange vegetables. (True)	66.49%	65.06%
Choosing wholemeal bread provides no health benefits. (False)	62.00%	71.14%
A high intake of saturated fat can protect against heart diseases. (False)	49.32%	64.74%
According to experts around 30% of the calories in a day should come from saturated fat. (False)	36.01%	50.05%
For a healthy adult it is recommended to limit sodium intake at dinner to at most 1500 mg. (False)	19.26%	20.99%
No. of resp	1,916	953

Table 7: Average marginal effects calculated from mixed logit models with all normally distributed coefficients

	No health info.	Health info.	Explicit health info.
Price=6 euro	−0.0838***	−0.0756***	−0.0948***
	(0.0069)	(0.0066)	(0.0057)
Price=10 euro	−0.2065***	−0.1703***	−0.2365***
	(0.0138)	(0.0136)	(0.0153)
Time=30 min.	−0.0141**	−0.0210***	−0.0425***
	(0.0065)	(0.0052)	(0.0050)
Time=50 min.	−0.0897***	−0.0860***	−0.1398***
	(0.0131)	(0.0124)	(0.0100)
Taste=good	0.1062***	0.0816***	0.0558***
	(0.0060)	(0.0066)	(0.0044)
Taste=very good	0.1718***	0.1323***	0.1251***
	(0.0090)	(0.0095)	(0.0075)
Calories=1100 cals.	−0.0722***	−0.0985***	
	(0.0040)	(0.0054)	
Calories=1400 cals.	−0.1564***	−0.1851***	
	(0.0090)	(0.0111)	
Saturated fat=20 gr.	−0.0340***	−0.0372***	
	(0.0056)	(0.0065)	
Saturated fat=30 gr.	−0.0790***	−0.0985***	
	(0.0064)	(0.0071)	
Sodium=1200 mg.	−0.0534***	−0.0794***	
	(0.0045)	(0.0060)	
Sodium=1500 mg.	−0.1126***	−0.1524***	
	(0.0074)	(0.0093)	
Health conseq.=neutral			0.3336***
			(0.0090)
Health conseq.=healthy			0.4541***
			(0.0132)
No. of observations	17,532	16,506	17,604
No. of respondents	974	917	978

Note: Omitted categories: Price: 2 euro, Time: 10 min., Taste: OK, Calories: 800 cals., Saturated fat: 10 gr., Sodium: 900 mg., Health: Unhealthy. Standard errors are obtained by using 100 bootstrap iterations. * p<0.1, ** p<0.05, *** p<0.01. Standard errors are in parentheses.

Table 8: Predictive validity of stated preferences for actual choices

Dependent variable	Model I SP Health	Model II SP Health	SP Health*Education
How often do you consume:			
Fruit	0.2430***	0.2285***	0.0412**
	(0.0387)	(0.0393)	(0.0199)
Vegetables	0.2496***	0.2336***	0.0449**
	(0.0395)	(0.0401)	(0.0204)
Soda	−0.1402***	−0.1291***	−0.0296
	(0.0361)	(0.0367)	(0.0184)
Snacks	−0.2463***	−0.2465***	0.0007
	(0.0371)	(0.0378)	(0.0187)
Candy	−0.1063***	−0.1164***	0.0261
	(0.0357)	(0.0364)	(0.0181)
Home cooked meal	0.1662***	0.1670***	−0.0020
	(0.0372)	(0.0380)	(0.0189)
Ready meal at home	−0.1235***	−0.1430***	0.0487**
	(0.0375)	(0.0383)	(0.0190)
Take-away food	−0.1297***	−0.1356***	0.0156
	(0.0397)	(0.0404)	(0.0202)
Number of observations	978	978	

Note: The independent variable "SP Health" is the vector of individual-specific coefficients on the attribute level "Healthy" from the mixed logit model, estimated for scenario III (see section 5.2). In Model II we include, apart from "SP Health", the independent variable "SP Health*Education" which refers to the interaction term between "SP Health" and "Education". We use these independent variables to explain observed food choices given in the column "Dependent variable" among the respondents of the explicit health information scenario, by using ordered probit regressions. Dependent variables take the values 1: Never, 2: Less than once a week, 3: 1-2 times per week, 4: 3-4 times per week, 5: 5-6 times per week, 6: Everyday. Standard errors are presented in parentheses. * p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01

Table 9: Average marginal effects calculated from mixed logit models by education groups

