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Facilitating healthy dietary habits: An experiment with a low income population☆

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ABSTRACT

This paper tests an intervention aimed at facilitating (cognitively) the adoption of healthy dietary habits. We provide easy-to-understand information about the risks of developing diabetes or heart diseases and give easy-to-follow dietary recommendations to minimize these risks. We implement two variations, one consisting of generic information, the other consisting of information tailored to the individual, the latter resembling newly developed on-line health assessment tools. On top of the information treatment, we implement a second experimental variation encouraging people to spend more time thinking about their decisions. We find evidence that the information intervention leads to healthier choices in the short run, but mostly in the generic treatment. Surprisingly, we find that people are on average pessimistic about their health, and therefore receive good news on average when the information is tailored to them. We find no evidence that increasing the time available to make choices leads to healthier choices, and find no evidence of long-term changes in habits. These results do not support a bounded rationality explanation for poor dietary choices.

1. Introduction

A poor diet is now the leading contributor to early deaths around the world (Forouzanfar et al. (2015)). Poor dietary choices have been linked to various risk factors and diseases, such as high blood pressure, diabetes and obesity.

Over the last decade behavioral economists have developed interventions targeting unhealthy habits. The prevalent approach has followed the Becker and Murphy (1988) view of habits, where habits are modelled as the result of a process of

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consumption shaping future preferences and future consumption. However, as it is, there is so far little evidence for such a process being at work in the context of diet (Belot et al. (2018)). In contrast, psychologists view habits as the result of a cognitive process (see Verplanken and Aarts (1999), Wood and Rünger (2016), Wood and Neal (2016)). The idea is that optimizing is cognitively costly, and developing simple heuristics (habits) saves on cognitive costs. Such heuristics should a priori be optimal, but they may not be if the environment changes and individuals do not re-optimize. In a bounded rationality world, re-optimization only takes place when changes in the environment are sufficiently large for people to notice them and find it worthwhile to re-optimize (see Wood and Neal (2016) for a recent discussion). In the context of health-related behaviors, an example could be an information shock, such as being diagnosed with a disease. One worry is that at that point changes may not be as effective, and as a consequence, it may be useful to think of interventions that alert individuals early on about the necessity to change their behavior. It is also plausible that heuristics are suboptimal because adopting a healthy diet is not straightforward. In contrast to other health-related behaviors such as smoking or exercising, eating healthily entails a more complex set of choices. Finally, dietary heuristics could also be suboptimal because people are systematically misinformed, e.g. are too optimistic about their health or unaware of the link between their lifestyle and their health. Previous research has found that individuals have incorrect beliefs about health risks (see next Section).

In this paper, we conduct a laboratory experiment testing an intervention designed around the cognitive approach to habits. The intervention aims at facilitating re-optimization and the adoption of healthy dietary habits. We provide easy-to-understand information about health risks and give simple recommendations. We implement two variations: One group receives generic information on the average risks of contracting heart disease or diabetes, as well as easy-to-follow recommendations on lifestyle changes that can reduce the risks of developing either of these diseases. The information is provided in an easy-to-understand manner (e.g. "eat 5 portions of fruit and vegetables a day"), but is not tailored to the individual. The second group of participants receives *personalized* health information via a specialized computer-based tool. The tool is an adapted version of a publicly available assessment tool called 'Your Disease Risk' (YDR) (Baer et al. (2013)), which provides individual information about risks of developing diabetes and heart disease, and then provides tailored recommendations to reduce the risks. A third group (control), receives neutral information that has no link to health or diet (an article on architecture). We measure participants' dietary choices through an incentivized shopping task on a digital platform. Participants receive GBP 30 to spend and can choose across over 100 food and drink items, varying in their nutrition profiles.

On top of this intervention, we test the bounded rationality hypothesis more directly by encouraging people to devote more time to their dietary choices. Participants (across all information groups) are split into two further groups - a 'long time' group and a 'short time' group. The long time group has 10 minutes to choose their basket of food and drinks, while the short time group has 3 minutes. Note that the only variation we introduce here is in the time participants have to ponder their purchases. We deliberately do not give them access to more or less information about products across treatments. The idea here is simply to induce participants to spend more time "thinking" about their choices, holding information constant.

We recruited participants with a household income below the UK median. We focus on this group for two reasons: First, disadvantaged socioeconomic groups appear more vulnerable to the obesity epidemic. Levine (2011) finds that in the U.S. the prevalence of obesity among adults is 145% higher in counties with poverty rates over 35%. Second, recent evidence by Mani et al. (2013) and Laraia et al. (2015) argue that the poor may be more at risk of poor decision-making. The hypothesis is that poverty takes up a considerable proportion of cognitive resources, and therefore could causally impair decision-making. If this view is correct, interventions that minimize the cost of re-optimizing may be particularly appropriate for this group.

Using the nutritional information from the chosen basket of food and drink items, we evaluate the impact of health information and time availability on food choices, controlling for a number of factors like current state of hunger, prior health knowledge, prior health status (and knowledge of such status), current dietary habits, socio-economic factors and demographic indicators. We also conduct a follow-up session 3 months later in order to measure the long-term impact of information provision on people's food choices.

The results provide evidence that participants in the information treatments select healthier food baskets that contained a lower proportion of unhealthy items. The results are however stronger in the generic health information treatment where selected food baskets contained around 17% less total fat, 20% less saturated fat and 15% less salt relative to the no information group.

The fact that the effects are stronger in the generic treatment may appear surprising. To understand why this may be the case, we examine how the treatments affected participants' beliefs about their health. We find that participants in the tailored health information group received good news on average, that is, they were told that their relative risk of heart disease and diabetes is lower than they thought. As a consequence, beliefs about their own health status became more optimistic after receiving the tailored information. The good news did not translate into statistically worse dietary choices, however. If anything, we find evidence that participants chose food items with lower calories, irrespective of whether they received good or bad news. Because of the randomization, we can assume that participants in the generic information were most likely too pessimistic as well, but they did not receive tailored information and they did not update their beliefs about their own health. Most participants report that the information was not novel, thus, it seems unlikely that the channel driving behavioral change is information. Rather it seems that the intervention affected behavior through salience.

