July 2015

Cognition for dinner

Does financially impaired cognitive function affect healthy meal choice?

Arik Beremzon
Student nr: 416202ab

Supervisor: Dr. Hans van Kippersluis
Co-reader: Dr. Jan Stoop
Degree: Msc. Economics
Specialization: Health Economics

Erasmus Universiteit Rotterdam
Erasmus School of Economics

Abstract

Neglecting health consequences when establishing dietary habits can lead to poor health outcomes. Earlier research has argued that counterproductive behavioral outcomes may be caused by resource scarcity, forcing individuals to shift cognitive resources towards dealing with immediate expenses and neglecting decision–making in other avenues as well as increasing overall cognitive load. We examine how impaired cognitive function affects the decision–making process of meal choice through an online experiment. We experimentally prime richer and poorer individuals to consider varying levels of immediate financial expenses and examine how that affects their meal choice by means of a discrete choice (stated choice) experiment. Our results indicate weak mixed evidence suggesting that poverty impedes cognitive function. We do not find evidence of reduced cognitive function negatively affecting healthy meal choice among the poor relative to the rich. A power analysis indicates that our research is underpowered and we highlight potential issues with our experimental approach.

I would like to thank Dr. Hans van Kippersluis for his excellent support and guidance throughout the creation of this thesis. Dr. Jan Stoop for co–reading the thesis. Dr. Hale Koç for access to MTurk and her support in using it. Dr. Laura Matzen for providing me with her materials for cognitive testing. Dr. Marcel Jonker and Dr. Eldar Shafir for comments and suggestions regarding the experimental setup. Dr. Arne Risa Hole for his assistance with the estimation methodology. My mom and dad for allowing me to act like a hermit as I was writing this.

Here be dragons. . .

Introduction

Dietary habits form an important determinant of various health-outcomes, with prevalence of type 2 diabetes mellitus, gallbladder disease, coronary heart disease, high blood cholesterol level, high blood pressure, or osteoarthritis directly attributable to obesity or excessive weight in U.S. adults (Must et al., 1999). Furthermore, according to the U.S. Department of Health and Human Services (2011) obesity trends follow a clear socioeconomic gradient, such that the burden of disease falls immoderately on the poor.

From a social sciences perspective, explaining the link between poverty and dietary habits has turned out to be challenging: previous attempts have focused on limited access to nutrient–dense food by lower–income households (e.g. Rose, 1999), the inverse relationship between energy-density (MegaJoule / Kilogram) and energy cost ($ / MegaJoule) (Basiotis, 1992; Drewnowski & Specter, 2004), the effect of the education gradient in health (Cawley & Ruhm, 2011), and several hypotheses involving health knowledge (Grossman, 1972; Meara, 2001). Links have also been established between non–cognitive (personality) traits, such as increased self–regulation, and health behaviours (Conti & Hansman, 2013; Saffer, 2014).

Our research delves into the yet unexplored area of cognitive function and dietary habits. By experimentally varying cognitive load among a sample of individuals and subsequently eliciting preferences using a discrete choice experiment (DCE), we hope to shed light on a potential relationship between cognitive function and meal choice. Building upon the work of Mani, Mullainathan, Shafir, and Zhao (2013a), who have shown that poverty impedes cognitive function we furthermore attempt to elucidate the relationship between poverty, cognitive function, and meal choice by conducting a subgroup analysis wherein we examine food choice preferences over dichotomous levels of cognitive function and poverty. Though we are unaware of any existing literature tying together cognitive function and dietary habits, there exists a body of economic research on dietary habits and assorted factors.

Basiotis (1992) formulated and empirically validated a framework wherein household members faced with diminishing income opted for less expensive foods in order to maintain their energy intake. The hypothesis put forth in the framework linked obesity and poverty by noting that energy-density of foodstuffs (MegaJoule / Kilogram) and their energy–cost ($/MegaJoule) are inversely related which facilitates overconsumption. As food costs diminish, their dietary energy–density rises leading to a possible increase of total energy intake. While it may be tempting to argue that poor dietary habits are a consequence of diminishing income, the relationship does not appear to be as simple for other, more costly health behaviours such as smoking and excessive consumption of alcohol. Therefore, other behavioral characteristics may play a role.

Indeed, Cawley and Ruhm (2011) have shown that the education gradient in health behaviours is closely associated with the education gradient in health, independent of income effects. Furthermore, higher education is associated with several personality traits such as the ability to delay immediate gratification in exchange for a future reward (self-regulation), perceived level of autonomy over one's life and life choices (internal locus of control) and self efficiacy, which are all associated with practising healthy lifestyles.

Tangent to health education, health knowledge is perceived to be an important determinant of lifestyle habits. Grossman (1972) and Meara (2001) argue in support of the "productive efficiency" hypothesis, which states that better educated individuals are able to more efficiently integrate existing knowledge into their decision making. A second hypothesis states that higher educated individuals possess higher "allocative efficiency", meaning that they are better at choosing inputs into their health investment. Kenkel (1991), Meara (2001), and D. M. Cutler and Lleras-Muney (2010) have provided support for the allocative efficiency hypothesis by demonstrating a positive association between education disparity and knowledge on the health consequences of smoking, drinking and exercise; though these differences account only for a limited portion of education differences.

To summarize, the majority of current economic research has focused on environmental or individual characteristics of the poor, with mixed support for various mechanisms. The common thread of the reviewed literature is that it is founded in the theoretical notion that the decision maker acts as a *homo economicus*: an agent maximizing their objective function given a set of constraints in a calculated, unemotional fashion. Mullainathan and Thaler (2000) explain that traditionally economists have argued that due to market forces or evolution, only rational agents should survive; or, that at least the effects of the quasi–rational are irrelevant. The authors argue that such views do not hold up to empirical scrutiny, demonstrating several examples in the domains of finance and savings which cannot be explained by the standard model of economics. Instead, they argue that limited brain power and time play an important role in decision making. Additionally, a lack of willpower can cause individuals to forego an apparently optimal choice (Mullainathan & Thaler, 2000). According to Duflo (2006) boundaries on willpower, self–interest, and rationality need to be incorporated into economic theory. She argues that this is particularly true for the poor, who face different trade–offs than the average person.

In an attempt to understand why, in the presence of poverty, shortcomings in decision making can lead to counterproductive outcomes, Shah, Mullainathan, and Shafir (2012) argue that *scarcity* plays an important role. They argue that resource scarcity creates a different mindset, leading to different ways of dealing with problems and decisions. Firstly, mundane expenses such as groceries or rent seem more urgent because financial scarcity entails that these expenses cannot be easily met. The consequence is that decision makers divert more attention to such issues. This mechanism is independent of the circumstances of poverty, nor does it assume anything about the behavioral characteristics of the poor (Shah et al., 2012). It is simply a consequence of having less resources. The second part of their theory states that as some issues become more pressing, other issues become neglected. As the human cognitive system has limited capacity (Baddeley, Hitch, & Bower, 1974; Luck & Vogel, 1997; Miller, 1956; Neisser, 1976), diverting mental resources in order to deal with budgetary matters decreases the mental resources allocated to choice and decision making in other avenues. This manifests in behaviors such as overborrowing. Because individuals are focused on pressing expenses today they fail to properly account for the future costs brought on by high–interest loans (Shah et al., 2012).

While Shah et al. (2012) showed that scarcity reallocates cognitive resources from one issue to another, another possibility is that scarcity creates cognitive load, thereby worsening cognitive function. For instance, cognitive load may impair individuals' ability to figure out the optimal borrowing rates. Mani et al. (2013a) have shown that financial concerns lead to reduced cognitive function in poorer individuals. They experimentally primed individuals to consider varying levels of unexpected financial expenses. When the financial scenario was relatively "easy", there was no notable difference in cognitive function between poorer and richer individuals. When the financial scenario was relatively "hard", the poor performed worse than the rich. Subsequently they performed a field experiment among sugarcane farmers in India. Their results have shown that farmers perform better on tests of cognitive function after harvest, when they experience less financial pressure.

Our research builds upon Mani et al. (2013a) and Shah et al. (2012). Our hypothesis is that decreased cognitive function due to financial pressure may manifest itself as poor decision making with respect to healthy meal choice. Specifically, we expect that poor individuals who face relatively "hard" financial constraints will not only perform worse on tests of cognitive function than richer individuals facing similar constraints, but we also expect them to assign less importance to the health consequences attribute of food choice during a DCE. In contrast, we expect to see no significant difference in either cognitive function or meal choice between richer and poorer individuals when faced with relatively "easy" financial constraints. To test our hypothesis, we attempt to replicate the research of Mani et al. (2013a) wherein individuals are randomized and primed to think about everyday financial situations. One group is presented with a relatively "easy" set of hypothetical financial scenario's, while the other group is presented with a relatively "hard" set of hypothetical financial scenario's.

The setup of the DCE closely follows Koç and Van Kippersluis (2015), whereby individuals are asked to choose between two unlabelled meals taking into account taste, price, preparation time and health consequence attributes. As noted by the authors, the advantage of using stated preferences over revealed preferences lies within the ability to discern explicitly between the various attributes. Unlike a revealed choice approach, where assumptions must be made about interactions between attributes[1], in a DCE the choice sets and attributes have been explicitly defined.

The potential policy implications entail that policy makers should focus their efforts on prevention of income shocks and lifestyle management among the poor. If poor decision making is indeed a result of cognitive processes, then policies aimed at altering environmental factors, such as providing more health information or taxing unhealthy food items more heavily, may prove to be less effective than previously believed. Instead focus should be placed on alleviating the cognitive burden of poverty. Our contribution to the literature consists in combining the study of scarcity and the use of a DCE. In doing so, this is the first study to measure the effect of experimentally induced financial scarcity constrained cognitive function on explicitly formulated attributes regarding healthy meal choice.

The remainder of this thesis is structured as follows: In the next section we present the methodology of our experimental setup. Next we discuss the data, and perform an initial exploratory analysis of our sample. After that we analyze differences in cognitive performance between subgroups. Following this we discuss the methodology and results pertaining to our empirical model. Afterward we conduct a final discussion of our results and conclude with the takeaways of our research as well as potential directions for future research.

[1] An example would be that some individuals may implicitly assume that healthier food is less tasty, thus the correlation between the healthiness and taste attributes makes it difficult to discern their true marginal effects on the likelihood of choosing one over the other

Experimental Survey Design and Materials

The aim of the online experiment is twofold. Firstly, we attempt to corroborate the results of Mani et al. (2013a) by demonstrating that similarly sized financial challenges lead to different cognitive performance between poorer and richer individuals. The second part examines the differences in meal choice between richer and poorer individuals when faced with experimentally induced easier or tougher financial conditions.