	No health info.			Health info.			Explicit health info.		
	Low educated	High educated	Δ	Low educated	High educated	Δ	Low educated	High educated	Δ
Calories=1100 cals.	−0.0644***	−0.0810***	−0.0166	−0.0909***	−0.1081***	−0.0172			
	(0.0066)	(0.0081)	(0.0106)	(0.0066)	(0.0090)	(0.0108)			
Calories=1400 cals.	−0.1382***	−0.1815***	−0.0433**	−0.1719***	−0.2030***	−0.0311			
	(0.0118)	(0.0164)	(0.0204)	(0.0129)	(0.0166)	(0.0202)			
Saturated fat=20 gr.	−0.0254***	−0.0514***	−0.0260**	−0.0367***	−0.0429***	−0.0062			
	(0.0069)	(0.0092)	(0.0117)	(0.0076)	(0.0110)	(0.0140)			
Saturated fat=30 gr.	−0.0666***	−0.0982***	−0.0316**	−0.1013***	−0.1010***	0.0003			
	(0.0077)	(0.0120)	(0.0142)	(0.0106)	(0.0112)	(0.0155)			
Sodium=1200 mg.	−0.0463***	−0.0684***	−0.0220**	−0.0832***	−0.0710***	0.0121			
	(0.0062)	(0.0079)	(0.0098)	(0.0071)	(0.0091)	(0.0111)			
Sodium=1500 mg.	−0.1064***	−0.1247***	−0.0183	−0.1572***	−0.1321***	0.0251			
	(0.0097)	(0.0132)	(0.0159)	(0.0111)	(0.0128)	(0.0170)			
Health=neutral							0.3287***	0.3383***	0.0096
							(0.0225)	(0.0154)	(0.0274)
Health=healthy							0.4431***	0.4786***	0.0354
							(0.0234)	(0.0190)	(0.0295)
No. of observations	11,124	6,408		10,980	5,526		12,384	5,220	
No. of respondents	618	356		610	307		688	290	

Note: Omitted categories: *Calories*: 800 cals. *Saturated fat*: 10 gr. *Sodium*: 900 mg. *Health*: Unhealthy. The standard errors for the difference of the marginal effects are obtained using 500 bootstrap iterations. * p<0.1, ** p<0.05, *** p<0.01. Standard errors are in parentheses.

Table 10: Determinants of the value of health

	Base	W/ Income	W/ Future	W/ Health	Full	Base r/s
Education	0.1184*	0.0831	0.1084*	0.1165	0.0819	0.1329*
	(0.0651)	(0.0656)	(0.0656)	(0.0758)	(0.0765)	(0.0756)
Age	0.0199**	0.0168*	0.0197*	0.0134	0.0116	0.0127
	(0.0101)	(0.0101)	(0.0101)	(0.0121)	(0.0121)	(0.0121)
Age-squared	−0.0002*	−0.0001	−0.0002	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Male	−0.1669***	−0.1781***	−0.1652***	−0.2232***	−0.2310***	−0.2206***
	(0.0599)	(0.0597)	(0.0599)	(0.0681)	(0.0679)	(0.0683)
Diet	0.0716	0.0610	0.0650	0.1226	0.1052	0.1126
	(0.0861)	(0.0857)	(0.0862)	(0.0999)	(0.0999)	(0.1001)
Income		0.2093***			0.1758**	
		(0.0602)			(0.0695)	
Future			0.0800		0.0525	
			(0.0603)		(0.0692)	
Health				0.1880**	0.1690**	
				(0.0861)	(0.0860)	
No. of observations	978	978	978	725	725	725

Note: Dependent variable is the vector of individual-specific coefficients on the attribute level "Healthy" from the mixed logit model, estimated for scenario III (see section 5.2). Column "Base" refers to the baseline specification which includes demographic variables, education, age and gender, and diet status. Columns "W/ Income", "W/Future", "W/Health" add income, measure of future orientation and self-reported health status to the base specification, respectively. Column "Full" is the full specification which includes all controls at the same time. Since self-reported health is not available for everyone, column "Base r/s" estimates the base model for the sub-sample of respondents whose health status is available. See section 4.2 for all variable descriptions. * p<0.1, ** p<0.05, *** p<0.01. Standard errors are in parentheses.

Table 11: Average marginal effects for the MTurk sample

	No info.	Health info.	Δ	No info.	Time info.	Δ
Price=6 euro	−0.1425***	−0.1291***	0.0133	−0.1425***	−0.1180***	0.0244*
	(0.0103)	(0.0171)	(0.0188)	(0.0103)	(0.0108)	(0.0133)
Price=10 euro	−0.2788***	−0.2385***	0.0403	−0.2788***	−0.2437***	0.0350
	(0.0232)	(0.0403)	(0.0456)	(0.0232)	(0.0228)	(0.0326)
Time=30 min.	−0.0349***	−0.0394***	−0.0045	−0.0349***	−0.0416***	−0.0067
	(0.0070)	(0.0089)	(0.0116)	(0.0070)	(0.0070)	(0.0100)
Time=50 min.	−0.1643***	−0.1342***	0.0301	−0.1643***	−0.1844***	−0.0201
	(0.0220)	(0.0188)	(0.0290)	(0.0220)	(0.0219)	(0.0317)
Taste=good	0.0990***	0.0831***	−0.0159	0.0990***	0.0982***	−0.0008
	(0.0081)	(0.0102)	(0.0134)	(0.0081)	(0.0084)	(0.0119)
Taste=very good	0.2054***	0.2093***	0.0039	0.2054***	0.2241***	0.0187
	(0.0159)	(0.0237)	(0.0274)	(0.0159)	(0.0164)	(0.0227)
Calories=1100 cals.	−0.0404***	−0.0693***	−0.0288**	−0.0404***	−0.0501***	−0.0096
	(0.0073)	(0.0111)	(0.0133)	(0.0073)	(0.0078)	(0.0101)
Calories=1400 cals.	−0.1166***	−0.1561***	−0.0394**	−0.1166***	−0.1396***	−0.0230
	(0.0117)	(0.0176)	(0.0189)	(0.0117)	(0.0140)	(0.0170)
Saturated fat=20 gr.	−0.0241***	−0.0292***	−0.0050	−0.0241***	−0.0234***	0.0008
	(0.0081)	(0.0113)	(0.0136)	(0.0081)	(0.0074)	(0.0118)
Saturated fat=30 gr.	−0.0470***	−0.0759***	−0.0288**	−0.0470***	−0.0514***	−0.0044
	(0.0104)	(0.0115)	(0.0144)	(0.0104)	(0.0120)	(0.0158)
Sodium=1200 mg.	−0.0469***	−0.0362***	0.0107	−0.0469***	−0.0318***	0.0151
	(0.0068)	(0.0065)	(0.0099)	(0.0068)	(0.0060)	(0.0093)
Sodium=1500 mg.	−0.0878***	−0.0898***	−0.0020	−0.0878***	−0.0855***	0.0023
	(0.0093)	(0.0107)	(0.0143)	(0.0093)	(0.0082)	(0.0126)
No. of observations	5,256	5,436		5,256	5,436	
No. of respondents	292	302		292	302	