Our second experimental variation - variation in the allotted time to shop for a food basket - did not affect dietary choices significantly. End surveys suggest that the variation worked in the sense that people spent more time on their choices: those in the longer time treatment were more likely to report they had enough time to choose their purchases. But this extra time did not affect choices. In fact, combining with the results on the effects of information, the evidence suggests that people do not need much thinking time to adjust their choices. They can easily follow simple healthy dietary recommendations.

A follow-up session held three months after the initial experiment shows no strong evidence of long term changes in dietary habits. We only find a negative effect of the tailored health information treatment on the number of calories in foods chosen. Overall, our results confirm that salience and attention may play a key role in behavior that is habitual in nature, but also suggest that people are in fact not too optimistic about their risks of developing diabetes or heart disease. This may explain why recent efforts by public health agencies to offer personalized health information have had limited success so far. For example, the NHS's Health Check programme, aimed at providing a free health assessment for people aged 40 to 74, appears to have had limited effectiveness despite its £165 million annual cost (Chang et al. (2016)).

The remainder of the paper is structured as follows. Section 2 summarizes the related literature. Section 3 presents a conceptual frame work. Section 4 describes the design of our experiment. Section 5 presents the results and Section 6 concludes.

2. Related literature

There has been relatively little work on interventions targeting re-optimization of dietary choices. Carrera et al. (2020) looks at whether the provision tailored health information of cholesterol levels has an impact on food choices among employees at a hospital in the US. Workers were incentivised to undertake a biometric health screening test. Measurements of this test included: cholesterol, glucose levels, blood pressure and BMI (the authors focus solely on cholesterol levels in their study). They combine these readings with data on weekly food purchases from the hospital cafeteria. The results show a statistically-significant decline in total spending on food purchases among those who were diagnosed as 'high risk', particularly among those who were previously unaware of their cholesterol status.

Another related study is Oster (2018) who looks at the impact of diabetes diagnosis on food purchases using household scanner data. Diagnosis of diabetes is inferred from purchases of glucose testing products, since such items are required in order to manage their disease and track their blood sugar levels. The results show that, post-diagnosis, households purchase slightly fewer calories (around 6.4 percent) in the two months around the diagnosis, this declines to an imprecisely estimated 2.5 percent one year after the diagnosis. These changes reflect some improvements in diet quality with reductions in non-whole grains, fizzy soft drinks, and whole milk products. These results are in line with a growing literature on the impact of disease diagnosis on eating patterns. Both Zhao et al. (2013) and Bhalotra et al. (2020) examine hypertension diagnosis. Zhao et al. (2013) find that people reduce their intake of fat in the 12 months immediately after the diagnosis and that this effect is strongest among the richest third of the population. Bhalotra et al. (2020) find an imprecisely estimated improvement in diet quality.

These papers focus on the effects of tailored information. In contrast to these studies, the interventions we propose aim at facilitating re-optimization by making concrete easy-to-follow recommendations, in addition to providing information about health. We also have a generic information treatment, which does not require access to individual information and may therefore be easy to implement.[1,2] Another important difference is the nature of our sample. We focus on a low-income population, whereas these studies do not have a specific target group. It could be that re-optimization is a more acute issue in a poor population, as hinted by the recent work by Mani et al. (2013). Finally, our data comes from a lab experiment whereas the other studies use data from the field. The advantage here is that we have detailed information on the individuals, their health history, as well as their beliefs about their health and anthropometric measurements. The caveat is that the choices we study are made in a laboratory setting. We discuss external validity in Section 4.8.

Also relevant for our work, a number of recent studies look at the effects of providing general health and nutritional information to consumers on food choices. For example, Wisdom et al. (2010) find that providing calorie content information on menus at Subway restaurants reduced calorific intake by approximately 7%. Similarly, Bollinger et al. (2011) look at calorie posting at Starbucks showing that although average calories per transaction fell by around 6%, this was solely driven by changes in food choices, with zero impact on drinks. Our paper differs in that we study the impact of more general, easy-digestible health information that incorporates facts regarding heart disease and diabetes as well as dietary and lifestyle recommendations to reduce the risk of illness.

[1] To classify items in the tool as healthy or unhealthy we use the nutrient profiling technique developed by the UK's Food Standards Agency (FSA). This is set out in more detail in section 4.6.

[2] The type of tailored information we provide is also different. In Carrera et al. (2020) participants were told their cholesterol levels (among other biometric measures), which is one of the risk factors that can lead to cardiovascular disease. At the other end of the scale, in Oster (2018) people have received a diagnosis of diabetes. Our tailored information lies somewhere in between, since although the Your Disease Risk (YDR) tool is not intended to diagnose either heart disease or diabetes (in fact people with pre-existing diseases were excluded from this study), it combines several risk factors (including self-reported cholesterol, among other things) to calculate the relative risk of developing heart disease and diabetes over the next 10 years relative to the average person of the same age and gender living in Scotland. In this respect, our paper is more in line with the likes of Dupas (2011), who find that providing teenagers in Kenya with the relative risk of developing HIV according to their partner's age significantly reduces the risk of unprotected sex.

We also contribute to the literature on uncertainty and updating of beliefs regarding people's health and associated behaviors. The uncertainty and lack of knowledge regarding health or disease incidence is well-documented (e.g. Crossley and Kennedy, 2002 and Barrett-Connor et al., 2011), as is the general lack of awareness regarding lifestyle risk factors (e.g. Sanderson et al., 2009). In both cases, standard economic theory would suggest that people will update their beliefs when receiving new information, and will adjust their behaviour as a consequence. However, there is also evidence to suggest that when it comes to certain health-related behaviors, people actually *overestimate* the risks involved in terms of falling ill or developing a disease.

Appendix Table A.1 presents papers that examine health risks and people's perception of those risks. We categorise risks into three categories: i) smoking, ii) obesity, and iii) alcohol consumption. Smoking is an example of health behaviour where people's beliefs are typically pessimistic. Viscusi (1990), Viscusi and Hakes (2008), (Lundborg and Lindgren, 2002), and Khwaja et al. (2009) all examine people's perception of the risk of developing lung cancer and find that both smokers and non-smokers overestimate this risk. Viscusi and Hakes (2008) report that adults on average overestimate the lung cancer risks of smoking, as well as the mortality risks and life expectancy losses. They find that higher risk beliefs reduce the likelihood of starting to smoke, and increase the probability of smoking cessation among smokers. Khwaja et al. (2009) expand the range of health outcomes to include heart disease and stroke as well as examining longevity. Similarly they find overestimation of the risks of developing these diseases as a result of smoking. Arni et al. (2020) look at the extent to which people overestimate their health along two dimensions which are normally asymptomatic - having high cholesterol and having high blood pressure. They find that those who overestimate their health beliefs (i.e. those who have say they do not have high blood pressure or high levels of cholesterol but they do) are not more likely to smoke.