Priming and Cognitive performance

Upon initiation of the survey, individuals are randomly assigned to either an "easy" or "hard" hypothetical financial scenario. By touching upon monetary issues, the aim is to trigger the participants to consider their own financial situation. The hypothetical scenarios used are duplicated from Mani et al. (2013a). However, unlike Mani et al. (2013a) we do not perform our experiment in a controlled laboratory environment. Instead, our experiment was administered through the Internet; hence, there was no accounting for the behavior of individuals while taking the survey. Thus, in order to insure that individuals do not take breaks during tasks, our experiment is significantly shorter compared to Mani et al. (2013a). Our aim was to keep the duration of the entire experiment under 15 minutes. This means that in contrast to Mani et al. (2013a) we employ two hypothetical scenarios rather than four and we conduct one experiment instead of four. Mani et al. (2013a) note that the second, third, and fourth experiment are consistent with the results from their first experiment, thus there is no reason to believe that we incur a significant loss by excluding additional experiments. The first easy (hard) hypothetical scenario reads:

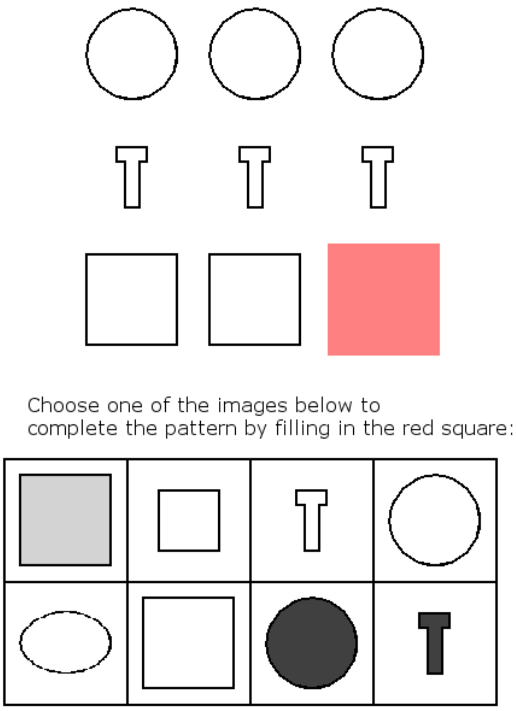
"*The economy is going through difficult times; suppose your employer needs to make substantial budget cuts. Imagine a scenario in which you received a 5% (15%) cut in your salary. Given your situation, would you be able to maintain roughly your same lifestyle under those new circumstances? If not, what changes would you need to make? Would it impact your leisure, housing, or travel plans?*"

And the second scenario reads:

"*Imagine that an unforeseen event requires of you an immediate $200 ($2,000) expense. Are there ways in which you may be able to come up with that amount of money on a very short notice? How would you go about it? Would it cause you long–lasting financial hardship? Would it require you to make sacrifices that have long-term consequences? If so, what kind of sacrifices?* "

After viewing each scenario and while considering their response, the participants' cognitive function was evaluated using a computer–based task. The task consisted of an analog to the Raven's Progressive Matrices (RPM). Due to material constraints we are unable to afford the official (RPM). Instead, we use matrices developed by Matzen et al. (2010). In their paper, the authors analyze the relations underlying Raven's (2000) matrices and subsequently design a program which generates similar matrices with normed properties. We randomly selected 16 matrices from a set of around 800 matrices provided by Matzen et al. (2010) and conducted a pilot with randomized ordering of the matrices among 43 participants. After each matrix was ranked by score, we selected the median six matrices in order to ensure that the tasks were neither too easy nor too difficult. The test consists of a series of shapes, with one shape missing. Participants are asked to identify which shape completes the pattern (fig. 1):

Figure 1. Example of a Raven (2000)–like test as generated by Matzen et al. (2010)



Notes: This particular example was used to ensure comprehension of the task, it is not one of the six matrices used in the testing section. See appendix A for all matrices.

The Raven's test is a common component in IQ tests intended to measure "fluid intelligence". Fluid intelligence is the ability to think logically and solve novel situations, independent of acquired knowledge (Engle, Tuholski, Laughlin, & Conway, 1999; Hunt, 2010). This is different from "crystallized intelligence", which is the ability to use learned skills, knowledge, and experience for problem solving.

To ensure that individuals were paying attention and understood the task, we included a written instruction as well as the *two* simplest matrices (e.g. fig. 1) generated by Matzen et al. (2010) before presenting the hypothetical scenarios. Individuals who failed to identify correct answers in *both* practice matrices were removed from the sample. Furthermore, to avoid potential sequencing effects, the order of matrices was randomized across the panel. The final design can be found in appendix A.

We deviate from Mani et al. (2013a) by excluding the cognitive control task, which involves recording individual response times to differing stimuli. This decision follows the fact that we're unable to guarantee the integrity of timing data because we cannot observe whether the individual pays attention to the screen nor can we correct for possible inaccuracies resulting from the respondent's hardware and software combination. Furthermore, the use of a cognitive control task has attracted considerable scrutiny, with Wicherts and Scholten (2013) arguing that there could be possible ceiling effects among the richer participants.

Discrete Choice Experiment

A Discrete Choice Experiment (DCE) is the end result of consumer theory, experimental design theory, random utility theory (RUT) and econometric analysis (de Bekker-Grob, Ryan, & Gerard, 2012). Fundamentally it is grounded on the assumption that individiuals will choose to maximize their utility given a set of discrete alternatives and constraints (Ben-Akiva & Lerman, 1985). The effects of the alternatives are described according to Lancaster's (1966) theory of value. The theory states that an indivdiual derives utility from the attributes of a bundle of goods rather than the goods themselves. However, individual choice may be affected by unobserved variables such as socioeconomic characteristics of the respondents, omitted attributes, measurement error, and heterogeneity of preferences (Hanemann & Kanninen, 1999). To address these inconsistencies RUT is used to analyze the discrete choice. RUT links the deterministic behavioral model with a statistical model by representing the indirect utility function U as the sum of deterministic choice V and an error term ε (Manski, 1977; McFadden, 1974b):

$$U_{njk} = V_{njk} + \varepsilon_{njk} \tag{1}$$

Where individual $n \in \{1, 2, \ldots, N\}$ obtains utility U from choosing alternative $j \in \{A_1, A_2, \ldots, A_N\}$ over choice set $k \in \{1, 2, \ldots, N\}$.

Setting of our design. The setting of our design is identical to Koç and Van Kippersluis (2015, p.9). Respondents are asked to choose a dinner meal. Dinner is the largest meal source of daily nutrient intake (D. Cutler, Glaeser, & Shapiro, 2003). Furthermore, dinner is arguably a better indicator of dietary habits between population groups with differing income and education gradients, as individuals in all ranges of income and education may indulge in unhealthy snacking, even though some individuals may snack more often than others. In order to avoid having to control for the attitudes which respondents may have towards the consumption of snacks, dinner was chosen as a more appropriate option. In an attempt to avoid biased responses depending on the time of day or what participants ate recently, the question was phrased in a manner to elicit which meals respondents would eat at least twice a week. The full introductory text is displayed in appendix B.

An example of a choice set is shown in fig. 2. Respondents are asked to choose between two unlabelled alternatives, in order to avoid the effects of intrinsic preferences on the choice.[2] We also did not include an opt–out alternative in order to avoid loss of data. Arguably, given that we do not label the alternatives, it is unlikely that a respondent would rather forego the opportunity to have dinner than choose between the two alternatives based solely on the attributes and levels.

Figure 2. Example of a choice set containing two alternatives

7	Meal A	Meal B
Price	\$2	\$6
Preparation time	10 minutes	30 minutes
Taste	Very Good	OK
Healthiness	Healthy	Unhealthy

Notes: The choice set contains a dominant alternative (meal A) which we used as an attention check. It was included as the 7th choice set between 12 generated choice sets. This particular choice set was therefore discarded before analysis. All choice sets can be found in appendix B.

Attributes, levels and priors. We follow Koç and Van Kippersluis (2015, p.10) in our development of attributes and levels. The attributes consist of (I) taste, (II) monetary cost, (III) preparation time, and (IV) health consequence. These attributes also coincide with the four factors most typically endorsed in the Food Choice Questionnaire (Steptoe, Pollard, & Wardle, 1995, p.282). Copying Koç and Van Kippersluis (2015) we also erred on the side of caution and 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 stimulate that the choice is made under a ceteris paribus condition.

All attributes consist of three levels. This allows for the detection of non–linearities while minimizing the cognitive processing requirements of the respondent (Mangham, Hanson, & McPake, 2009). According to Hensher (2006) the range of the levels should be

[2]If we had labelled the alternatives, e.g. "burgers" and "'meatloaf", regardless of the attribute levels, individuals are likely to select a choice based upon their experience of consuming either food item.

wide enough for individuals to perceive an actual difference in the values, such that they do not ignore the attribute.

In determining the levels of taste and time, we follow Kamphuis, de Bekker-Grob, and van Lenthe (2015) who determined that taste levels such as "non–tasty" resulted in a dominated choice and thus other attributes were ignored. People require a meal that is at least "OK" tasting. The other levels for taste are "good" and "very good". Kamphuis et al. (2015) furthermore distinguish between cooking time and preparation time, but find that this difference does not matter. Thus, as Koç and Van Kippersluis (2015) we consider time to include all time necessary to prepare the meal, setting levels at 10, 30 and 50 minutes.

For the price, we converted the Euro denominated prices from Koç and Van Kippersluis (2015, p.43) to United States Dollars.[3] The resulting price levels of $2, $6, and $10 reflect meals which run the gamut from cheap to a homemade meal using luxurious ingredients. Note that these prices reflect single portions.

With respect to the health consequences attribute, Koç and Van Kippersluis (2015) argue that the provision of health information affects the marginal value attached to the health attribute. Because we want to minimize the interaction between cognitive performance and cognitive processing of different levels of health information, our levels correspond to the most explicit health information scenario in Koç and Van Kippersluis (2015, p.44; p.46): "unhealthy", "health neutral", and "healthy". As such, individual choice concerning health consequences should not be influenced by the ability to interpret food label attributes such as the amount of calories or fats. Prior values follow the mixed panel logit results of Koç and Van Kippersluis (2015, pp.49-50). An overview of attributes, levels, and priors is displayed in table 1

[3] While it would be more accurate to investigate the price of a meal in the US, we note that the purchasing power parity factor is 1.1 according to the World Bank (`http://data.worldbank.org/indicator/PA.NUS.PPPC.RF`) and the exchange rate has been around 1.10-1.15 USD/EUR over 2015. Furthermore, as prices differ across states, in part due to varying tax policies, we would need to investigate each state separately and derive a mean estimate.

Table 1
Attributes, values, and priors specification

Price – Base: \$2	
\$6	$N(-0.682; 0.033)$
\$10	$N(-1.797; 0.074)$
Taste – Base: “OK”	
“Good”	$N(0.404; 0.032)$
“Very Good”	$N(0.908; 0.041)$
Time – Base: 10 minutes	
30 minutes	$N(-0.306; 0.031)$
50 minutes	$N(-0.987; 0.055)$
Health consequence – Base: “Unhealthy”	
“Health Neutral”	$N(2.611; 0.061)$
“Healthy”	$N(3.771; 0.093)$

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

Experimental design. We chose a fractional factorial design with 12 choice sets presented to each respondent.[4] An efficient design was generated using Ngene 1.1.2 (ChoiceMetrics, 2014).[5] The efficiency of the design is achieved by maximizing the D–optimality criterion, which seeks to minimize the determinant of the asymptotic variance–covariance (AVC) matrix (ChoiceMetrics, 2014; Train, 2009). We use a cross–sectional multinomial logit (MNL) model to generate the design set to 250 Halton draws. This allows us to use both a conditional logit and mixed panel logit model in our analysis with only minor loss of efficiency. Koç and Van Kippersluis (2015, p.44) note that ideally the design should reflect the model, but that using a mixpanel logit model with Bayesian priors is too computationally intensive according to Bliemer and Rose (2010).[6]

[4]According to Hanson, McPake, Nakamba, and Archard (2005) boredom sets in at 18 choice sets. A full factorial design would require $3^4 = 81$ choicesets, which is far too large for any single individual to complete. Furthermore, since our individuals are primed, our aim is to conduct the DCE as fast as possible before the priming effect dissipates. Blocking the experiment into chunks requires additional statistical guidelines on how to allocate the choice sets into blocks (Lancsar & Louviere, 2008) and would require a sample size that is beyond our material limits. Finally, personal correspondence between the author and Koç and Van Kippersluis revealed that two-way interactions are not present, thus it is possible to estimate just the eight primary effects.

[5]The code is attached in appendix C.

[6]The cross–sectional multinomial logit assumes that all observations are from the same person, while the cross–sectional mixed logit assumes that all responses are from different individuals. The panel mixed logit lies in between: because we do not block our design, each individual answers all questions but at the same time we allow for heterogeneity between individuals.

Data and Descriptive Statistics

Population and Data Collection

The studied population consists of United States individuals aged 18 and over. By limiting our choice to citizens of the U.S. we do not have to correct poverty measures for cross–country differences. Secondly by randomly sampling from one population we reduce the heterogeneity of unobserved characteristics as compared to sampling from multiple populations. Furthermore, sufficient English proficiency can be assumed to persist within the sample.[7] An added benefit of an adult (≥ 18 years) population is that individuals are more likely to be responsible for their own financial matters. Finally, as noted by Koç and Van Kippersluis (2015) younger individuals typically live with their parents and do not cook, which means that they are less suitable for our DCE.

Data were collected on July 3rd, 2015 using Amazon Mechanical Turk (MTurk). MTurk is an online labor market where “requesters” offer jobs and “workers” choose which jobs to perform for pay. MTurk participants are slightly more diverse than other Internet samples and far more diverse than college samples; data quality is not influenced by realistic compensation rates, and obtained data are at least as reliable as when obtained by traditional methods (Buhrmester, Kwang, & Gosling, 2011; Mason & Suri, 2012). Of the 250 respondents who started the survey, 217 complete responses were received.