Note: Omitted categories: Price: 2 euro, Time: 10 min., Taste: OK, Calories: 800 cals., Saturated fat: 10 gr., Sodium: 900 mg. Estimates based upon mixed logit models with all normally distributed coefficients. Standard errors (in parentheses) are obtained by using 100 bootstrap iterations. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendices

A First-order conditions

Associated with the Hamiltonian (equation 7) we have the following conditions:

$$\begin{aligned}
\frac{\partial q_A(t)}{\partial t} &= -\frac{\partial \Im}{\partial A} \Rightarrow \\
\frac{\partial q_A(t)}{\partial t} &= -r q_A(t) \Leftrightarrow \\
q_A(t) &= q_A(0) e^{-rt}, \qquad (20)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial q_H(t)}{\partial t} &= -\frac{\partial \Im}{\partial H} \Rightarrow \\
\frac{\partial q_H(t)}{\partial t} &= q_H(t)\lambda(E)\frac{\partial d}{\partial H} - \frac{\partial U}{\partial H} e^{-\rho t} - q_A(0) w(t;E)\left[-\frac{\partial s}{\partial H}\right] e^{-rt} \qquad (21)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \Im}{\partial X_h} &= 0 \Rightarrow \\
\frac{\partial U}{\partial C_h} e^{-\rho t} &= q_A(0) \frac{p_{X_h}(t)}{\partial C_h / \partial X_h} e^{-rt} + q_H(t)\lambda(E)\frac{\partial d}{\partial C_h}, \qquad (22)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \Im}{\partial \tau_{C_h}} &= 0 \Rightarrow \\
\frac{\partial U}{\partial C_h} e^{-\rho t} &= q_A(0) \frac{w(t;E)}{\partial C_h / \partial \tau_{C_h}} e^{-rt} + q_H(t)\lambda(E)\frac{\partial d}{\partial C_h} \qquad (23)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \Im}{\partial X_u} &= 0 \Rightarrow \\
\frac{\partial U}{\partial C_u} e^{-\rho t} &= q_A(0) \frac{p_{X_u}(t)}{\partial C_u / \partial X_u} e^{-rt} + q_H(t)\lambda(E)\frac{\partial d}{\partial C_u}, \qquad (24) \\
\frac{\partial \Im}{\partial \tau_{C_u}} &= 0 \Rightarrow \\
\frac{\partial U}{\partial C_u} e^{-\rho t} &= q_A(0) \frac{w(t;E)}{\partial C_u / \partial \tau_{C_u}} e^{-rt} + q_H(t)\lambda(E)\frac{\partial d}{\partial C_u} \qquad (25)
\end{aligned}$$

Equation (21) gives the co-state equation for the marginal value of health (see footnote 5) and its solution (8). Equations (22) and (23) provide the first-order condition for healthy consumption (9). Similarly, equations (24) and (25) provide the first-order condition for unhealthy consumption (11).

B Experimental design

B.1 Selection of attribute levels

All attributes have three evenly-spaced levels, which draws a balance between ease of cognition for respondents, but still permits detecting non-linearities (Mangham et al., 2009). While the levels should be realistic, the range should be as wide as possible to avoid that respondents ignore the attributes because of little variation in the levels (Hensher, 2006).

Regarding **Taste** and **Time** we followed Kamphuis et al. (2015) in establishing the levels, which were tested in pilots. They realized in pilots that using levels such as "non-tasty" for the attribute Taste would render all other attributes meaningless. Apparently, all individuals require a meal that is at least "OK" in terms of taste before starting to consider other attributes. While the attribute "Time" was split into travel time and preparation time by Kamphuis et al. (2015), both of these turned out be relatively unimportant, such that we decided to merge them into one attribute, and determined the levels on basis of the sum of travel and preparation time.