For obesity (Appendix Table A.1B), Winter and Wuppermann (2014) find mixed evidence on people's perception of the risks of developing various diseases. They consider a range of diseases and conditions ranging from asymptomatic conditions such as hypertension to serious health events namely strokes and heart attacks. They find that people overestimate the risks of a heart attack (a leading cause of death and hence a salient condition) and underestimate the risk of hypertension (a typically symptomless condition which has longer term consequences). Arni et al. (2020) also find that those with optimistic beliefs about two asymptomatic conditions are more likely to have a high BMI and are more likely to be obese.

For alcohol consumption (Appendix Table A.1C), Lundborg and Lindgren (2004) find that those aged between 12–18 overestimate the addictive nature of alcohol and substantially overestimate the risks of becoming an alcoholic. Sloan et al. (2013) find that drinkers overestimate the probability of getting alcoholic-related liver disease and that heavy binge drinkers also overestimated this probability but on average were more accurate. Arni et al. (2020) find that those unaware of their high cholesterol or blood pressure are more likely to drink suggesting health overconfidence leads to more risky health behaviours.

Therefore, the literature on risk perception and health status shows a mixed picture of both pessimism and optimism. This may be partly due to successful public health messaging, such as in the case of smoking, but also the salience of the condition. People appear to be too optimistic when the event is either not salient, or is of low probability (Viscusi, 1985), and too pessimistic for high probability events or more salient conditions.

Our paper also contributes to the broader topic of belief updating and information processing. In economics, Villeval (2020) reviews the evidence on how people respond to performance feedback. There is evidence that good news is reinforcing and that bad news can be discouraging. Some studies do not find much effect of feedback though. In psychology, a recent influential and related paper by Sharot et al. (2011) shows that people are more likely to embrace good news than bad news. They elicit beliefs about the probability of experiencing adverse life events, including including health-related events such as developing cancer. They show that when learning that the risk of experiencing future negative events, such as cancer, is higher than expected, people are less likely to update their beliefs relative to a situation when they learn that their risk is lower than expected.

Finally, our paper relates to the vast literature on bounded rationality (see Conlisk, 1996 for a comprehensive survey). There is however limited evidence on the role of bounded rationality in health-related decisions, and in food choices in particular. In a computerized experiment, Scheibehenne et al. (2007) find that a simple heuristic whereby participants focused on one food product attribute (e.g. convenience) could be used to explain people's food choices during the experiment. Another related experiment by Reutskaja et al. (2011) uses eye-tracking technology to analyze the computational processes that people undertake when selecting among various snack items, with a time limitation of 3 seconds to make each choice, in order to mimic a real-world supermarket situation. The authors find that in general when making choices people search for a random amount of time, depending on the value of the items under selection, and then pick the best option that they have seen, at odds with optimal search models. Our paper fits in with this literature by introducing a time availability treatment whereby some participants only have 3 minutes to select their £30 food and drink basket as opposed to 10 minutes. The key difference in our case is that rather than looking at 'optimal' choices, our aim is to see whether restricted time availability has any effect on the healthiness of the food choices.

3. Conceptual framework

In the Appendix, we present a simple model capturing how bounded rationality may translate into unhealthier choices. Here we describe the intuition behind the model, and the predictions that we derive from it.

We consider a world where agents have limited cognitive resources that need to be allocated among various decisions, including health or dietary choices. Each domain is associated with an individual-specific optimal decision. We assume that agents have imperfect (yet unbiased) knowledge regarding these optimal decisions, and that any actions taken which deviate from this optimal in each domain yield disutility. However, the agent can devote cognitive resources to each problem to reduce the expected uncertainty surrounding this optimum. For example, she can spend time thinking about the problem or acquire and process information relevant to the problem, although at a cost, that we will refer to as *cognitive cost*. Furthermore, in our bounded-rational world, agents have a limit on the amount of cognitive resources that they can allocate across different decision domains.

We assume that individuals have unbiased yet noisy prior beliefs regarding the optimal action. The agent derives disutility from deviating from her optimal decision. To capture the fact that payoffs of these decisions may materialize at different times in the future, we introduce domain-specific discount factors, which can be interpreted as the product of an individual-specific discount factor and a parameter capturing the delay associated with the materialization of payoffs. A domain with a high discount factor is one where payoffs materialize relatively late. The lower the domain-specific discount factor, the less impact deviations from the optimal decision will have on today's utility.

The agent has the opportunity to reduce the expected deviation from the optimal decision, thereby increasing what we refer to as *mental clarity*. For example, in the case of health and nutrition, this could be understanding better what constitutes a healthy diet and what food items are needed to achieve it. Mental clarity comes at a cognitive cost and individuals face a cognitive resource constraint, that is, they have limited cognitive resources they need to allocate optimally across each of the decision domains.

We show under mild assumptions that the optimal level of mental clarity in one decision domain depends on domain-specific cognitive costs, degree uncertainty about the optimal action and the discount factors. If the discount factor is higher, then payoffs will have more weight in today's decision, meaning that it would be worthwhile for her to allocate more resources towards reducing the expected deviation from her optimal decision. All else equal, prioritization will be given to decisions in domains that have a lower discount factor (more immediate payoffs). On top of that, Haushofer and Fehr (2014) show that lower-income groups are less patient on average. For these reasons, we would expect lower income groups to focus on other more pressing concerns.

Turning to the interventions we consider in the study, we conceptualize them as follows.

Information interventions correspond to a subsidy to the cost of obtaining mental clarity, which should result in a lower deviation from the agent's optimal decision relative to the no-information situation. In the simple model we present we assume that individuals do not have biased beliefs on average. If they do have biases, we would then also expect the tailored information intervention to correct for these biases. For example, if people underestimate their disease risks on average, receiving information should lead to healthier choices.