Background questions

The final section of our survey involved collecting demographic data. Besides basic information such as age, gender, and U.S. state, we also asked individuals to report their gross and net income. In an attempt to elicit accurate information, we used the English phrasing from the German Socio Economic Panel SOEP questionnaire:[8]

“*If you take a look at the total income from all members of the household: how high is the* ***gross [net]*** *monthly household income today in* ***US dollars****? Please state the* ***gross [net]*** *monthly income, which means* ***before [after]*** *deductions for taxes and social security. Please include regular income such as pensions, housing allowance, child allowance, grants for higher education support payments, etc. If you do not know the exact amount, please estimate the amount per month.*”

As self–reported income can be noisy, we also asked individuals whether they receive state aid. Finally we asked individuals to report their education based on the

[7] It should be noted that we test whether individuals understand what is asked of them throughout the survey. However, given our material constraints, collecting data in another country may have caused a significant amount of the sample to be dropped before the analysis

[8] The original (SOEP) question can be found at `https://data.soep.de/questions/10719`

Table 2
Number of sample deletions by reason

Number of respondents	Reason for deletion
217	Number of completed survey responses
-34	1. Is not located in the U.S.
183	
-2	2. Failed attention check in cognitive testing
181	
-3	3. Failed attention check during DCE
178	
-12	4. Net income exceeds gross income
166	
-2	5. Declined to disclose whether receiving state aid
164	
-1	6. Gross income reported as 0
163	Sample used for analysis

following options: (I) did not complete high school, (II) completed high school / GED, (III) completed some college, (IV) completed a bachelor's degree, (V) complete a master's degree, (VI) Advanced graduate work or PhD, (VII) not sure, (VIII) Refuse to Answer.

Sample selection

Of the 217 respondents in the sample, 34 were removed because we were unable to verify their geographic location; 2 failed the attention check in the cognitive testing section of the survey; 3 failed the attention check during the DCE; 12 stated that their net income exceeds their gross income; 2 respondents declined to disclose whether they receive state aid; 1 respondent reported 0 gross income. The deletions associated with each criterion are summarized in table 2.

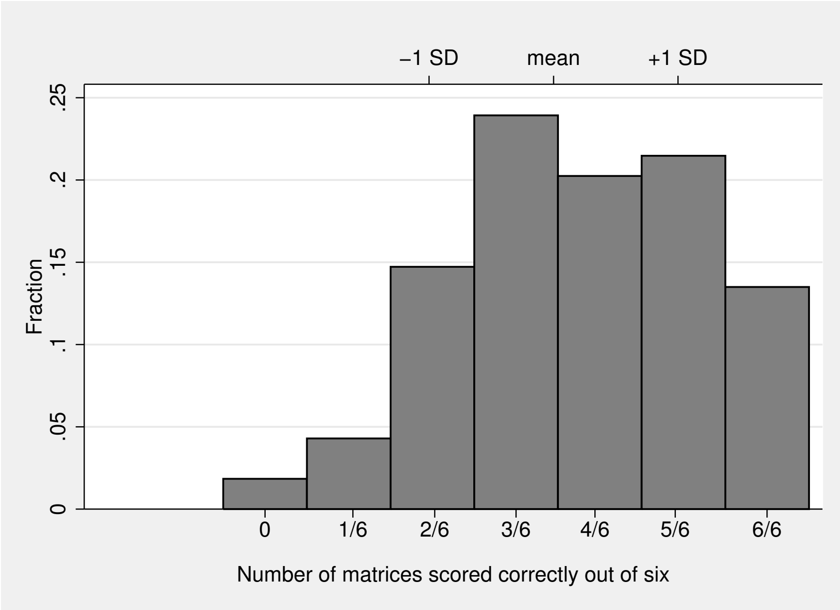
Descriptive Statistics

In this subsection we will sketch a general picture of our sample focusing on the variables of interest: cognitive score, gross and net income, the dummy for state aid, education, and gender.

fig. 3 shows the distribution of cognitive score within our sample. Each bar represents the number of Raven–like matrices answered correctly. The figure displays considerable heterogeneity. The mean [median] score is 0.625 [0.667] with standard deviation of 0.248. While the modal response equals 3 of 6 matrices being correct, 3

(1.84%) respondents have scored 0 and 22 (13.5%) achieved a perfect score.

Figure 3. Distribution of cognitive scores.



Notes: the distribution is shown for the full sample.

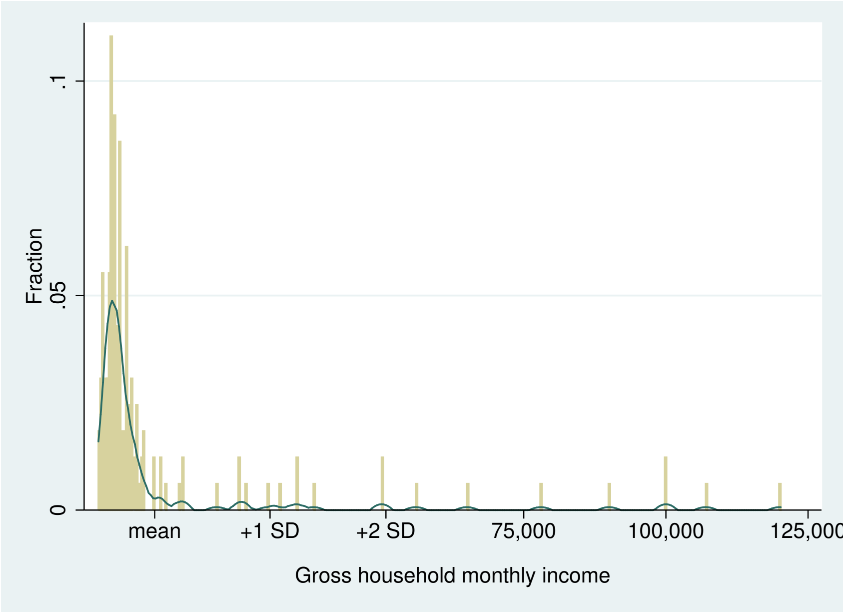
Next, we break down the analysis into the "easy" and "hard" scenario to which individuals were randomly assigned. The mean of the "easy" group equals 0.588 while the mean of the "hard" group equals 0.657, a two–sided t–test showed no significant difference in means [$t(150.385) = -1.7937; P(|T| > |t|) = 0.0757$] at a 5% significance level. However, given the small sample size it is prudent to consider a 10% significance level, at which the difference in means is significant. This could potentially indicate a randomization failure.

Subsequently we turn our attention to monthly household income (fig. 4). Gross and net income are highly correlated ($\rho = 0.88$; Cronbach's $\alpha = 0.9127$). The mean [median] monthly gross household income equals $10,999 [$3,500]. The discrepancy between the mean and the median indicates a high skewness (3.61). The standard deviation equals $20,380.

Based on fig. 4 we can furthermore see that there are several outliers in the right tail. The four largest outliers in the sample are $100,000 , $100,000 , $107,000 and $120,000. These figures would imply annual household incomes of roughly $1.2-$1.4 million. While such household incomes are certainly possible, it is also quite possible that individuals failed to properly read the instructions. We investigate the implications of these potentially noisy measurements in the next section. Mean income does not differ significantly between the randomly assigned conditions
[$t(161) = -0.8811; P(|T| > |t|) = 0.3796$].

Next we analyze the categorical variables. Briefly, of the 163 individuals in our sample, 26 (%15.95) receive state aid and 137 (%84.05) do not. Of the 26, 13 were assigned to the "easy" and 13 to the "'hard" scenario. Of the 137 who do not receive

Figure 4. Distribution of monthly gross household income.



Notes: the distribution is shown for the full sample. A kernel density estimate is overlaid on top of the data.

state aid, 63 were assigned to the "easy" scenario and 74 to the "hard" scenario. A two-sample test of proportion yielded no significant difference between the different scenarios [$z = 0.362$; $P(|Z| < |z|) = 0.7068$].

Lastly an examination of gender and educational attainment is presented in table 3. Education follows a unimodal distribution. Pairwise proportion testing of each level showed that there is no significant difference between the hypothetical scenarios in terms of education and gender.

Table 3
Gender and education

	N	Percentage
Gender:		
1. Female	78	47.85
2. Male	85	52.15
Total	163	100
Education (CASMIN):		
(I) did not complete high school	2	1.23
(II) completed high school /GED	24	14.72
(III) completed some college	65	39.88
(IV) completed a bachelor's degree	56	34.36
(V) complete a master's degree	14	8.59
(VI) Advanced graduate work or PhD	2	1.23
Total	163	100

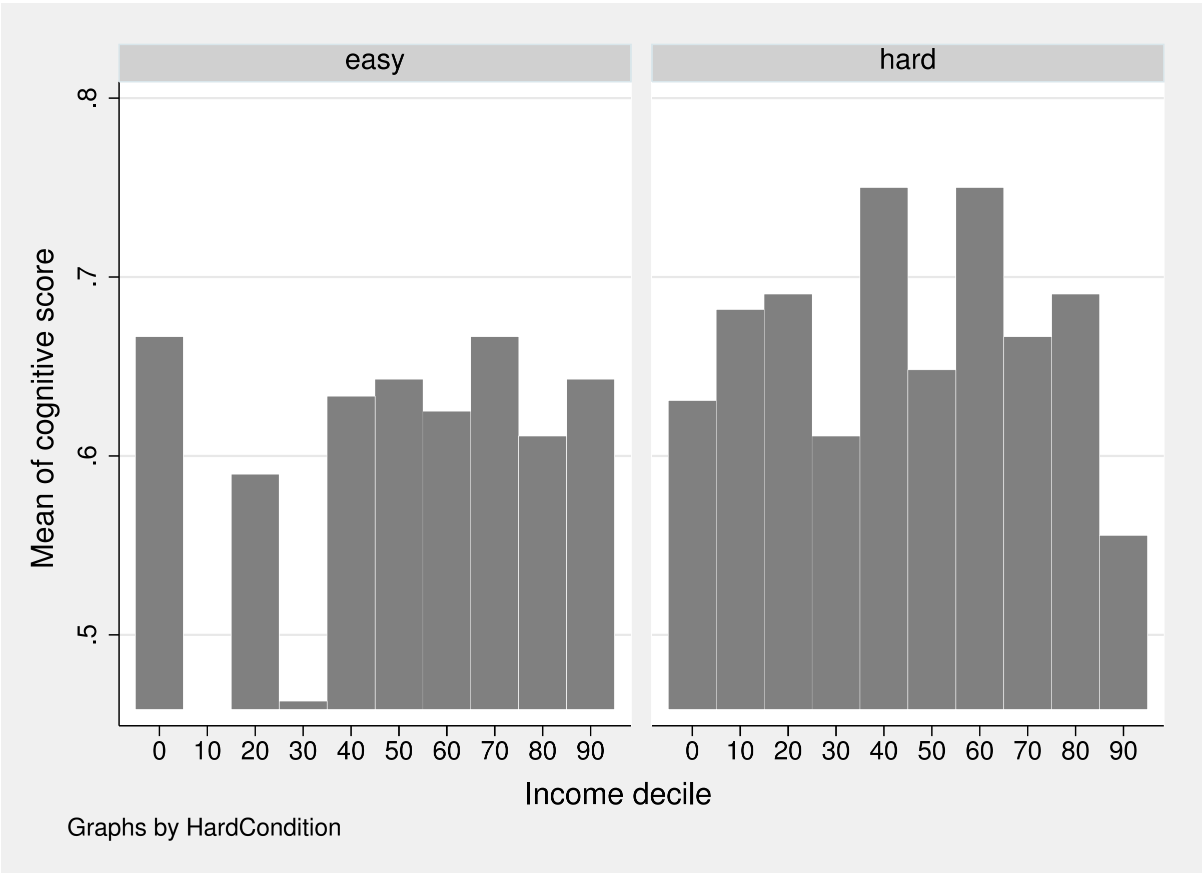
Cognitive performance and poverty

The objective of this section is to replicate the results obtained by Mani et al. (2013a), who demonstrate that poorer individuals achieve lower cognitive scores in the "hard" scenario, while in the "easy" scenario there is no statistically significant difference in mean cognitive score between poorer and wealthier individuals.