For **Price**, the lowest level, 2 Euros, is consistent with a cheap but still realistic home-prepared dinner – the average price per person for a meal in a 2-person household is 2.37 Euro (NIBUD, 2014). The middle category, 6 Euros, reflects either a more luxurious home-prepared meal or a 'ready-to-serve' processed meal from the supermarket – processed meals at Dutch supermarkets typically cost between 3 and 6 Euros.[27] The top-level, 10 Euros, would correspond to very luxurious ingredients in case of a home-made meal, or more typically a standard take-away meal – the average price of take-away or home-delivery meals is around 10 Euros.[28]

Regarding the health attributes calories, saturated fat, and sodium we chose the recommended level as the lowest level, since the Dutch population is known to overeat all of these ingredients, on average (Van Rossum et al., 2011). The middle level coincides roughly with the average intake, while the highest level is still realistic and falls within the 95% percentile of the regular Dutch diet. For **Calories**, we choose the levels 800 calories, 1100 calories, and 1400 calories. The daily recommended intake is 2000 calories for women, and 2500 calories for men. Given that dinner on average makes up for 36% of total calorie consumption (Van Rossum et al., 2011), the recommended caloric intake for dinner is about 720 (women) and 900 (men). Taking an average implies an average recommended caloric intake of 800 for dinner, which comprises our lowest level. 1100 calories corresponds to an average dinner, while 1400 calories represents a high-calorie dinner, but is still realistic and corresponds roughly to the 95th percentile (total calories for men in the 95th percentile are around 3,700, of which 36% is between 1,300 and 1,400 calories for dinner, see Van Rossum et al., 2011).

For **Saturated fat**, we choose the levels 10 gram, 20 gram, and 30 gram. The recommended

[27] Author's calculations on basis of the website of the largest Dutch supermarket Albert Heijn: www.ah.nl

[28] Author's calculations from the main Dutch food delivery website www.thuisbezorgd.nl.

daily intake of saturated fat is 24 gram for an average 2200 total calorie intake (Thompson and Veneman, 2005), yet saturated fat is highly overconsumed. At dinner, 42% of fat is consumed (Van Rossum et al., 2011). 42% of 24 gram implies around 10 gram, which forms our lowest level. To generate wide, evenly-spaced, but still realistic levels the remaining levels are set at 20 and 30 gram (the 95% percentile for Dutch men is 56 gram of saturated fat per day, Van Rossum et al., 2011). For **Sodium** the daily recommended intake is currently 2400 milligram (FDA, 2012). Around 36% of salt is consumed for dinner, which implies (2400*0.36=) around 900 milligram, which is set as our lowest level. Average daily intake for Dutch men and women is around 3500 milligram of sodium, which corresponds to around 1200 milligram at dinner, which comprises our middle level. Using evenly spaced levels, the highest level is correspondingly set at 1500 milligram, which is still realistic.

B.2 Design inputs and priors

In this subsection the experimental design is presented, with a discussion of the choices regarding input and priors.

Scenarios I and II We generate a design with two alternatives (alt1 and alt2), with in total 90 choice sets (rows) divided in 5 blocks. We use a Multinomial Logit Model (mnl) to generate the design. While ideally the design reflects the ultimate model to be estimated, the generation of 90 choice sets using a panel mixed logit specification with Bayesian priors is infeasible given the computational complexity (Bliemer and Rose, 2010, p. 732; Rose and Bliemer, 2013). Instead, we opt for the cross-sectional multinomial logit model with Bayesian priors to generate our design. While this seems like a large departure from a panel mixed logit model, numerous case studies and simulations show that there is only a slight loss in efficiency, and the performance of cross-sectional multinomial logit is better than cross-sectional mixed logit if the true model is panel mixed logit (Bliemer and Rose, 2010).[29]

The algorithm minimizes the median D-error, uses row swapping, and we set the convergence criterion such that convergence is achieved if no improvement is found in 60 minutes. Since one iteration takes around 0.5 seconds, this implies that 60 minutes handles around 7200 iterations.

Since we have an unlabeled design, all parameters are generic across the alternatives, and there is no constant specified (Hensher et al., 2005, p. 151). The prior values of the parameters are set using Bayesian priors using 1000 Halton draws from a Normal distribution (see Table A1 for an overview). The mean values are, where possible, based on Kamphuis et al. (2014). For

[29] Bliemer and Rose (2010) explain this finding by noting that cross-sectional multinomial logit assumes all observations are from the same person, while cross-sectional mixed logit assumes that all observations are from distinct individuals. The panel mixed logit model is in between, where a single respondent answers a subset of the questions. In our case the subset of questions answered by a given respondent is pretty large, 18, so theoretically the panel mixed logit is better approximated by the cross-sectional multinomial logit rather than the cross-sectional mixed logit model.