Time constraints can be modeled as a reduction in cognitive resources available to make a decision. Inevitably time constraints should lead to higher deviations from the agent's optimal actions in *all* domains and less information acquired, relative to a situation where more time is available. This variation is a more direct test of the bounded rationality hypothesis for poor dietary choices: we would expect that an increase in time available would lead to a healthier food basket (which is presumably complex to identify).

Note that we chose this intervention rather than an intervention aiming at depleting cognitive resources, because cognitive resource depletion may affect behavior through self-control, which is not the mechanism we are interested in here. We want to test for a cognitive mechanism and test whether nudging people to think harder about their choices has an effect on their decisions, holding self-control constant.

With this conceptual framework in mind, we will derive specific predictions after having described the experimental design in detail.

4. Experimental design

The first and main part of the study was conducted from Monday 13th June to Friday 17th June 2016, and was held in the Behavioural Laboratory at the University in Edinburgh (BLUE). Each day there were four time slots: 9.30am-11am, 11.30am - 1pm, 2.30pm - 4pm, 5.30pm - 7pm. We conducted the experiment in 20 sessions, with up to 18 individuals per session. The 20 sessions were spread over 5 consecutive days. We assigned treatments to sessions and pre-assigned sessions to specific slots in order to guarantee a balance of treatments across times of the day and days of the week. Participants were offered £50 compensation for taking part in the experiment. Participants were able to indicate their preferred time slots, but were not informed in advance of the treatments associated with each time slot. Participants received an information leaflet in advance at their home address and were asked to sign a consent form on the day of their first visit.

4.1. Sample and recruitment procedure

In total, we recruited a sample of 318 participants, with a focus on low-income individuals (with an annual income below £26,500) living in the proximity of the University of Edinburgh's main campus. More specifically, participants had to satisfy the following eligibility criteria:

- Must be over 18 years of age;

- Must live in Edinburgh;
- Must be fluent in English;
- Must have an annual household income below £26,500;
- Must not be currently undertaking any regular medical treatment;
- Must not be pregnant.

We recruited participants via three main channels, namely the distribution of information leaflets by post to home addresses in the more deprived neighborhoods in the vicinity of the University, which was done through a local marketing intelligence firm; online advertisements on one of the leading classified advertising websites in the UK (Gumtree); as well as promotional emails sent out to non-academic and non-student members of the BLUE mailing list.[3]

4.2. Procedure

Upon arriving at the BLUE lab, all participants were asked to fill out an initial questionnaire, which included questions related to demographics, socio-economic background, education, employment status, as well as various questions related to their prior knowledge regarding health, nutrition and their own health status. Participants were also asked to complete a short food frequency questionnaire[4] (based on the National Cancer Institute's Dietary Screener Questionnaire) in order to obtain a measure of their typical eating habits.

Following this initial stage, we then moved on to the actual interventions.

Participants were assigned to one of six (6) groups upon registration (based on their registration slot, which was pre-assigned to a specific treatment[5]):

1. No Information/Short Time
2. No Information/Long Time
3. Generic Information/Short Time
4. Generic Information/Long Time
5. Tailored Information/Short Time
6. Tailored Information/Long Time

4.3. Information intervention

The first intervention in our study is related to the provision of different types of health information to our participants. In particular, we are interested in understanding the impact of providing easy-to-digest information, and the distinction between tailored versus generic health information. We had a no information (control) group, which was asked to read a non-health related article on architecture, taken from Wikipedia. This article was chosen following a pre-experimental session held on Thursday June 2nd 2016 at 4pm, where it was deemed by participants to be both unrelated to health and emotionally-neutral, which is particularly important given the well-documented impact of emotional state on food choices (Gibson 2006).

The tailored information treatment group was provided with personalized health information via an adapted version of a computer-based health assessment tool called 'Your Disease Risk' (YDR) (Baer et al. 2013). The algorithms developed for this tool are used to predict the chances of developing a particular disease over the next 10 years, relative to the average person of the same age and gender. We adapted the algorithm for the Scottish population using data from the Scottish Health Survey, 2008–2012. These calculations are done on the basis of a series of questions that respondents are asked to fill in, related to their medical history, their parents' medical history, dietary habits (e.g. consumption of fruit and vegetables per day) and lifestyle choices (e.g. smoking, exercise, average daily alcohol consumption). Once these questions are answered, the YDR tool provides a scale showing the respondent's relative risk of developing a particular disease, which ranges from 'Very Much Below Average' to 'Very Much Above Average'. The system also provides tailored recommendations to respondents which would help them to lower their risk (e.g. 'Eat more unsaturated fats', 'Stop smoking'.). For the purpose of this study, we focus solely on two diseases, namely heart disease and diabetes. Note that the questions required as inputs for the YDR tool are already included in the initial questionnaire described earlier, and hence were answered by all participants. However, the Tailored Information group are the only participants to receive the YDR risk and recommendations (other groups were not aware of this treatment).

The generic information treatment group saw a two-page document with information published by the NHS and Harvard Medical School. In essence, this document first provided information regarding the average risk of developing heart disease and diabetes in Scotland (for the entire adult population), as well as some details regarding each disease. The wording is exactly identical to that used in the tailored information treatment, with the only difference being that in this case the risk is general for the entire population rather than personalized for each individual based on their answers. The document also

[3] A dedicated website and registration page was created in order to handle registrations, and prospective participants were given a contact number and email address in case of any queries. Appendix Figure A.1. shows the recruitment leaflet. Ethical approval was granted on May 10th, 2016 by the School of Economics' Ethics Committee. A pre-analysis plan was submitted and published on the American Economic Association's RCT Registry in May 2016 (reference: AEARCTR-0001189). The analysis in this paper, except where otherwise stated, follows what was originally set out in this plan.

[4] The food frequency questionnaire is shown in full in the appendix (Figure A.2).

[5] The allocation of treatments to session days and times can be found in Appendix Table A.2 in the appendix.

provided the full list of recommended actions that would lower the risk of developing each disease, as specified in the YDR tool. Again, the wording is exactly identical to that used in the tailored info treatment, with the only difference being that in this case the full list of potential recommendations is provided rather than those specifically pertaining to each individual. Thus, the design is set up to ensure maximum comparability across treatments as this allows us to assess the marginal impact of tailored health information relative to generic information. A copy of the generic information document related to heart disease is provided in the Appendix, along with a sample results page from the tailored information tool (Figure A.3A and A.3B).