We are unable to reproduce the results from Mani et al. (2013a) using our sample. When taking a median split on gross and net income, we do not observe any statistically significant difference in mean cognitive score between richer and poorer individuals in either the "easy" nor "hard" condition. Likewise splitting the gross and net income variables along the 10th, 15th, 20th and 25th percentiles does not yield results. Finally, splitting the sample by individuals who receive state aid and those who do not does not produce significant results.

Examination of the mean cognitive score by income decile over the two hypothetical scenarios (fig. 5) may offer an insight into the underlying causes of our results. Immediately two things are noticeable. data appears to be sparse with no observations for the 2nd decile in the "easy" group, and we can see that the scores of the poorest 10% are some of the highest in the "easy" scenario.

Figure 5. Mean cognitive score by income decile and randomly assigned scenario.



There may be several issues which bring about such a distribution of mean cognitive scores: it is possible that we failed to properly prime individuals. Perhaps the scenario's which we used were too hard, too easy, or simply did not differ significantly from each other to evoke a different response pattern. Although this is unlikely because the same scenario's have been validated by Mani et al. (2013a). It may also be the case that our measurements of cognitive ability have not been accurate enough, even though the matrices had been piloted beforehand.

Next, it is possible that our sample is not entirely random. Perhaps MTurk is not an accurate representation of the U.S. adult population. Considering that the responses were collected during evening and night time in the United States, it is possible that individuals who go to bed early have been selected out. One could hypothesize that some of these individuals may perform physical labor and thus belong to a relatively poor group of society. Assuming that the experimental setup is valid, it is possible that individuals reported the wrong income. This could place relatively wealthy individuals in the brackets among the poor or vice versa.

Lastly, perhaps income is not the appropriate measurement given our context. Consider a (under)graduate student who earns relatively very little income, but whose family income is relatively wealthy. This student should not be classified as "poor", and a high cognitive score would be unsurprising. Even though we did ask individuals to record household income, it is possible that they consider themselves a one person household or that they simply misread the instructions.

Instead we propose to use education as a proxy for income. There are several arguments as to why education may prove to be a better measure within the context of our research. Firstly, it is most likely not as noisy as our income measurement, because individuals are unlikely to accidentally report the wrong education as the choice is constrained over the earlier discussed categories (table 3). Admittedly, absent panel data, it is difficult to detect intentional misreporting or potential changes in education; however, considering that the minimum age of our sample is 21 and that 90% of the sample consists of individuals aged 25 or over, it is unlikely that education is subject to change significantly for the majority of individuals.

Secondly, the objective is to use a measure which is indicative of socioeconomic status (SES). Indeed, in the case of Mani et al. (2013a) it makes sense to consider income as their field research focused on sugarcane farmers in India. Arguably, the education gradient may not be significantly pronounced in their study population. However, in our research the focus is on U.S. citizens. Not only is education a valid and preferred predictor of (SES), most notably in the context of health (Winkleby, Jatulis, Frank, & Fortmann, 1992), but it would also be a better indicator of potential future income given our sample.[9] Consider the earlier example of an (under)graduate student who has

[9]Accurate SES measurement may be obscured by respondent heterogeneity over hidden variables such

relatively little income, but still obtains a high cognitive score. By examining educational attainment we do not classify the student as “poor” but instead take into account the student’s family income (Acemoglu & Pischke, 2001) as well as the potential future income of the student and the associated lifestyle.[10]

Finally, the dichotomization of quantitative variables has been criticized (MacCallum, Zhang, Preacher, & Rucker, 2002). As it happens, Wicherts and Scholten (2013) have argued that this may affect the analysis performed in Mani et al. (2013a). The authors rebut this critique by noting that it is common to dichotomize noisy income variables at the median (Mani, Mullainathan, Shafir, & Zhao, 2013b). Our approach mitigates this issue since our education variable is categorical.

Moving forward we split individuals by education into two groups. The lower educated group consists of individuals who have completed at most some college (groups I-III in table 3) and the higher educated group, consisting of individuals with at least a bachelor’s degree ((groups IV-VI in table 3). In the “easy” scenario, we do not find a statistically significant difference in mean cognitive score [$t(74) = 1.1383$; $P(|T| > |t|) = 0.2587$] between low educated (0.5593) and high educated (0.6290). Yet, as we examine the “hard” scenario the mean score of the low educated (0.6123) group is statistically lower than the mean score of the high educated group (0.7073) at a significance level of 5% [$t(85) = 1.9486$; $P(T > t) = 0.0273$] (fig. 6). Both results are in accordance with Mani et al. (2013a).

Using Cohen’s d, an estimation of the effect size results in a difference of 0.4185 [95% CI(-0.0083;0.8429)] standard deviations.[11] we do not find a significant interaction effect between education and the randomly assigned scenario [$F = 0.11$; $P = 0.7451$]. Lower educated individuals did not perform differently in the easy scenario than Lower educated individuals in the hard scenario [$t(55) = -1.0110$; $P(|T| > |t|) = 0.0.3148$], and higher educated individuals did not perform better in the easy condition than higher educated individual in the hard condition [$t(55) = -1.3448$; $P(|T| > |t|) = 0.0.1842$].

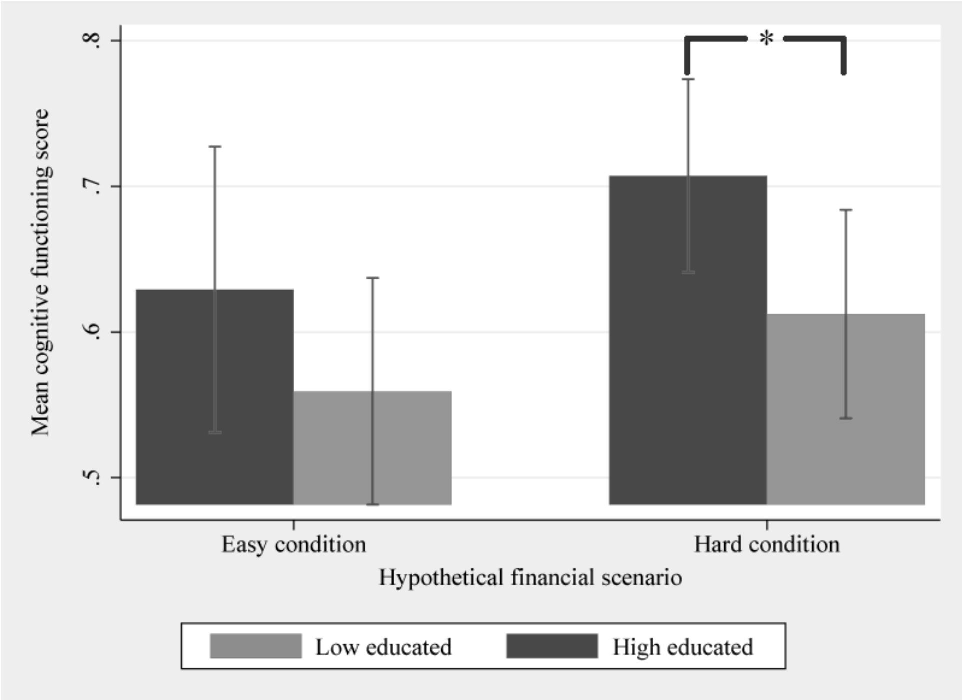
Concluding this section, we have found mixed statistical evidence suggesting that lower educated individuals perform worse than better educated individuals in the high cognitive load scenario. The difference between the two subgroups does not appear in the low cognitive load scenario. While there appears to be an effect, unlike in Mani et al.

as ethnicity (Braveman et al., 2005); however, our approach randomly assigned individuals over the main variable of interest.

[10]The example of a student appears to be inconsistent with our earlier argument that the age distribution of our sample suggests that most individuals are no longer students; however, given our sample size, effects at the tail of the distribution may influence our results. Secondly, one might argue that education and income are not perfectly collinear; e.g. an individual with higher educational attainment does not necessarily receive a larger income. Indeed, this may hold for levels of education which are fairly close to one another (e.g. high school/GED and community college), but our analysis splits education levels into groups that are below and at university education.

[11]Mani et al. (2013a) report an effect between 0.88 and 0.94 standard deviations] Using a two-way ANOVA.

Figure 6. Cognitive functioning by education group and hypothetical financial scenario



Notes: Performance on the Raven–like test. Error bars indicate 95% CI. $^{*}p < 0.05$.

(2013a) it is both small and uncertain given the 95% confidence interval as well as the lack of a robust interaction between the hypothetical scenario and education dummy. In the next section we investigate the link between cognitive performance, wealth (through education as a proxy), and meal choice.

Estimation of DCE coefficients

Methodology

Recall eq. (1). We can simplify the equation slightly by only looking at the choice of individual n over alternative j:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{2}$$

Where V_{nj} is a function of the observable attributes of the alternatives, and the decision maker. The error component ε_{nj} is treated as random. The probability that the decision maker n chooses alternative i is then:

$$\begin{aligned}
P_{ni} &= \Pr(U_{ni} > U_{nj}) \quad \forall j \neq i \\
P_{ni} &= \Pr(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}) \quad \forall j \neq i \\
P_{ni} &= \Pr(\varepsilon_{ni} - \varepsilon_{nj} > V_{nj} - V_{ni}) \quad \forall j \neq i \\
P_{ni} &= \Pr(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}) \quad \forall j \neq i
\end{aligned} \tag{3}$$

Different assumptions about the distribution of the random terms lead to different discrete choice models (Ortuzar & Willumsen, 1994). If we assume that the random terms are independently and identically distributed (i.i.d.) and follow a type I extreme value (Gumbel) distribution, we obtain the conditional logit model (McFadden, 1974b):

$$P_{ni} = \frac{\exp(\sigma_n V_{ni})}{\sum_{j=1}^{J} \exp(\sigma_n V_{nj})} \tag{4}$$

Where σ_n is a scale parameter which is usually normalized to 1. The accompanying function representing the deterministic component of utility is typically specified as being linear–in–parameters:

$$V_{ni} = \mathbf{x}_{ni}^{'}\beta + \mathbf{z}_{n}^{'}\gamma \tag{5}$$

The specification in eq. (5) is a combination of the conditional logit and multinomial logit models whereby $\mathbf{x}_{ni}$ represents characteristics which vary across choices (whether they vary by individual or not) and $\mathbf{z}_n$ represents characteristics of individuals which are constant across choices. Additionally, ε_{nj} (eq. (2)) is assumed to be homoskedastic.

This formulation introduces several assumptions: firstly it is assumed that individual preferences depend only on observable characteristics. Secondly, because the error terms are assumed to be independent, there is invariant proportional substitution (IPS) between the alternatives (Steenburgh, 2008):

$$\frac{\partial P_{ni}}{\partial x_{nj}^{*}} \frac{x_{nj}^{*}}{P_{ni}} = -x_{nj}^{*} P_{nj} \beta^{*} \tag{6}$$

Note that the above expression does not depend on i. IPS implies that if one alternative is "improved" by changing an attribute, it will draw away choice probability from all other alternatives in equal measure instead of drawing most choice probability from the most similar alternative. This is not problematic for our research setting because we only have two alternatives. Another result is that the model assumes independence of irrelevant alternatives (IIA):

$$\frac{P_{ni}}{P_{nk}} = \frac{\exp(V_{ni})/\sum_{j=1}^{J}\exp(V_{nj})}{\exp(V_{nk})/\sum_{j=1}^{J}\exp(V_{nj})} = \frac{\exp(V_{ni})}{\exp(V_{nk})} \tag{7}$$

IIA implies that if one were to introduce a new alternative, it would draw choice probability from the existing alternative which is most similar to the new alternative. To illustrate the point, consider two alternatives: A and B; the decision maker indicates that she prefers B over A. Now if alternative C is added, her choice can switch to preferring A over B if the new alternative detracts the most choice probability from B. This has been demonstrated using examples such as Beethoven/Debussy (Debreu, 1960), pony/bicycle (Krantz, Suppes, Luce, & Tversky, 1971), and red bus/blue bus (McFadden, 1974a). Again, this doesn't affect our experimental setup as we only have two alternatives.