Table A1: Prior specification for scenario I and II

Price – Base 10 Euros	
2 Euros	$N(0.64; 0.068)$
6 Euros	$N(0.32; 0.034)$
Taste – Base "OK"	
"Very Good"	$N(0.06; 0.012)$
"Excellent"	$N(0.26; 0.052)$
Time – Base 50 minutes	
10 minutes	$N(0.4; 0.043)$
30 minutes	$N(0.2; 0.021)$
Calories – Base 1400	
800 calories	$N(0.2; 0.021)$
1100 calories	$N(0.1; 0.011)$
Sodium – Base 1500 mg	
900 mg	$N(0.1; 0.011)$
1200 mg	$N(0.05; 0.005)$
Saturated Fat – Base 30 gram	
10 gram	$N(0.1; 0.011)$
20 gram	$N(0.05; 0.005)$

Note: $N(\mu; \sigma)$ refers to a normal distribution with mean μ and standard deviation σ.

price they use a continuous specification with coefficient -0.08. Using 10 Euro as the baseline category, this translates into a prior of 0.64 for 2 Euro and 0.32 for 6 Euro. The standard deviations of the priors are set such that the order of the levels $U[price = 2] > U[price = 6] > U[price = 10]$ is maintained in 99.9% of the cases. The critical value of the normal distribution corresponding to 99.9% certainty is $z_{0.999} = 3.1$. Since it seems plausible that the standard deviation is proportional to the mean, for price this implies finding the minimum value k that satisfies

$$0.64 - 3.1 \times \frac{0.64}{k} > 0.32 - 3.1 \times \frac{0.32}{k} > 0$$

which gives $k = 9.4$. Therefore, the standard deviation for 2 Euro is set at $0.64/9.4 = 0.068$ and for 6 Euro it is set at $0.32/9.4 = 0.034$.

With respect to time, Kamphuis et al. (2015) used the separate attributes travel time (coefficient -0.02) and preparation time (coefficient 0.00). We have one attribute for time, and decided to take the average of the coefficients, -0.01. Taking 50 minutes as baseline category, 10 minutes has a prior mean of -0.4, while 30 minutes has a prior of -0.2. With respect to taste, we could directly incorporate the estimates of 0.26 and 0.06, respectively. The standard deviations are set in a similar way as for price.

The priors for the three attributes calories, sodium and saturated fat are more uncertain, and we cannot base them on previous literature. Our prior was that calories are deemed more important compared to saturated fat and sodium, since apart from the health consequences calories may be associated with a weight control motive (Cawley, 2004; Lakdawalla and Philipson, 2009). Therefore, the priors for calories are set slightly higher than the ones for sodium and saturated fat, with standard deviations set following the practice for price.

Scenario III Scenario III contains 4 attributes, each with 3 levels. This implies that the full factorial requires $3^4 = 81$ choice sets. Using 90 choice sets divided into 5 blocks of 18 implies that for scenario III we are able to identify the full factorial, if necessary. Since scenario III is very similar to the study by Kamphuis et al. (2015), we set the mean of our Bayesian prior values equal to their parameter estimates, while standard deviations are again set such that sign reversals are avoided, and the ordering of attribute levels is maintained, in 99.9% of the cases.

The priors for price, time, and taste are set equal to their levels in scenario I. The priors for health consequences are mean 1.17 and standard deviation 0.244 for "healthy" and mean 0.24 and standard deviation 0.05 for "health neutral". All standard deviations are set such that the logical order of the attribute levels is maintained in 99.9% of the cases, as explained for the coefficient of price in scenario I and II.

B.3 Introductory text

Scenario I In this questionnaire we try to understand your food choice behaviour. Please respond as honestly as possible and avoid socially desirable answers.

Imagine it is a typical day and you are going to have a usual dinner at home. Depending on your habits, you can cook, you can order take out, or you can buy ready-made food from the grocery store. Eating out is no option. If you often visit a restaurant, we ask you to imagine a day where you would eat dinner at home. In the remainder of this questionnaire we will present you 18 times two meals, and we would like to know: "which of these two meals would you eat regularly (at least twice a week)?"

The two meals differ in terms of their taste, price, convenience, calories, saturated fat, and sodium. These attributes are explained below.

1. Taste: How does the meal taste? Is it (i) OK (taste not distinctly good or bad), (ii) Good (pretty good taste) or (iii) Very Good (very good taste)?

2. Price: How much does the meal cost per person? Think about the total cost of the ingredients if it is a self-made dish. Consider the total amount you pay if it is take-out or ready-made food. It will take the levels (i) 2 Euros, (ii) 6 Euros, or (iii) 10 Euros.

3. Convenience: How much time does it take before the meal is on your plate – including both travel and preparation time? It will take the levels (i) 10 minutes, (ii) 30 minutes, or (iii) 50 minutes.

4. Calories: What is the energy content of the meal in terms of calories? We distinguish between (i) 800 calories, (ii) 1100 calories, and (iii) 1400 calories.

5. Saturated Fat: How many grams of saturated fat does the meal contain? We distinguish between (i) 10 gram, (ii) 20 gram, and (iii) 30 gram.

6. Sodium: How many grams of sodium does the meal contain? We distinguish between (i) 900 milligram, (ii) 1200 milligram, and (iii) 1500 milligram.