4.4. Time intervention

The second intervention in our study is related to the time available for each participant to make their food choices. At the start of this intervention, all participants were allocated a budget of £30 to spend on food and drink from a specially-designed choice tool that appears similar to an online supermarket developed specifically for this study.[6] The choice tool contains a total of 120 food and drink items. We chose the 10 most popular items across the following grocery categories: fruit and vegetables, meat, fish, confectionery, chilled meals and drinks. We ended up with a mix of 66 ”healthy” and 54 ”unhealthy” items.[7] Apart from capturing the participants' food choices in terms of which items were actually selected, the system has been designed to calculate the nutritional value of each basket along several key nutrients, namely calories, carbohydrates, total fats, saturated fats and sugar content. These will be used to construct our main outcome variables. All prices used in the supermarket tool reflect current market prices at the leading high street supermarkets in the UK, in order to make the food selection task more realistic. Participants were allowed to spend their budget on any of the items listed in the supermarket tool, just as long as they did not exceed the £30 limit.

The experimental variation is related to the *time* available to select food and drink items. The Long Time group were given 10 minutes to make their choices (and were required to stay for the entire duration), while the Short Time group were given just 3 minutes. Both time periods were pre-tested in BLUE before the start of the experiment. At the end of each session, 1 subject per session was picked at random and his/her food basket was delivered to his/her home address two weeks after participation. This waiting period was chosen to ensure that their choices would not in some way be influenced by the current stock of food that participants had at home at the time of the experiment.

4.5. Post-Treatment and follow-up

At the end of the session, all participants were asked to fill in a short questionnaire, which is primarily designed to answer three questions:

- Whether the participants updated their beliefs regarding their own health status following the information treatment;
- Whether the participants believe that the information provided was credible/trustworthy or not;
- Whether the choice tool was easy to use and comparable to their typical supermarket shopping experience.

In order to gauge the long-term impact of the health information intervention, we also ran a follow-up session 3 months later from Monday 12th September to Friday 16th September 2016. Participants were asked to complete a short questionnaire aimed at eliciting their beliefs regarding their health status and whether they had undertaken any dietary changes (particularly for those who received tailored health information). They were also asked to complete a food frequency questionnaire, a 24-hour dietary recall (using the INTAKE24 software developed specifically for the UK[8]), and were once again allocated a £30 budget to spend using our food choice tool. In this instance there were no time restrictions on their food choices - all participants had a maximum of 10 minutes to make their choices.

4.6. Outcome variables and hypotheses

As mentioned above, we use the data gathered from the food choice stage to construct our outcome variables, which include the following:

- The primary outcome is the proportion of unhealthy items, where an item is classified as ‘unhealthy’ is based on the UK Food Standards Agencys nutrient profiling technique. Points for each item are allocated on the basis of the nutrient content of 100g of a food or drink. Points are awarded for energy, saturated fat, total sugar and sodium (A-nutrients), and for fruit, vegetables and nut content, fibre and protein (C-nutrients). The points from C-nutrients are then subtracted from the score for A-nutrients to calculate a final score. The unhealthy items are then classified as foods with 4 or more points and drinks with 1 or more points.[9]
- The nutrient content of each participant's food basket, where the nutrients under consideration are calories, total fat, saturated fat, sugar, salt, fibre, and protein (we estimate a separate regression for each nutrient).[10]

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[6] For a full presentation and evaluation of the tool see Spiteri et al. (2019).

[7] A complete list of all the food and drink items included in this food choice tool is provided in Appendix Table A.3 in the appendix.

[8] Screenshots of the programme can be found in appendix (Figure A.4.)

[9] For full details of how the points are calculated see https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/216094/dh_123492.pdf

[10] We present total nutrient content in the main text and nutrients per 100g in the appendix.

- The proportion of the budget (£30) spent on fruit and vegetables;

The hypothesis we will test are the following:

1. Participants who receive generic health information will on average select healthier food/drink items relative to those who receive no health information.
2. Participants who receive tailored health information will on average select healthier food/drink items relative to those who receive no health information.
3. Participants who have more time available to make their food choices will select a healthier food basket than those with less time availability.

The first two hypotheses will hold if participants lack information and tend to underestimate their health risks. For the second hypothesis, the direction of the change should depend on the type of health information received (good or bad news): those with below average risks could 'reward' themselves with unhealthier choices, while those with above average risks could pick healthier choices.

The third hypothesis ties in with the literature on the impact of time constraints on decision-making (Svenson and Edland, 1987; Van Herpen and Van Trijp, 2011). However, it is important to note that this prediction is highly dependent on the type of decision-making rule used by individuals when making choices under time pressure. Findings from the sizable literature on behavioral psychology (e.g. Beach and Mitchell, 1978 and Ford et al., 1989) suggest that time limitations have a significant impact on people's decision-making processes, leading to the minimization of cognitive effort as people increasingly rely on a variety of heuristics or shortcuts rather than carefully-considered judgments. These heuristics can be both intrinsic to the individual and related to his/her own biases or extrinsic and part of the decision-making context. In our case, the somewhat artificial laboratory setting, where participants are fully aware that they are part of a study, may lead to healthier choices even under time constraints. Similar to the previous discussion, the way in which intrinsic heuristics may influence people's food choices will to some extent depend on the individual's existing diet/health, with people typically relying on what they are already familiar with in order to make rapid decisions (Dijker and Koomen (1996)).

For the long term analysis, we will also look at dietary or lifestyle changes that the participants report having undertaken in the 3 months after the initial intervention. The follow-up questionnaire contains two questions related to this matter. The first question states: "Looking back over the last 3 months, have you made any changes to your diet or lifestyle habits?", which elicits a simple 'Yes' or 'No'. The second question follows-up on this point: "If yes, please indicate the change in your diet or lifestyle that you have undertaken from the list below", which then lists the following options: "Stop smoking, Do more exercise, Eat more fruit and vegetables, Eat less junk food and processed foods, Eat less sugar, Eat less red meat, Take vitamins and other supplements, Drink less alcohol". Therefore, we can use this data to obtain two outcome variables:

1. A simple dummy variable indicating whether any changes have been made;
2. A series of eight dummy variables for each response.