The mixed logit model allows for coefficient heterogeneity (different preferences) between decision makers and thus drops the earlier listed assumptions. The choice probability is given by:

$$P_{ni} = \int \frac{\exp(\mathbf{x}_{ni}^{'}\beta)}{\sum_{j=1}^{J}\exp(\mathbf{x}_{nj}^{'}\beta)} \mathrm{f}(\beta|\theta)\mathrm{d}\beta \tag{8}$$

Where $\mathrm{f}(\beta|\theta)$ is the density function of β. Equation (5)is modified to include $\mathbf{z}_{ni}^{'}\gamma$, which depends on both individual preferences n and alternative i. This means that preferences are now allowed to vary over alternatives:

$$V_{ni} = \mathbf{x}_{ni}^{'}\beta + \mathbf{z}_{ni}^{'}\gamma \tag{9}$$

For a treatment on how to estimate the simulated log–likelihood using maximum likelihood extending from eq. (8) we refer the reader to Hole (2007).

Results

In this section we examine the results of our mixed panel logit estimation. The estimated coefficients are presented in table 4. Willingness-to-pay (WTP) estimates are omitted because price linearity is rejected in two subgroups at a 10% significance level. Globally we can see that with the exception of "time: 30 minutes" all coefficients are significant at the 5% percent level. The size of the subgroups ranges from 744 to 1104 observations. At 24 observations per respondent this accounts for 31 to 46 individuals per subgroup. Given that this is a relatively small sample size, it could explain some of the significance issues of the obtained results. The signs and ordering of coefficients are as expected: higher prices and longer preparation time are negatively associated with the choice of an alternative, while increasing taste and health consequences levels are associated positively with choice probability. With the exception of "taste: good" and "time: 30 minutes" the other attributes and levels have a majority of significant standard deviation parameters, indicating that there is considerable choice heterogeneity among respondents.

Because the estimated coefficients from a mixed panel logit model are not directly interpretable, the average marginal effects (AME) are reported in table 5. The AME for the "easy" scenario are shown in columns 1 and 2, for high educated and low educated individuals respectively. The spread between these two subgroups is shown in column 3. Columns 4-6 serve the same function for the "hard" scenario. Finally, the last column contains the absolute difference between spread coefficients. This allows us to see whether the spread between high and low educated individuals changes between scenario's. Note that most spreads are not significant at the 10% level. We will proceed with discussing the results by attribute. Because our experimental design was generated without taking into account interactions between attributes, we will only discuss the individual effects.

Price. As expected, there is a negative association between choice probability and price. Relative to the base category of $2, a price level of $6 causes the choice probability to drop by 11.6-14.8 percentage points (pp) for the high educated, and 12.7-16.6 pp for the low educated. A price level of $10 relative to the base category is associated with a drop of 24-30.4 pp for the high educated and 30.9-40.9 pp for the low educated. Furthermore, we can see that the low educated (poor) are more sensitive to price than the high educated (rich).

The theory developed by Shah et al. (2012) implies that as individuals face financial difficulties, they pay more attention to managing their expenses. In our case, this manifests itself in the spread between individuals belonging to the same educational attainment group, yet in different scenario's. Comparing across columns 1 and 4, we can see that high educated individuals in the "hard scenario" are 3.2 pp less likely to choose a meal with a price of $6 than high educated individuals in the "easy" scenario. An even larger decrease of 3.9 pp occurs among the poor (columns 2 and 5). At $10, the decrease among high educated individuals is 6.4 pp and for the poor it's 10.0 pp. In short, higher cognitive load induces increased price sensitivity across all subgroups. A potential explanation for this is that individuals are reacting to the financial prime. Because the high cognitive load scenario, by definition (see appendix A, consists of a stronger financial prime than the low cognitive load scenario, individuals are primed to be more sensitive towards price.

Next we look at the differences between high and low educated groups. At the $6 price, the spread between high and low educated individuals in the "easy" scenario is 1.1

pp (column 3), while in the "hard" scenario the spread increases to 1.8 pp (column 6), neither significant at the 10% level, hence the effective difference is 0. At the $10 level, the spread in the "easy" condition is 7.0 pp and in the hard condition it is 10.5 pp. Neither spread is significant at 10%. This it is not in line with theoretical predictions. If indeed scarcity causes individuals to focus on price (Shah et al., 2012) and the poor are more sensitive to tough financial conditions than the rich (Mani et al., 2013a) then we expect that the increase in the price coefficient for the poor across the financial scenario's to be larger than the increase for the rich. This should result in a significant difference of spreads between higher educated (rich) and lower educated (poor) groups across the two conditions. This is not the case.

Time. The theory set out in Shah et al. (2012) predicts similar effects for time scarcity as it does for price scarcity; however, in our experiment we did not explicitly prime individuals to experience time scarcity. As such we do not have expectations regarding the outcomes. Furthermore we only discuss the "time: 50 minutes" level, since the AME for "time: 30 minutes" are not significant.

Relative to the base level of 10 minutes we see a 18.6-23.3 pp drop in the probability of choosing a meal if the preparation time is 50 minutes among the high educated and a 18.0-21.6 pp drop among the low educated. Comparing columns 1 and 4, the "hard" financial scenario results in an additional 4.7 pp drop relative to the "easy" scenario for the high educated. For the low educated the difference is 3.6 pp. In the "easy" scenario, the difference between high and low educated individuals is 0.6 pp and not significant at %10, with the higher educated placing more emphasis on time than the low educated. In the "hard scenario" the difference is larger at 1.7 pp but not significant at %10, again with the high educated placing more emphasis on the time attribute relative to the base level. Given the insignificance of the results, there is statistically no difference between higher and lower educated groups.

Our data suggests that unlike with the price attribute, where the low educated are more sensitive than the high educated, the time attribute is more valued by the high educated than the low educated within each scenario. A potential explanation is that the higher educated (higher income) group has a higher opportunity cost of time. For the rest we see a similar pattern whereby the hard scenario increases the coefficient for both the high and low educated groups.

Taste. In like manner to the time attribute, we cannot make any predictions regarding the taste attribute based on theory. We see that "good" taste relative to "OK" taste leads to an increase in the associated choice probability by 5.1-13.3 pp for high educated individuals, and 7.1-10.7 pp for low educated individuals. For the "very good" level relative to the base category "OK" increase in assigned choice probability is 11.9-26 pp. High educated individuals in the "hard" scenario assign less importance to the taste attribute than high educated individuals in the "easy" scenario with a difference of 8.1 pp at the "good" level and 14.3 pp at the very good level. In contrast, low educated individuals do the opposite. Those in the "hard" scenario are more likely to choose a "good" tasting meal relative to an "OK" tasting meal by 3.5 pp, and the probability spread increases to 5.3 pp for a "very good" tasting meal. This leads to the next observation: the absolute spread between high and low educated is smaller in the "hard" scenario at 5.5 and 8.7 pp for "good" and "very good" respectively, than in the easy scenario, where it is 6.1 and 10.9 pp for "good" and "very good" respectively. Of these spreads, only the spread in column 3 for the "good" level is significant at %10. Thus we cannot compare spreads across scenario's.

This result shows that different groups have different attitudes towards taste. Whereas higher educated individuals place less importance on taste in the "hard" scenario, the opposite is true for "low" educated individuals. None of the earlier theories explain this finding. What is possible, is that low educated (poor) individuals are more prone to experience stress in the "hard" condition relative to the "easy" condition when compared with high educated individuals. Stress is associated with increased intake of comfort food: food that is energy dense and associated with pleasurable taste and thoughts (Dallman et al., 2003). Thus the mechanism could be that poverty triggers individuals to assign more weight to the taste attribute through a stress response. However, we emphasize, that we did not test this.

Health consequences. Lastly we discuss the AME of the health consequences attribute. Our hypothesis is that the spread between low and high educated individuals should increase in the "hard" condition relative to the "easy" condition. This follows from Shah et al. (2012) and Mani et al. (2013a): firstly as individuals face more strenuous financial circumstances, they divert their cognitive resources towards dealing with expenses and away from decision making in other avenues. Secondly, as cognitive load increases, individuals have less cognitive bandwidth remaining for decision making. Within the context of our research this means that individuals spend more attention towards catering for *immediate* and *urgent* financial matters such as paying rent or groceries, and less resources are allocated towards considering the potential future health implications of their decision-making. Thus individuals become more concerned with price and less with their health.[12] This effect is expected to be more pronounced among lower educated (poorer) individuals than higher educated (wealthier) individuals because the financial constraints form a larger fraction of their income.

Nevertheless our data reveals different results. Both high and low educated

[12]Earlier research has suggested that poor decision making in this case can be attributed to the temporal discounting of health consequences at a higher rate than monetary rewards (see e.g. Cairns, 1992; Chapman & Elstein, 1995); however, we are not discussing the rationality of deciding between future monetary rewards and health gains or health losses. Instead our argument is that scarcity triggers individuals to make bad decisions with respect to their health simply because they are too mentally preoccupied with considering their expenses.

individuals assign *more* importance to the health consequences attribute in the "hard" scenario than in the "easy" scenario at the "health neutral" level. Relative to the base level "unhealthy", the difference at the "health neutral" level for high educated individuals between the "hard" and "easy" scenario's is 0.5 pp, while for low educated individuals it is 1.8 pp. At the "healthy" level, the high educated assign 5.1 pp *less* to the health attribute in the "hard" scenario compared to the "easy" scenario. Meanwhile the choice probability among low educated respondents rises by 1.7 pp from 0.3071 to 0.3242.

Consequently, at the "health neutral" level the spread between low and high educated individuals in the easy scenario is 5.6 pp, while in the hard scenario it is 4.3 pp. Both not significant at %10. For the "healthy" level, the spread between high and low educated individuals in the "easy" scenario is 6.4 pp, while in the hard scenario it is -0.4 pp. Again, neither being significant at %10. This means that there is no significant difference in the gravitas assigned to the health attribute between low and high educated individuals in either financial scenario. If anything, the low educated appear to assign more importance to the health consequences attribute than the high educated in the "hard" scenario, which is the opposite of what would be expected.

To summarize, our results contradict the theoretical predictions by Shah et al. (2012), and our initial hypothesis in three ways: Firstly, individuals in the hard scenario assign more importance to the average marginal effect of health consequences relative to those in the "easy" scenario. This contradicts Shah et al. (2012) who argue that scarcity leads individuals to neglect other attributes when making decisions. Secondly, based on Mani et al. (2013a) we expected the average marginal effects for the health attribute to follow a similar pattern as the cognitive score in the previous section. We expected to see a small difference between high and low educated individuals in the "easy" scenario, and a larger difference between high and low educated individuals in the "hard" scenario. Instead the difference between high and low educated individuals is smaller in the "'hard" scenario, and none of the spreads are statistically significant. Lastly, following from the previous observation, we expected the changes in coefficients to mainly occur among the "low" educated, in line with the decreased cognitive score among the low educated in the "hard scenario". In fact, our data shows that the main drop in average marginal effects occurs among the "high" educated group, mainly at the "healthy" level. Thus, it appears that the financial scenario does not have the predicted effect on the choice probabilities, and that the marginal value assigned to the "health consequences" attribute does not track cognitive functioning as measured in our research.