Assume all other characteristics of the meals are the same, e.g. they are equally filling, contain equal amount of carbohydrates and proteins, biological and fair-trade, etc. Below you find an example. You don't have to answer this one.

Scenario II Scenario II is identical to scenario I except that the attribute descriptions are supplemented with some health information:

4. Calories: What is the energy content of the meal in terms of calories? Intake of too much calories can lead to overweight, cardiovascular diseases, and type II diabetes. The average recommended intake for calories is around 800 for a dinner meal. We distinguish between (i) 800 calories, (ii) 1100 calories, and (iii) 1400 calories.

5. Saturated Fat: How many grams of saturated fat does the meal contain? Eating too many grams of saturated fat is bad for one's health and can lead to cardiovascular diseases and a high cholesterol. The recommended intake for saturated fat at dinner is at most 10 gram. We distinguish between (i) 10 gram, (ii) 20 gram, and (iii) 30 gram.

6. Sodium: How many grams of sodium does the meal contain? Salt contains sodium. Eating too much sodium is bad for health and can lead to high blood pressure and cardiovascular disease. The recommend intake for dinner is at most 900 milligram. We distinguish between (i) 900 milligram, (ii) 1200 milligram, and (iii) 1500 milligram.

Scenario III Scenario III follows scenario I yet replaces the individual attributes **Calories**, **Saturated fat**, and **Sodium** by the attribute **Health consequences**:

4. Health consequences: How healthy the alternative? We distinguish between a meal that (i) healthy (associated with reduced risk of disease), (ii) health neutral, and (iii) unhealthy (associated with increased risk of disease).

C Design for Amazon Mechanical Turk

The design of Amazon Mechanical Turk survey is the same as the original survey design as explained in the previous section, apart from some slight differences. First of all, since we are only interested in identifying the main effects, we generated an efficient design which picks the 18 – instead of 90 as in the original design – most informative choice sets, based on the criteria explained in section 3.3. After careful consideration of the differences between the Netherlands and the United States in terms of price level and consumption habits, we decided to keep all attribute levels as they are, and only replaced euros with dollars.

We generated four different scenarios, each with 18 identical choice sets. The first two scenarios are identical to the original design where we provide respondents in the first scenario ("no information") with no information, and in the second scenario ("health information") with health information on the recommended daily amounts of calories, saturated fat and sodium. In the third scenario ("time information"), we supplemented all choice sets with the uninformative sentence "If you spend 10/30/50 minutes on preparing food, you can not do anything else in those 10/30/50 minutes". Table A2 illustrates an example choice set. The idea behind the time information scenario is making the time attribute salient by giving the respondents a sentence about time, but keeping the information content of the sentence at zero. Comparison of the three scenarios will tell us the driving source behind our main result: salience or information.

In the last scenario, we replaced the name of attribute **Taste** with **Sensory Appeal** to see whether it makes a difference to describe sensory appeal of the meal in broader terms. We described this new attribute in the introductory text as the following:

Table A2: Example choice set MTurk Scenario III

	Meal A	Meal B
Price	2 dollars	6 dollars
Time	10 min	50 min
Taste	Very good	OK
Calories	1400 calories	1100 calories
Sodium	1500 mg	1200 mg
Saturated Fat	10 gram	30 gram

If you spend 10(50) minutes on preparing food, you cannot do anything else in those 10(50) minutes.

1. Sensory appeal: How does the meal taste, look and smell? Is it (i) OK (not distinctly good or bad) (ii) Good (iii) Very good?

To monitor whether our respondents are indeed paying attention and not speeding through questions, we added two attention checks to our survey – one after the 9th choice set, and one, at the end, after the 18th choice set. The first attention check is shown in Table A3, and takes the form of a choice set with an objectively dominant alternative. Meal B is cheaper, tastier, and takes less time to prepare. Health related attributes are kept the same for both meals to avoid heterogeneity in dietary preferences leading to controversy over which alternative is dominant. Respondents who chose Meal A are not shown the rest of the survey and their responses have been discarded.

Table A3: Attention check for Scenario I

	Meal A	Meal B
Price	10 dollars	6 dollars
Time	30 min	10 min
Taste	OK	Good
Calories	1100 calories	1100 calories
Sodium	1200 mg	1200 mg
Saturated Fat	20 gram	20 gram

The second attention check tests whether respondents read the instructions, and goes as follows:

Recent research on decision making shows that choices are affected by context.

Differences in how people feel, their previous knowledge and experience, and their environment can affect choices. To help us understand how people make decisions, we are interested in information about you. Specifically, we are interested in whether you actually take the time to read the directions; if not, some results may not tell us very much about decision making in the real world. To show that you have read the instructions, please ignore the question below ***about*** *how you are feeling and instead check only the "none of the above" option as your answer. Thank you very much.*

Please check all words that describe how you are currently feeling.

- *Interested*
- *Distressed*
- *Excited*
- *Upset*
- *Strong*
- *Guilty*
- *Scared*
- *Hostile*
- *Enthusiastic*
- *Proud*
- *Irritable*
- *Alert*
- *Ashamed*
- *Inspired*
- *Nerveous*
- *Determined*
- *Attentive*
- *Jittery*
- *Active*
- *Afraid*
- *None of the above*

Respondents who fail to choose “none of the above” or choose other other options besides none of the above are screened out of the survey and their responses are discarded.