In addition, we will also look at the changes in BMI and waist circumference.

The hypothesis we wish to test here is that those who received generic or tailored information will have report more lifestyle changes than the control group, and as a consequence may have a lower BMI and waist circumference.

4.7. Power calculations

We ran power calculations on our data, based on the sample of 309 subjects across all interventions, both in terms of the information treatments (90 control group; 111 generic information group; 108 tailored information group) and time treatments (153 short group; 156 long group). When it comes to the information treatments, our power calculations show that our sample size is sufficient to detect aggregate nutrient content differences of 15% across treatments with over 80% power for total calories, sugar, fibre and protein, 76% power for differences in salt content, 67% power for differences in fat content, and 48% power for differences in saturated fat content. In the time availability intervention the sample size is enough to detect effect sizes of 15% in nutrient content with at least 80% power, depending on the nutrient under consideration.

4.8. External validity

The design has been chosen to mimic a familiar shopping environment for food choices. There are however potential limitations to the external validity of the study, which we discuss briefly here.

First, one may be concerned that the procedure (lab experiment) may lead to a Hawthorne effect. In contrast to studies conducted in the field, where participants are unaware they are part of an experiment, here participants will easily understand that the study is about health and food choices. They may therefore make healthier choices than they otherwise would. Perhaps even more relevant for our research question, the fact that participants are put in a novel environment and are presumably paying more attention to the tasks than they would in the field, could by itself trigger re-optimization for everyone, including the control group. This is plausible, and of course means that the treatment effects would be underestimated.

Another related concern is that our participants may perceive the £30 budget as a 'windfall' gain, and as a consequence spend it differently than they normally would. To gauge whether these concerns are legitimate, we compare the average proportion of the total budget spent on different food categories in our experiment to the mean household choices as recorded in ONS Family Spending data. The results for each category are shown in Appendix Table A.4. Because of the experiment we would of course expect that choices may be healthier than the average. Also, as we will show below, our cohort is on average relatively healthier than the Scottish population. Nevertheless, we find that spending across each category is relatively comparable across both our experiment and the population average. Crucially, our participants spent almost an identical percentage of their budget on meat and fish relative to the household mean (34.1%), which in our food choice tool was the most expensive category with a average price per item of £3.06. We do however observe that participants in our experiment spent a higher proportion of their budget on fruit and vegetables (34.6%), which could be due to the composition of participants but also to a possible Hawthorne effect.

Second, our experimental sample is not representative of the (low income) Scottish population and may be positively selected in terms of health. We will show below that this is indeed the case. However, there is concern and evidence that those who participate and take up the NHS health check are the so-called "worried well" - those who are already healthy and proactive and are looking for reassurance, (Riley et al. (2016) Gøtzsche et al. (2014)). Therefore, we would argue that the sample could be more representative of potential users of this type of tools than a random sample of low income individuals.

Third, the study also focuses on planned consumption rather than immediate consumption. It may be that different heuristics apply in the case of immediate consumption. Nevertheless, about 5 percent of purchases in Great Britain now takes place on-line and therefore involves planned consumption[11] and the online supermarket shopping channel is the fastest growing food purchase channel. There is evidence that planned food choices tend to be healthier than immediate food choices (Milkman et al. (2010)), thus we will not claim the conclusions we find here apply to immediate consumption as well.

5. Results

5.1. Summary statistics

We begin by presenting summary statistics of participants across the different treatment groups. Table 1 looks at participant demographic characteristics, education, and income. We also examine features of the experiment such as the timing of the experiment, which page the participants saw first from the food choice tool, and whether they were hungry at the time of the experiment. Finally, we present summary statistics on measures of pre-experiment dietary habits and health behaviours.

The first column presents the summary statistics for all the 309 participants who took part in the experiment. The sample was 39% male. Most were single (70%) with an average age of 36. The average participant was just overweight with a BMI of 25. The majority of the sample had a University degree, and 56% were employed. Nearly all (93%) had a household income lower than £25,000 which is in line with the recruitment criteria.

In Appendix Table A.5 we present a comparison of our sample to that of the Scottish population from the Scottish health survey (SHS). Our sample, despite being drawn from the Scottish population as opposed to the student cohort, is healthier than the average person living in Scotland. We can examine this by comparing various health and dietary measures in our data with the average recorded in the Scottish Health Surveys from 2008 to 2015. We make two comparisons. First, with all those in the Scottish Health Survey, and second with those with a household income below £26,000 to match as closely as possible to our experimental sample income criteria. Our sample has a similar gender composition compared to that from the SHS, however, it is younger, less white and more likely to be married. Our sample exhibits several characteristics that are consistent with a healthier lifestyle relative to the general Scottish population, including a lower proportion of overweight or obese people (BMI $\geq$ 25), a lower incidence of family heart problems, a higher proportion of people who eat five or more portions of fruit and vegetables a day. There is similarity in taking of vitamins between our sample and the two samples of the SHS. The experimental sample seems to be similar to the overall Scottish population along the lines of current smoking prevalence but the prevalence is lower compared to the low income sample. One health behaviour where our sample displays less healthier behaviours is that of alcohol consumption. Our sample have a higher rate of daily alcohol consumption than both SHS samples.

Returning to Table 1, the distribution of front pages of the food choice tool is broadly even between the various categories, as is the timing of the experiment. Most (around 80%) of those taking part were not hungry at the time of the experiment. Respondents were also asked about their diet and health behaviours. The majority of the participants followed a diet without dietary restrictions (78%), 48% eat fish at least twice a week, however 52% did not regularly eat 5 or more fruits and vegetables per day. Around 20% currently smoke and just under 30% have quit smoking.

Columns 2 to 4 in Table 1 present the means of variables by treatment group for the information treatment and columns 6 and 7 present the means for the time treatment. We test for balance in the information treatment by regressing the

[11] Statistics reported by Kantar WorldPanel for 2017.

Table 1
Summary Statistics and Balancing .