Table 4
Mixed logit estimation of DCE *coefficients.*

	"easy" financial scenario		"hard" financial scenario	
MEANS	(1) high edu	(2) low edu	(4) high edu	(5) low edu
Price: \$6	-0.8193***	-1.6463****	-1.8257***	-1.5635****
	(0.2414)	(0.4626)	(0.5464)	(0.3486)
Price: \$10	-1.7394***	-3.4003****	-3.0303****	-3.7234****
	(0.5107)	(0.7226)	(0.8023)	(0.7154)
Time: 30 minutes	0.3035	-0.1552	-0.2709	-0.1943
	(0.2105)	(0.2293)	(0.2689)	(0.1951)
Time: 50 minutes	-1.0707***	-2.3365****	-2.3429****	-1.9149****
	(0.3454)	(0.6208)	(0.6115)	(0.4411)
Taste: Good	0.8892****	0.7963 ***	0.5553**	0.9391****
	(0.2222)	(0.2896)	(0.2496)	(0.2666)
Taste: very good	1.715****	1.6705****	1.2594***	1.7995****
	(0.022)	(0.4198)	(0.3780)	(0.3888)
Health neutral	2.1809****	3.0360****	3.3641****	2.4714****
	(0.4848)	(0.6842)	(0.7989)	(0.5593)
Healthy	3.3431****	4.3751****	4.3070****	3.4907****
	(0.7279)	(1.0433)	(1.1352)	(0.7875)
STANDARD DEVIATIONS	(1) high edu	(2) low edu	(4) high edu	(5) low edu
Price: \$6	0.1460	1.2140***	0.7960**	0.3597
	(0.7045)	(0.4072)	(0.3427)	(0.4124)
Price: \$10	1.7178****	3.1491****	2.5786****	2.4501****
	(0.022)	(0.7406)	(0.6121)	(0.5580)
Time: 30 minutes	0.0047	0.0948	1.0320**	0.1488
	(0.4176)	(0.2357)	(0.5006)	(0.4858)
Time: 50 minutes	0.7364**	2.1611****	2.0944***	0.9852***
	(0.2954)	(0.4522)	(0.6126)	(0.2965)
Taste: Good	0.0303	0.2859	0.1653	0.2632
	(0.6217)	(0.3247)	(0.022)	(0.3586)
Taste: very good	1.0483****	1.0721***	0.7225**	0.5428**
	(0.2926)	(0.3267)	(0.3245)	(0.2705)
Health neutral	0.5498*	1.5437***	0.07311*	0.5518
	(0.2961)	(0.4632)	(0.4112)	(0.3516)
Healthy	0.3001	1.9554****	1.7542**	0.7630*
	(0.5207)	(0.7286)	(0.7416)	(0.4597)
Log likelihood	-212	-288	-270	-273
Observations	744	1080	984	1104

Notes: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$.

Table 5
DCE *average marginal effects with bootstrapped standard errors.*

	"easy" financial scenario			"hard" financial scenario			
	(1) high edu	(2) low edu	(3) high-low	(4) high edu	(5) low edu	(6) high-low	|(6)-(3)|
Price: $6	-0.1159***	-0.1268****	0.0109	-0.1480****	-0.1660****	0.0180	n/a
	(0.3603)	(0.0277)	(0.0458)	(0.0315)	(0.0212)	(0.0354)	
Price: $10	-0.2395***	-0.3091****	0.0696	-0.3038****	-0.4088****	0.1050	n/a
	(0.0713)	(0.0562)	(0.0877)	(0.0623)	(0.0561)	(0.0820)	
Time: 30 minutes	0.0315	-0.0184	0.0499	-0.0323	-0.0326	n/a	n/a
	(0.0282)	(0.0164)	(0.0325)	(0.0317)	(0.0214)	(0.0387)	
Time: 50 minutes	-0.1860****	-0.1801****	-0.0059	-0.2333****	-0.2162****	-0.0171	n/a
	(0.0454)	(0.0412)	(0.0604)	(0.0464)	(0.0330)	(0.0575)	
Taste: Good	0.1325****	0.0712***	0.0613*	0.0514**	0.1066****	-0.0552	n/a
	(0.0271)	(0.0237)	(0.0373)	(0.0250)	(0.0265)	(0.0374)	
Taste: very good	0.2623****	0.1538****	0.1085*	0.1193****	0.2063****	-0.087**	0.1955
	(0.0516)	(0.0353)	(0.0617)	(0.0279)	(0.0309)	(0.0394)	
Health neutral	0.2984****	0.2422****	0.0563	0.3032****	0.2601****	0.0431	n/a
	(0.0615)	(0.0451)	(0.0675)	(0.0437)	(0.0389)	(0.0583)	
Healthy	0.3707****	0.3072****	0.0636	0.3199****	0.3242****	-0.0043	n/a
	(0.0512)	(0.0446)	(0.0682)	(0.0434)	(0.03529)	(0.0540)	

Notes: Bootstrapped standard errors (200 repetitions) in parentheses.
$^{*}p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$, $^{****}\ p < 0.001$.

Discussion

We set out to elucidate the relationship between financial scarcity, poverty, and healthy meal choice. We relied on the work of Shah et al. (2012) and Mani et al. (2013a) to form our hypothesis: If poverty decreases cognitive function, it also negatively affects healthy meal choice. To test the first part of our hypothesis we attempted to recreate the work of Mani et al. (2013a). In doing so we measured whether priming richer and poorer individuals to consider various levels of financial expenses affects their cognitive function. To test the second part of our hypothesis we recreated the DCE of Koç and Van Kippersluis (2015). Subsequently we analyzed the AME. We expected to see that in the “hard” condition, positive average marginal effects for the health consequences attribute would drop compared to the “easy” condition. We expected that this drop would be relatively larger for low educated individuals than for high educated individuals.

Answering the first part of our hypothesis, we found weak mixed statistical evidence confirming the results of Mani et al. (2013a). After we used education as a proxy for a noisy income measure, we did not find a statistically significant difference–in–means between low and high educated respondents in the “easy” condition. In the “hard” condition we did find a statistically significant difference–in–means. We note, however, that the size of the effect is twice as small as that of Mani et al. (2013a) and that the 95% confidence interval includes 0 at the lower end. Furthermore, unlike Mani et al. (2013a) we did not find a robust interaction between education and the hypothetical financial scenario, meaning that the effect of the hypothetical financial scenario on cognitive score is not influenced by education and vice–versa.

Next we examined the second part of our hypothesis. We found that the average marginal effects of the price attribute follows the theory of Shah et al. (2012) but not that of Mani et al. (2013a). At both the $6 and $10 levels. in the “hard” condition, both high and educated respondents place more emphasis on price than in the “easy” condition. This could also be explained by noting that individuals are primed for money. However, the spread between the “easy” and ‘hard” conditions between the low educated and the high educated groups is not statistically significant. For the health attribute we saw that the low educated assign more marginal probability to the health coefficient in the “hard” condition than they do in the “easy” condition. For the high educated this holds at the “health neutral” level, but at the “healthy” level the high educated assign less value to the health attribute under the “hard” condition than under the “easy” condition. We expected to see both low and high educated groups to assign less value to the health attribute under the “hard” condition, relative to the “easy” condition. We also expected to see a bigger difference in the low educated group than in the high educated group. Thus our results do not follow our hypothesis based upon the theories of Shah et al. (2012) and Mani et al. (2013a). Furthermore, differences between “high” and “low” educated groups are not significant in either hypothetical scenario.

There are three main limitations to our research; these can be categorized into problems with the data, problems with the experimental setup, and problems with the use of a DCE. Issues with the data relate to noise and sample size. While we believe that we have adequately dealt with the issue of noise in our data by not relying on self–reported income, there is of course a possibility that individuals misrepresented their educational attainment. Furthermore, because cognitive function was not assessed in a laboratory setting, we cannot eliminate the possibility that individuals were distracted while taking our survey. However, because we paid respondents a fixed amount to complete our survey, there is an incentive to complete it as fast as possible. Furthermore an analysis of the survey duration did not yield any outliers. All individuals completed the survey in a time span between roughly 7 and 15 minutes. Individuals who were assigned to the "easy" scenario were able to complete the survey faster because their answers to the hypothetical financial scenario's were usually shorter, as was expected.

The small sample size does pose a threat to our results. On p.15 we reported that a two–sided t–test of cognitive function between the "easy" and "hard" condition yielded a p–value of 0.0757. We conduct a power analysis for the same test and find that at $\alpha = 0.10$ the probability of type II error is 0.4497 and at $\alpha = 0.05$ the probability of type II error is 0.5763.[13] Thus there is a 45.0-57.6% chance that we missed a significant difference–in–means of cognitive score between the "easy" and "hard" conditions. In order for the type II error probability to not exceed 20% (power=0.80) at $\alpha = 0.05$ we would require at least 201 respondents in both groups, totalling 402 respondents. One could argue that the power should be higher than 0.80, because type II error (claiming there is no difference–in–means when there is) leads to arguably worse results – we assume successful randomization where there is none – than type I error (claiming there is a difference–in–means when there is none) since the latter would simply cause us to abandon our research. In a similar fashion, we stated on p.20 that there is no difference–in–means between the cognitive scores of the low educated and the high educated groups in the "easy" scenario. In this case a power analysis yields a type II error probability of 0.6979 at $\alpha = 0.10$ and 0.8004 at $\alpha = 0.05$, meaning that there is a 69.8-80.0% probability of a missed difference–in–means effect. This indicates that our test is significantly underpowered. Again, to reduce this probability to 20% (power = 0.80) at $\alpha = 0.05$ would require both the low and high educated groups to consist of 226 individuals, i.e. 452 individuals total in the "easy" condition group. Setting $\beta = 0.05$ and keeping $alpha = 0.05$ the minimum sample size becomes 746 for the "easy" group and 298 for the "hard" group, totalling 1,044 individuals. Note, however, that these numbers for sample size follow an assumption that we keep the means and standard deviations fixed at their observed levels. In addition to providing more statistical power during testing, a

[13]The probability of type II error is denoted by β which is calculated as $\beta = 1 - \text{power}$.

larger sample size would also be beneficial for the maximum likelihood estimation underlying the mixed panel logit model. The small sample size could explain why some of the coefficients and average marginal effects were not or barely statistically significant.

Inefficiencies in our experimental design are another source of potential problems. Mani et al. (2013a) showed highly significant effects using samples of around 100 individuals, which is far smaller than the minimum required sample size calculated in the previous section. It is possible, that even if the randomization was successful, we failed to properly prime the respondents. We do not expect that the priming failed because the hypothetical scenario's were either too easy or too hard, because these scenario's have been tested by Mani et al. (2013a). We also argue that the matrices selected from Matzen et al. (2010) are accurate enough to detect differences in cognitive function between the subgroups because (I) difference–in–means have been observed, and (II) the matrices were piloted before the study.

Instead it is possible that our experiment was too short. We remind the reader that we shortened our study relative to Mani et al. (2013a) because we did not want individuals to take breaks while participating in the experiment at their location of choice, and because material constraints meant that a longer experiment would be too expensive. Because of this we used two hypothetical scenario's instead of four, with six Raven–like tests instead of twelve, and no cognitive control task. The result is that individuals spend less time thinking about the hypothetical scenario's and thus the priming effect is weaker. This could potentially explain why the effect size of our experiment is roughly half of Mani et al. (2013a) and why the 95% confidence intervals are quite wide.

Furthermore, respondents were not presented with new hypothetical financial scenario's before or while taking the DCE. This means that the priming effect may have worn off or significantly weakened during the DCE. The latter is more likely compared to the former since we have observed a significantly higher sensitivity towards the price coefficient in the "hard" scenario relative to the "easy" scenario indicating that some priming effect is probably present. It is worth noting that experimental studies involving scarcity are designed with scarcity built into the experiment; i.e. individuals remain primed throughout the entire duration of the experiment (Shah et al., 2012). In similar future experiments it would be wise to maintain priming throughout the DCE portion of the experiment; with one caveat, namely that additional priming can have additional effects on the cognitive function. This would mean that analysis would have to account for interaction effects between the estimated DCE coefficients and the change in cognitive function.

The third source of criticism focuses on the use of a DCE and associated issues. Firstly, one may raise the point that stated preference (SP) environments differ from revealed preference (RP) environments in the sense that "noise" is more present in an RP environment where extraneous factors compete for the decision maker's attention.

According to Louviere, Flynn, and Carson (2010, p.67) this implies that the magnitude of the SP (DCE) coefficients is overestimated; in the same article, however, Louviere et al. (2010) also note that in a DCE it is possible to scale the parameters because DCE error components contain scaling factors. We argue furthermore that this "hypothetical bias" does not influence our analysis as we are interested in the differences (spreads) between subgroups and not in the overall magnitude, while the bias is systematic and thus should offset all coefficients in equal amounts. We are careful not to interpret individual coefficient magnitudes.

Another critique of the DCE approach is that it is not based on fundamental theory. Louviere et al. (2010) note that this is usually a result of confusion between conjoint analysis (CA) which is based on the purely mathematical theory of "Conjoint Measurement" (CM) and discrete choice experiments (DCE) which are based on "Random Utility Theory" (RUT). Although (RUT) does have its own limits (see Hensher, Rose, & Greene, 2005, for a discussion) it provides a comprehensive conceptual view of the process by which individuals arrive at a choice (Louviere et al., 2010, pp.63-65).