At the end of the survey, we collected background information on the respondents’ gender, race, level of education and income, household size.

MTurk respondents come from 190 different countries, India and United States being the two biggest pools. Thinking that the US, rather than India, is more similar to the Netherlands in terms of price levels and life styles, we chose to restrict our pool of respondents to individuals residing in the US. To keep the original and MTurk samples as similar as possible, we did not let respondents below the age of 18 participate in our survey. Each respondent is randomly assigned to one of the four scenarios, where (s)he answers 18 randomly presented choice sets. We prevented the same individual from participating in more than one scenario. Moreover respondents who fail an attention check were not allowed to come back again.

D Additional Tables

Table A4: Estimation results from mixed logit models with all normally distributed coefficients

		No health info.	Health info.	Explicit health info.
Price – Baseline is 2 Euro				
6 euro	Mean coefficient	-0.516***	-0.483***	-0.682***
		(0.031)	(0.032)	(0.033)
	Std. dev. of coefficient	0.383***	0.365***	0.189**
		(0.052)	(0.051)	(0.088)
10 euro	Mean coefficient	-1.341***	-1.121***	-1.797***
		(0.068)	(0.068)	(0.074)
	Std. dev. of coefficient	1.190***	1.167***	1.511***
		(0.059)	(0.059)	(0.056)
Preparation time – Baseline is 10 minutes				
30 min.	Mean coefficient	-0.087***	-0.134***	-0.306***
		(0.029)	(0.031)	(0.031)
	Std. dev. of coefficient	0.133*	0.187**	0.064
		(0.069)	(0.076)	(0.069)
50 min.	Mean coefficient	-0.537***	-0.535***	-0.987***
		(0.051)	(0.054)	(0.055)
	Std. dev. of coefficient	0.935***	0.967***	1.152***
		(0.048)	(0.049)	(0.046)
Taste – Baseline is "OK"				
Good	Mean coefficient	0.661***	0.524***	0.404***
		(0.032)	(0.033)	(0.032)
	Std. dev. of coefficient	0.129**	0.057	0.004
		(0.057)	(0.053)	(0.057)
Very good	Mean coefficient	1.066***	0.848***	0.908***
		(0.043)	(0.043)	(0.041)
	Std. dev. of coefficient	0.744***	0.675***	0.554***
		(0.039)	(0.043)	(0.048)
Calories – Baseline is 800 cals.				
1100 calories	Mean coefficient	-0.447***	-0.632***	
		(0.028)	(0.030)	
	Std. dev. of coefficient	0.026	0.013	
		(0.049)	(0.050)	
1400 calories	Mean coefficient	-0.967***	-1.179***	
		(0.041)	(0.044)	
	Std. dev. of coefficient	0.753***	0.784***	
		(0.040)	(0.042)	
Saturated Fat – Baseline is 10 gram				
20 gram	Mean coefficient	-0.210***	-0.239***	

		(0.030)	(0.031)	
	Std. dev. of coefficient	0.043	0.054	
		(0.043)	(0.048)	
30 gram	Mean coefficient	-0.488***	-0.629***	
		(0.031)	(0.034)	
	Std. dev. of coefficient	0.243***	0.323***	
		(0.057)	(0.052)	
Sodium – Baseline is 900 milligram				
1200 mg.	Mean coefficient	-0.330***	-0.508***	
		(0.028)	(0.030)	
	Std. dev. of coefficient	0.016	0.002	
		(0.046)	(0.045)	
1500 mg.	Mean coefficient	-0.695***	-0.971***	
		(0.035)	(0.037)	
	Std. dev. of coefficient	0.561***	0.609***	
		(0.044)	(0.042)	
Health consequences – Baseline is "Unhealthy"				
Health neutral	Mean coefficient			2.611***
				(0.061)
	Std. dev. of coefficient			0.168**
				(0.067)
Healthy	Mean coefficient			3.771***
				(0.093)
	Std. dev. of coefficient			1.182***
				(0.056)
No. of observations		17,532	16,506	17,604
No. of respondents		974	917	978

Table A5: WTP estimates derived from mixed logit models with non-random price coefficient

	No health info.	Health info.	Explicit health info.
Time=10 min.	2.90	3.74	4.30
	(0.27)	(0.31)	(0.20)
Time=30 min	2.64	2.59	2.87
	(0.24)	(0.27)	(0.17)
Taste=good	4.29	3.77	1.94
	(0.23)	(0.25)	(0.15)
Taste=very good	6.84	6.23	4.16
	(0.32)	(0.33)	(0.19)
Calories=800 cals.	6.23	8.83	
	(0.32)	(0.44)	
Calories=1100 cals.	3.15	3.90	
	(0.21)	(0.25)	
Saturated fat=10 gr.	3.10	4.69	
	(0.24)	(0.32)	
Saturated fat=20 gr.	1.78	3.13	
	(0.20)	(0.25)	
Sodium=900 mg.	4.91	7.27	
	(0.30)	(0.42)	
Sodium=1200 mg.	2.35	3.26	
	(0.21)	(0.25)	
Health conseq.=neutral			11.94
			(0.33)
Health conseq.=healthy			17.52
			(0.49)
No. of observations	17,532	16,506	17,604
No. of respondents	974	917	978