	All Participants		Information treatment			Info. p-value	Time treatment		Time p-value
	Mean (1)	SD	Control (2)	Generic (3)	Tailored (4)	All equal (5)	Short (6)	Long (7)	Short=Long (8)
Demographics/Body size									
Male	0.39	0.49	0.41	0.31	0.47	0.04	0.41	0.38	0.71
White	0.88	0.33	0.84	0.90	0.88	0.48	0.91	0.85	0.10
Single	0.70	0.46	0.68	0.75	0.66	0.32	0.67	0.72	0.39
Age	36.0	11.6	38.1	33.6	36.7	0.02	36.1	35.9	0.85
BMI	25.0	5.0	25.4	25.3	24.3	0.21	24.5	25.4	0.09
Waist	33.0	7.2	33.5	32.0	33.6	0.19	32.7	33.4	0.38
Qualifications/Employment									
Postgrad Degree	0.36	0.48	0.36	0.38	0.33	0.79	0.35	0.36	0.91
Undergraduate Degree	0.37	0.48	0.36	0.38	0.38	0.93	0.40	0.35	0.34
A-level	0.15	0.36	0.19	0.12	0.16	0.37	0.12	0.18	0.18
Employed	0.56	0.50	0.52	0.56	0.58	0.69	0.50	0.62	0.04
Unemployed	0.08	0.27	0.10	0.08	0.06	0.67	0.10	0.06	0.13
Income									
> £25,000	0.07	0.25	0.09	0.05	0.06	0.62	0.07	0.06	0.79
£20,000-25,000	0.28	0.45	0.24	0.31	0.30	0.60	0.25	0.32	0.16
£15,000-19,999	0.21	0.41	0.19	0.21	0.22	0.85	0.20	0.22	0.64
£10,000-14,999	0.22	0.41	0.24	0.23	0.19	0.55	0.23	0.21	0.72
£5,000-9,999	0.13	0.33	0.13	0.12	0.13	0.94	0.15	0.10	0.21
Experiment timing									
Time: 9.30am	0.23	0.42	0.32	0.23	0.16	0.02	0.29	0.17	0.01
Time 11.30am	0.25	0.43	0.33	0.15	0.27	0.01	0.32	0.17	0.00
Time 2.30pm	0.24	0.43	0.14	0.30	0.27	0.03	0.27	0.22	0.31
Front page of diet tool									
Meat	0.18	0.39	0.19	0.17	0.19	0.94	0.19	0.17	0.71
Bread	0.16	0.37	0.16	0.15	0.18	0.89	0.16	0.16	0.94
Confectionary	0.19	0.39	0.19	0.19	0.19	0.99	0.20	0.19	0.82
Ready meals	0.14	0.34	0.14	0.14	0.13	0.96	0.13	0.14	0.79
Drinks	0.17	0.38	0.18	0.18	0.17	0.96	0.18	0.17	0.94
Hungry at experiment	0.22	0.41	0.12	0.23	0.29	0.02	0.18	0.26	0.07
Pre-experiment Diet/Health Behaviours									
Regular Diet	0.78	0.41	0.77	0.79	0.79	0.90	0.79	0.78	0.75
Vegetarian	0.15	0.36	0.19	0.15	0.12	0.41	0.14	0.17	0.47
Fish 2/week	0.42	0.49	0.40	0.42	0.44	0.82	0.39	0.46	0.18
Fruit & Veg 5/day	0.48	0.50	0.54	0.39	0.52	0.05	0.45	0.51	0.33
Wholegrain 3/day	0.40	0.49	0.48	0.35	0.39	0.18	0.42	0.38	0.41
Refined grain 3/day	0.42	0.49	0.44	0.45	0.36	0.34	0.41	0.42	0.84
Sat fat 2/day	0.42	0.49	0.50	0.39	0.40	0.22	0.42	0.43	0.84
Trans fat daily	0.35	0.48	0.38	0.34	0.34	0.84	0.35	0.35	0.99
Drinks alcohol daily	0.18	0.39	0.16	0.17	0.21	0.55	0.18	0.18	0.94
Currently smokes	0.21	0.41	0.21	0.16	0.26	0.21	0.22	0.21	0.82
Quit smoking	0.29	0.46	0.29	0.28	0.31	0.84	0.27	0.31	0.45
N	309		90	111	108		153	156	

Note: This table presents summary statistics for the two treatment arms and the control group. Column (5) displays the p-value from a test of equal means of the three groups for the information treatment, and column (8) displays the p-value from a test of equal means of the three groups for the time treatment.