To conclude, while we have obtained weak mixed evidence corroborating the claims of Mani et al. (2013a) regarding poverty and cognitive function, we have not been able to show that reduced cognitive function is associated with unhealthy meal choice, specifically among the poor (lower educated). Our methodological approach contains flaws which stem both from an insufficiently large sample and possibly a poor experimental protocol. On that basis we advise future research in this area to gather more data and explore experimental designs which utilize a continuous and consistent priming effect.

References

Acemoglu, D., & Pischke, J.-S. (2001). Changes in the wage structure, family income, and children's education. *European Economic Review*, *45* (4), 890–904.

Baddeley, A. D., Hitch, G., & Bower, G. (1974). The psychology of learning and motivation. *The psychology of learning and motivation*, *8*, 47–90.

Basiotis, P. P. (1992). Validity of the self–reported food sufficiency status item in the us department of agriculture's food consumption surveys. In *Proceedings for the 38 Annual Conference of the American Council on Consumer Interest, March 25-28, Toronto, Ontario.*

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Bliemer, M. C., & Rose, J. M. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B: Methodological*, *44* (6), 720–734.

Braveman, P. A., Cubbin, C., Egerter, S., Chideya, S., Marchi, K. S., Metzler, M., & Posner, S. (2005). Socioeconomic status in health research: one size does not fit all. *Jama*, *294* (22), 2879–2888.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk a new source of inexpensive, yet high-quality, data? *Perspectives on psychological science*, *6* (1), 3–5.

Cairns, J. A. (1992). Health, wealth and time preference. *Project appraisal*, *7* (1), 31–40.

Cawley, J., & Ruhm, C. (2011). *The economics of risky health behaviors* (Tech. Rep.). National Bureau of Economic Research.

Chapman, G. B., & Elstein, A. S. (1995). Valuing the future temporal discounting of health and money. *Medical Decision Making*, *15* (4), 373–386.

ChoiceMetrics. (2014). Ngene 1.1.2 user manual & reference guide [Computer software manual].

Conti, G., & Hansman, C. (2013). Personality and the education–health gradient: A note on "understanding differences in health behaviors by education". *Journal of health economics*, *32* (2), 480–485.

Cutler, D., Glaeser, E., & Shapiro, J. (2003). *Why have americans become more obese?* (Tech. Rep.). National Bureau of Economic Research.

Cutler, D. M., & Lleras-Muney, A. (2010). Understanding differences in health behaviors by education. *Journal of health economics*, *29* (1), 1–28.

Dallman, M. F., Pecoraro, N., Akana, S. F., La Fleur, S. E., Gomez, F., Houshyar, H., ... Manalo, S. (2003). Chronic stress and obesity: a new view of "comfort food". *Proceedings of the National Academy of Sciences*, *100* (20), 11696–11701.

de Bekker-Grob, E. W., Ryan, M., & Gerard, K. (2012). Discrete choice experiments in health economics: a review of the literature. *Health economics*, *21*(2), 145–172.

Debreu, G. (1960). *Individual choice behavior-a theoretical-analysis-luce, rd.* AMER ECONOMIC ASSOC 2014 BROADWAY, STE 305, NASHVILLE, TN 37203.

Drewnowski, A., & Specter, S. (2004). Poverty and obesity: the role of energy density and energy costs. *The American journal of clinical nutrition*, *79*(1), 6–16.

Duflo, E. (2006). Poor but rational? *Understanding poverty*, 367–78.

Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. (1999). Working memory, short-term memory, and general fluid intelligence: a latent-variable approach. *Journal of experimental psychology: General*, *128*(3), 309.

Grossman, M. (1972). On the concept of health capital and the demand for health. *The journal of political economy*, 223–255.

Hanemann, W. M., & Kanninen, B. (1999). The statistical analysis of discrete-response cv data. *Valuing Environmental Preferences. Theory and Practice of the Contingent Valuation Method in the US, EU, and Developing Countries*, 302–441.

Hanson, K., McPake, B., Nakamba, P., & Archard, L. (2005). Preferences for hospital quality in zambia: results from a discrete choice experiment. *Health economics*, *14*(7), 687–701.

Hensher, D. A. (2006). How do respondents process stated choice experiments? attribute consideration under varying information load. *Journal of Applied Econometrics*, *21*(6), 861–878.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). *Applied choice analysis: a primer*. Cambridge University Press.

Hole, A. R. (2007). Estimating mixed logit models using maximum simulated likelihood. *The Stata Journal*, *7*(3), 388–401.

Hunt, E. (2010). *Human intelligence*. Cambridge University Press.

Kamphuis, C. B., de Bekker-Grob, E. W., & van Lenthe, F. J. (2015). Factors affecting food choices of older adults from high and low socioeconomic groups: a discrete choice experiment. *The American journal of clinical nutrition*, *101*(4), 768–774.

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

Koç, H., & Van Kippersluis, H. (2015). Thought for food: Understanding educational disparities in food consumption.

Krantz, D. H., Suppes, P., Luce, R. D., & Tversky, A. (1971). Chapter 6 - additive conjoint measurement. In *Additive and polynomial representations* (p. 245 - 315). Academic Press. Retrieved from http://www.sciencedirect.com/science/article/pii/B9780124254015500143 doi: http://dx.doi.org/10.1016/B978-0-12-425401-5.50014-3

Lancaster, K. J. (1966). A new approach to consumer theory. *The journal of political economy*, 132–157.

Lancsar, E., & Louviere, J. (2008). Conducting discrete choice experiments to inform healthcare decision making. *Pharmacoeconomics*, *26*(8), 661–677.

Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling*, *3*(3), 57–72.

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281.

MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychological methods*, *7*(1), 19.

Mangham, L. J., Hanson, K., & McPake, B. (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*(2), 151–158.

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013a). Poverty impedes cognitive function. *science*, *341*(6149), 976–980.

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013b). Response to comment on "poverty impedes cognitive function". *Science*, *342*(6163), 1169. doi: 10.1126/science.1246799

Manski, C. F. (1977). The structure of random utility models. *Theory and decision*, *8*(3), 229–254.

Mason, W., & Suri, S. (2012). Conducting behavioral research on amazon's mechanical turk. *Behavior research methods*, *44*(1), 1–23.

Matzen, L. E., Benz, Z. O., Dixon, K. R., Posey, J., Kroger, J. K., & Speed, A. E. (2010). Recreating Raven's: Software for systematically generating large numbers of Raven–like matrix problems with normed properties. *Behavior research methods*, *42*(2), 525–541.

McFadden, D. (1974a). Conditional logit analysis of qualitative choices. *Zarembka. P.(eds): Frontiers.*

McFadden, D. (1974b). The measurement of urban travel demand. *Journal of public economics*, *3*(4), 303–328.

Meara, E. (2001). *Why is health related to socioeconomic status?* (Tech. Rep.). National Bureau of Economic Research.

Miller, G. A. (1956). The magical number seven, plus or minus two: some limits on our capacity for processing information. *Psychological review*, *63*(2), 81.

Mullainathan, S., & Thaler, R. H. (2000). *Behavioral economics* (Tech. Rep.). National Bureau of Economic Research.

Must, A., Spadano, J., Coakley, E. H., Field, A. E., Colditz, G., & Dietz, W. H. (1999). The disease burden associated with overweight and obesity. *Jama*, *282*(16), 1523–1529.

Neisser, U. (1976). *Cognition and reality: Principles and implications of cognitive psychology.* WH Freeman/Times Books/Henry Holt & Co.

Ortuzar, J. d. D., & Willumsen, L. G. (1994). *Transport modelling.* John Wiley & Sons Ltd., England.

Raven, J. (2000). The raven's progressive matrices: change and stability over culture and time. *Cognitive psychology*, *41*(1), 1–48.

Rose, D. (1999). Economic determinants and dietary consequences of food insecurity in the united states. *The Journal of nutrition*, *129*(2), 517S–520S.

Saffer, H. (2014). *Self-regulation and health* (Tech. Rep.). National Bureau of Economic Research.

Shah, A. K., Mullainathan, S., & Shafir, E. (2012). Some consequences of having too little. *Science*, *338*(6107), 682–685.

Steenburgh, T. J. (2008). The invariant proportion of substitution property (ips) of discrete-choice models. *Marketing Science*, *27*(2), 300–307.

Steptoe, A., Pollard, T. M., & Wardle, J. (1995). Development of a measure of the motives underlying the selection of food: the food choice questionnaire. *Appetite*, *25*(3), 267–284.

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

U.S. Department of Health and Human Services. (2011). U.S. Department of Health and, Human Services: Healthy people 2020. *Office of Disease Prevention and Health Promotion, US Department of Health and Human Services.*

Wicherts, J. M., & Scholten, A. Z. (2013). Comment on "poverty impedes cognitive function". *Science*, *342*(6163), 1169. doi: 10.1126/science.1246680

Winkleby, M. A., Jatulis, D. E., Frank, E., & Fortmann, S. P. (1992). Socioeconomic status and health: how education, income, and occupation contribute to risk factors for cardiovascular disease. *American journal of public health*, *82*(6), 816–820.

Appendix A
Cognitive testing

Survey introduction

In this questionnaire we are trying to understand the link between cognition and food choice. The questionnaire consists of three parts. In the first part you will be presented with a financial choice and asked to perform several cognitive tasks. In the second part we will ask you to make a number of choices between different meals. The last part of the questionnaire consists of a number of background questions.

Please answer honestly and avoid socially desirable answers. YOUR RESPONSES ARE ANONYMOUS TO EVERYONE INCLUDING THE RESEARCHERS.

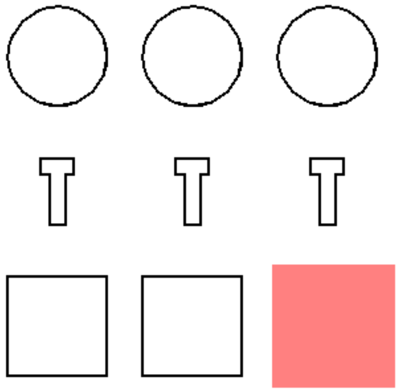
The estimated time to complete this survey is 15 MINUTES.

If you have any questions or comments, e-mail arik@student.eur.nl

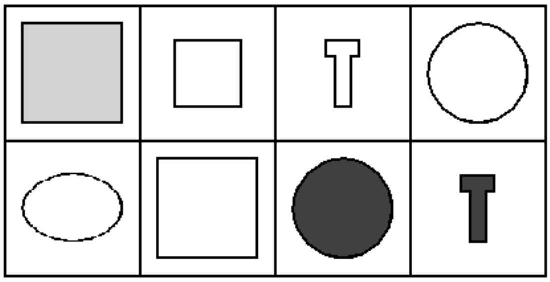
cognitive testing introduction

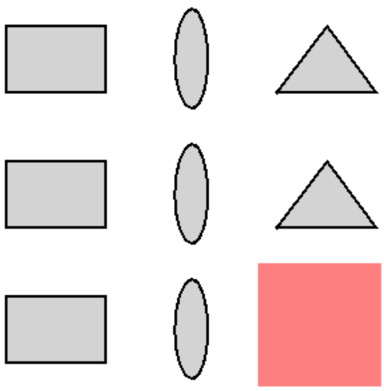
In this section you will be asked to consider a scenario which involves making a financial decision. While you are thinking about the scenario you will be asked to complete several tasks. Once you have completed the tasks you will be prompted to write down your answer regarding the earlier scenario. You are asked to do this entire process twice.