Note: Estimates obtained from a mixed logit model where we treat attribute "price" as continuous and non-random. The WTP is the ratio of the coefficient on the relevant attribute to the coefficient on the price attribute (e.g. Train, 2009). Omitted categories: Time: 50 minutes., Taste: OK., Calories: 1400 cals., Saturated fat: 30 gr., Sodium: 1500 mg., Health: Unhealthy. Standard errors are in parentheses.

Table A6: Average marginal effects calculated from mixed logit models by education groups

	No health info.			Health info.			Explicit health info.		
	Low educated	High educated	Δ	Low educated	High educated	Δ	Low educated	High educated	Δ
Price=6 euro	-0.0788***	-0.0883***	-0.0095	-0.0745***	-0.0756***	-0.0011	-0.0927***	-0.0897***	0.0030
	(0.0095)	(0.0107)	(0.0144)	(0.0086)	(0.0116)	(0.0147)	(0.0085)	(0.0114)	(0.0140)
Price=10 euro	-0.2132***	-0.1878***	0.0254	-0.1648***	-0.1834***	-0.0185	-0.2460***	-0.2270***	0.0190
	(0.0201)	(0.0223)	(0.0305)	(0.0177)	(0.0255)	(0.0316)	(0.0219)	(0.0264)	(0.0358)
Time=30 min.	0.0002	-0.0310***	-0.0312***	-0.0122	-0.0365***	-0.0243*	-0.0400***	-0.0458***	-0.0058
	(0.0080)	(0.0089)	(0.0117)	(0.0095)	(0.0104)	(0.0139)	(0.0062)	(0.0084)	(0.0105)
Time=50 min.	-0.0628***	-0.1146***	-0.0519**	-0.0602***	-0.1267***	-0.0665**	-0.1167***	-0.1897***	-0.0729***
	(0.0136)	(0.0213)	(0.0247)	(0.0153)	(0.0233)	(0.0274)	(0.0136)	(0.0229)	(0.0266)
Taste=good	0.0939***	0.1231***	0.0292**	0.0719***	0.1014***	0.0295*	0.0502***	0.0707***	0.0205
	(0.0073)	(0.0101)	(0.0121)	(0.0109)	(0.0105)	(0.0157)	(0.0184)	(0.0085)	(0.0203)
Taste=very good	0.1587***	0.1812***	0.0224	0.1210***	0.1457***	0.0248	0.1115***	0.1478***	0.0363**
	(0.0125)	(0.0156)	(0.0200)	(0.0129)	(0.0167)	(0.0218)	(0.0130)	(0.0121)	(0.0173)
Calories=1100 cals.	-0.0644***	-0.0810***	-0.0166	-0.0909***	-0.1081***	-0.0172			
	(0.0066)	(0.0081)	(0.0106)	(0.0066)	(0.0090)	(0.0108)			
Calories=1400 cals.	-0.1382***	-0.1815***	-0.0433**	-0.1719***	-0.2030***	-0.0311			
	(0.0118)	(0.0164)	(0.0204)	(0.0129)	(0.0166)	(0.0202)			
Saturated fat=20 gr.	-0.0254***	-0.0514***	-0.0260**	-0.0367***	-0.0429***	-0.0062			
	(0.0069)	(0.0092)	(0.0117)	(0.0076)	(0.0110)	(0.0140)			
Saturated fat=30 gr.	-0.0666***	-0.0982***	-0.0316**	-0.1013***	-0.1010***	0.0003			
	(0.0077)	(0.0120)	(0.0142)	(0.0106)	(0.0112)	(0.0155)			
Sodium=1200 mg.	-0.0463***	-0.0684***	-0.0220**	-0.0832***	-0.0710***	0.0121			
	(0.0062)	(0.0079)	(0.0098)	(0.0071)	(0.0091)	(0.0111)			
Sodium=1500 mg.	-0.1064***	-0.1247***	-0.0183	-0.1572***	-0.1321***	0.0251			
	(0.0097)	(0.0132)	(0.0159)	(0.0111)	(0.0128)	(0.0170)			
Health=neutral							0.3287***	0.3383***	0.0096
							(0.0225)	(0.0154)	(0.0274)
Health=healthy							0.4431***	0.4786***	0.0354
							(0.0234)	(0.0190)	(0.0295)
No. of observations	11,124	6,408		10,980	5,526		12,384	5,220	
No. of respondents	618	356		610	307		688	290	

Note: Omitted categories: *Calories*: 800 cals. *Saturated fat*: 10 gr. *Sodium*: 900 mg. *Health*: Unhealthy. The standard errors for the difference of the marginal effects are obtained using 500 bootstrap iterations. * p<0.1, ** p<0.05, *** p<0.001. Standard errors are in parentheses.