The tasks which you will be performing involve identifying the missing element which will complete the pattern. Click on one of the eight options to select a shape, click again to deselect:

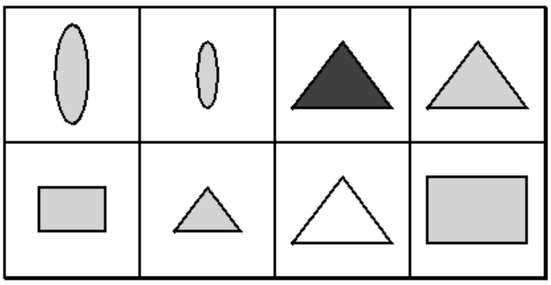


Choose one of the images below to
complete the pattern by filling in the red square:





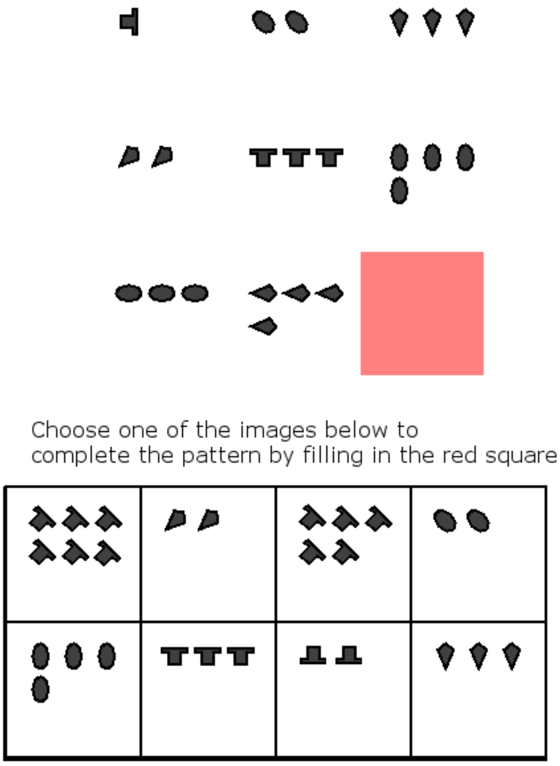
Choose one of the images below to
complete the pattern by filling in the red square:

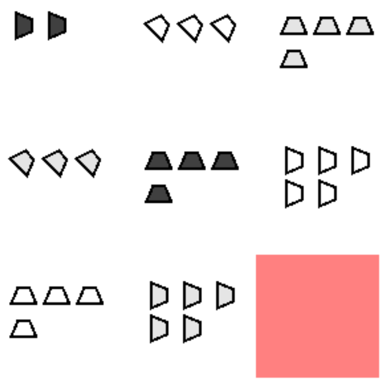


First round easy [hard] condition

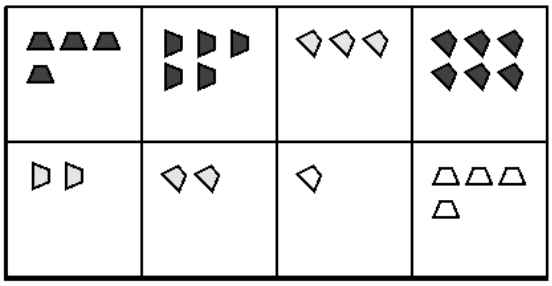
The economy is going through difficult times; suppose your employer needs to make substantial budget cuts. Imagine a scenario in which you received a 5% [15%] cut in your salary. Given your situation, would you be able to maintain roughly your same lifestyle under those new circumstances? If not, what changes would you need to make? Would it impact your leisure, housing, or travel plans?

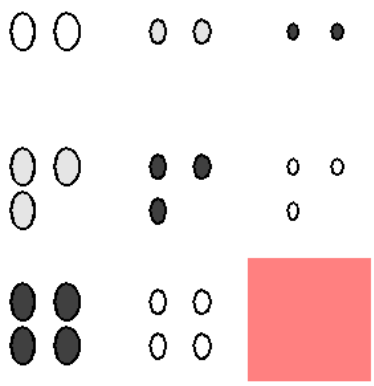
While you consider the question above, please complete the tasks on the next page.



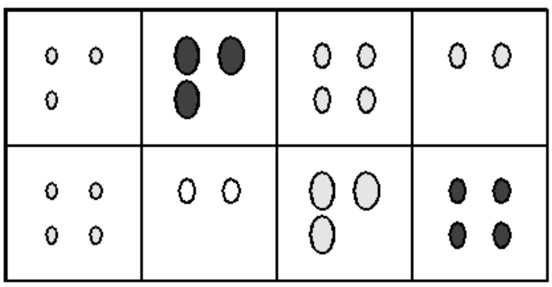


Choose one of the images below to
complete the pattern by filling in the red square:





Choose one of the images below to
complete the pattern by filling in the red square:



We asked you to consider the following scenario:

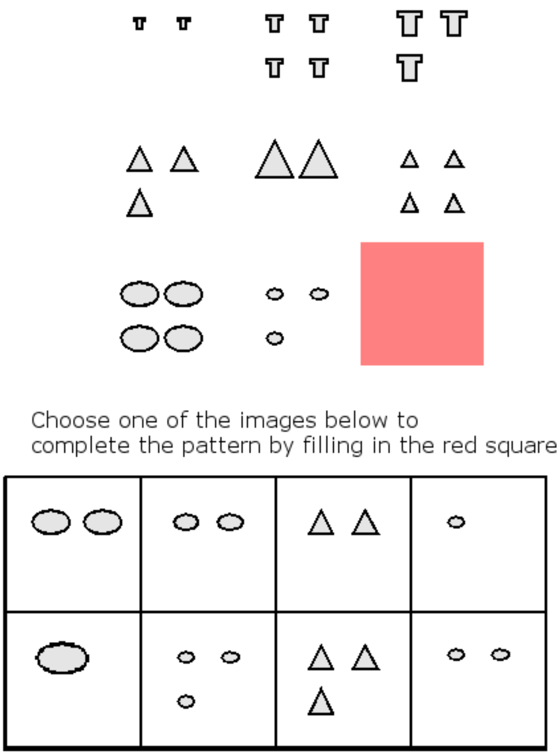
The economy is going through difficult times; suppose your employer needs to make substantial budget cuts. Imagine a scenario in which you received a 5% [15%] cut in your salary. Given your situation, would you be able to maintain roughly your same lifestyle under those new circumstances? If not, what changes would you need to make? Would it impact your leisure, housing, or travel plans?

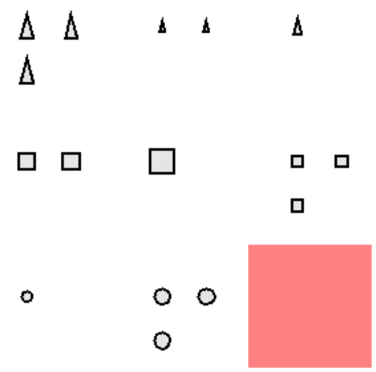
Please write your answer in the text box:

Second round easy [hard] condition

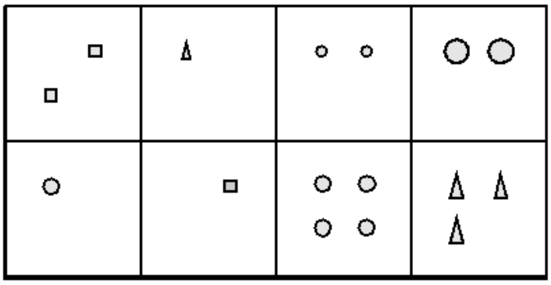
Imagine that an unforeseen event requires of you an immediate $200 [$2,000] expense. Are there ways in which you may be able to come up with that amount of money on a very short notice? How would you go about it? Would it cause you long-lasting financial hardship? Would it require you to make sacrifices that have long-term consequences? If so, what kind of sacrifices?

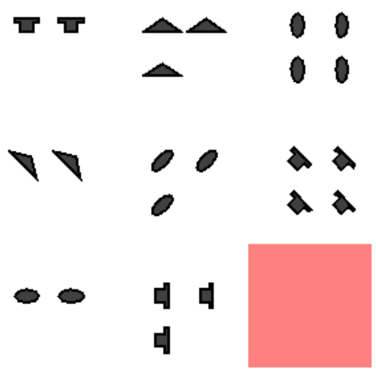
While you consider the scenario above, please complete the tasks on the next page.



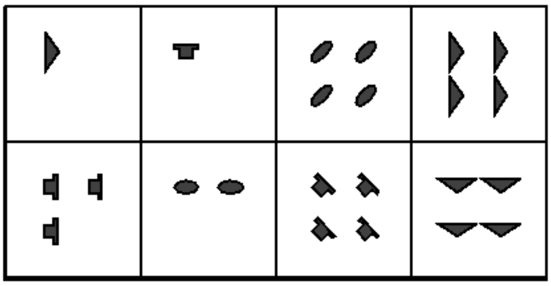


Choose one of the images below to
complete the pattern by filling in the red square:





Choose one of the images below to
complete the pattern by filling in the red square:



We asked you to consider the following scenario:

Imagine that an unforeseen event requires of you an immediate $200 [$2,000] expense. Are there ways in which you may be able to come up with that amount of money on a very short notice? How would you go about it? Would it cause you long-lasting financial hardship? Would it require you to make sacrifices that have long-term consequences? If so, what kind of sacrifices?

Please write your answer in the text box:

Appendix B
Discrete Choice Experiment

Introductory Text

In this section we try to understand your food choice behavior. 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. On the next page we will present you 13 choices between 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, preparation time, price, and healthiness. These attributes are explained below.

- 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)?
- 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. The price will take the levels (i) $2, (ii) $6, or (iii) $10.
- Preparation time: How much time does it take before the meal is on your plate? It will take the levels (i) 10 minutes, (ii) 30 minutes, or (iii) 50 minutes.
- Healthiness: : How healthy is the option? We distinguish between a meal that is (i) healthy (associated with reduced risk of disease), (ii) health neutral, and (iii) unhealthy (associated with increased risk of disease).

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

Choice Sets

1	Meal A	Meal B
Price	$2	$6
Preparation time	30 minutes	10 minutes
Taste	OK	Very good
Healthiness	Healthy	Health Neutral

2	Meal A	Meal B
Price	$2	$10
Preparation time	50 minutes	10 minutes
Taste	OK	Good
Healthiness	Healthy	Healthy

3	Meal A	Meal B
Price	$6	$2
Preparation time	50 minutes	30 minutes
Taste	Good	Very good
Healthiness	Healthy	Health Neutral

4	Meal A	Meal B
Price	$2	$10
Preparation time	30 minutes	50 minutes
Taste	OK	Good
Healthiness	Unhealthy	Healthy

5	Meal A	Meal B
Price	$6	$2
Preparation time	30 minutes	10 minutes
Taste	Good	Very good
Healthiness	Health Neutral	Unhealthy

6	Meal A	Meal B
Price	$10	$2
Preparation time	10 minutes	30 minutes
Taste	OK	Good
Healthiness	Health Neutral	Unhealthy

7	Meal A	Meal B
Price	$2	$6
Preparation time	10 minutes	30 minutes
Taste	Very Good	OK
Healthiness	Healthy	Unhealthy

DCE7 is an attention–check. Meal A is dominant. This choice set was not generated by Ngene and is not used for analysis.

8	Meal A	Meal B
Price	$6	$10
Preparation time	50 minutes	10 minutes
Taste	Very Good	OK
Healthiness	Health Neutral	Healthy

9	Meal A	Meal B
Price	$10	$6
Preparation time	50 minutes	10 minutes
Taste	Very Good	OK
Healthiness	Healthy	Health Neutral

10	Meal A	Meal B
Price	$6	$10
Preparation time	10 minutes	50 minutes
Taste	Very good	OK
Healthiness	Unhealthy	Health Neutral

11	Meal A	Meal B
Price	$2	$6
Preparation time	10 minutes	50 minutes
Taste	Good	OK
Healthiness	Health Neutral	Very good

12	Meal A	Meal B
Price	$10	$2
Preparation time	30 minutes	50 minutes
Taste	Very good	Good
Healthiness	Unhealthy	Unhealthy

13	Meal A	Meal B
Price	$10	$6
Preparation time	10 minutes	30 minutes
Taste	Good	Very good
Healthiness	Unhealthy	Unhealthy

Appendix C
Ngene code

```
design
;alts=altA, altB
;eff= (mnl, d)
;bdraws = halton(250)
;rows=12
;model:
U(altA) =  b0
         + b1.dummy[(n,-0.682,0.033)|(n,-1.797,0.074)] *price  [6,10,2]
         + b2.dummy[(n,-0.306,0.031)|(n,-0.987,0.055)] *time   [30,50,10]
         + b3.dummy[(n,0.404,0.032)|(n,0.908,0.041)]   *taste  [1,2,0]
/
U(altB) =  b1 *price
         + b2 *time
         + b3 *taste
         + b4 *health
$
```