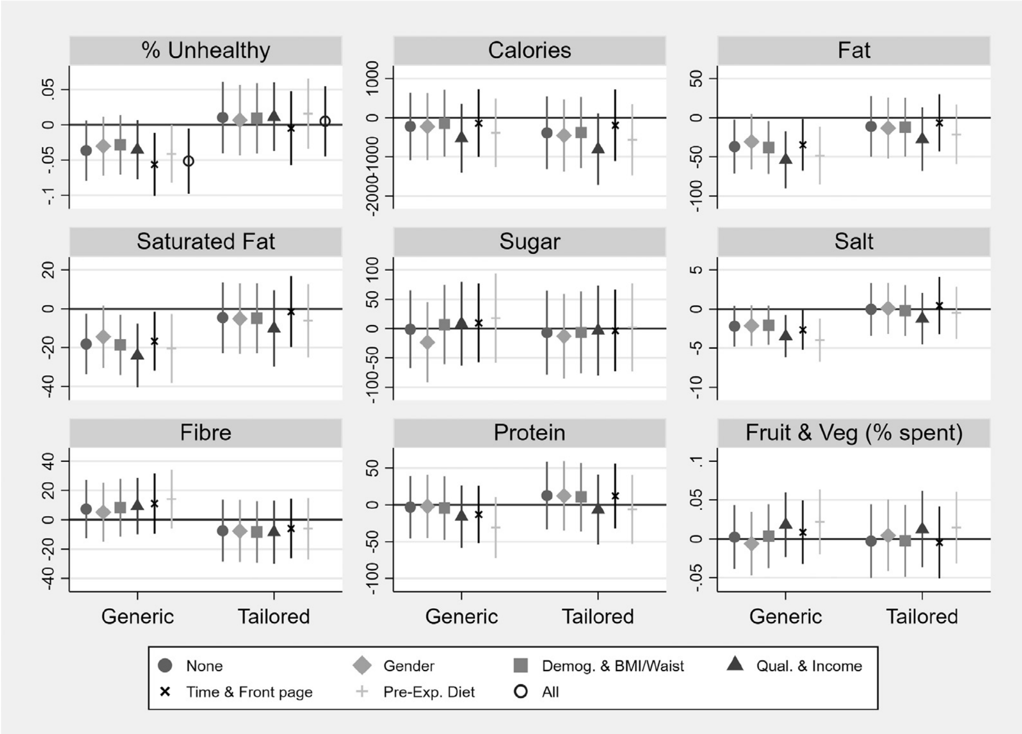

Fig. 1. The Impact of the Information Treatments on Dietary Choices with various control variables *Note*: Each shape per dependent variable comes from a separate regression with different sets of controls. "Gender" includes: an indicator for being male. "Demog. & BMI/Waist" includes: indicators for being male, white, married, and controls for age, BMI, and waist. "Qual. & Income" includes: indicators for having a postgraduate degree, undergraduate degree, A-level qualifications, being employed, being unemployed, and a set of income categories. "Time & Front page" includes: a set of indicators for when the participant's lab session took place, indicators for the first page they saw as part of the tool, and an dummy indicating whether they were hungry. "Pre-Exp. Diet" includes: an indicator for having no dietary restrictions or being a vegetarian, dummies that capture their regular diet (eating fish twice a week, eating fruit and vegetables 5 times a day, eating wholegrains 3 times a day, eating refined grains 3 times a day, eating foods high in saturated fat at least twice a day, eating foods high in transfats daily, drinking alcohol daily) and indicators for whether they currently smoke or have tried to quit smoking. "All" includes: all of the above.

characteristics on the two treatment indicators, column 5 presents the p-value of the test of their joint significance hence testing the equality of the three groups, and column 6 presents the p-value of the *t*-test of the 'long time' dummy.

There are a few significant differences between participants in the treatment and control groups. We find that there is a higher proportion of men in the tailored information treatment and a lower proportion in the generic information group relative to the control, the two treatment groups are also slightly younger than the control group. We also find that the tailored information group was on average more likely to report that they were hungry at the start of the experiment. We will address this and the other imbalances in more detail below. There are no differences across the control group and treatment groups in qualifications, employment, and income, nor for the view of the front page of the tool, or along the diet and health behaviors prior to the experiment. For the time treatment, we find a significantly higher proportion who are employed in the long time treatment. For the other categories (besides the timing of the experiment), we do not find other significant differences. For both treatment arms we do find systematic differences between the treatment and control groups along the timing of the experiment. It is worth recalling that we in essence have 6 treatment arms, and that treatments were assigned at the session level. Hence having one or two more sessions in the morning or afternoon with a particular treatment can lead to imbalance at the individual level. It was the case that all treatments took place at each time slot, but because of the session sizes, we have either 3 or 4 sessions for each of the main information treatments (tailored, generic, no info) in the morning or in the afternoon. Due to the differences across groups we will report how the treatment effects change when controlling for the variables for which there is imbalance. These are shown in Fig. 1 and are discussed in more detail later. In brief, our results are robust to the inclusion of these variables.

Next we present the results from the pre-intervention survey where we elicited the beliefs of the participants regarding their risk of developing heart disease and diabetes over the next ten years. Table 2 shows that participants systematically overestimate their risk of developing heart disease. The table shows the joint distribution of the participants beliefs about their pre-treatment risk of developing heart disease (panel A) and diabetes (panel B) and their risks as assessed by the Your Disease Risk tool. The percentage who hold correct beliefs are shown along the diagonal in bold. Only 18% and 24% correctly identify their correct risk for heart disease and diabetes respectively. We now turn to the main results of the experiment.

Table 2
Joint distribution of Pre-Information belief and risk from YDR.

		a) Heart disease							
		Pre-Information Belief							
		v. much below avg.	much below avg.	below avg.	avg.	above avg.	much above avg.	v. much above avg.	Total
Risk	v. much below avg.	**11.3**	11.0	17.8	11.7	5.8	0.3	0.0	57.9
Score	much below avg.	2.3	**2.6**	4.9	7.8	3.9	0.3	0.0	21.7
	below avg.	0.3	1.3	**1.9**	3.2	2.6	1.0	0.0	10.4
	avg.	0.0	0.0	0.3	**1.0**	1.6	0.0	0.0	2.9
	above avg.	0.0	0.3	0.3	2.3	**1.3**	0.7	0.3	5.2
	much above avg.	0.0	0.0	1.0	0.3	0.3	**0.0**	0.0	1.6
	v. much above avg.	0.0	0.0	0.0	0.3	0.0	0.0	**0.0**	0.3
	Total	13.9	15.2	26.2	26.5	15.5	2.3	0.3	100.0
					b) Diabetes				
					Pre-Information Belief				
		v. much below avg.	much below avg.	below avg.	avg.	above avg.	much above avg.	v. much above avg.	Total
Risk	v. much below avg.	**11.7**	9.1	10.0	10.0	4.9	1.0	0.0	46.6
Score	much below avg.	2.3	**4.9**	6.5	5.2	3.6	0.7	0.3	23.3
	below avg.	0.7	1.9	**2.6**	3.9	1.9	0.0	0.3	11.3
	avg.	0.7	0.0	1.3	**1.0**	0.7	0.3	0.0	3.9
	above avg.	0.3	0.7	1.6	1.9	**2.9**	0.0	0.0	7.4
	much above avg.	0.3	0.3	0.3	1.6	2.3	**1.0**	0.0	5.8
	v. much above avg.	0.0	0.0	0.0	0.3	1.0	0.3	**0.0**	1.6
	Total	15.9	16.8	22.3	23.9	17.2	3.2	0.6	100.0

Note: Risk score is calculated from the "your disease risk tool". Pre-Information belief was elicited via the survey question: "Please indicate the extent to which you believe that you may be diagnosed with one of the following diseases over the next 10 years compared to the average person your age and gender in Scotland?".

5.2. Information treatment

The most basic specification in this case is a linear model where we regress the nutritional content of each participant's food choices on each of the basic treatment dummies:

$$Y_i = \alpha + \sum_{k=1}^{2} \beta_k I_k + \mathbf{X}_i'\delta + \epsilon_i \tag{1}$$

where Y_i is one of the four outcome measures for participant i, β_k is the coefficient of interest related to each of the $k = 2$ treatments[12], I_k is a dummy variable for each of the information treatments, and ϵ is an idiosyncratic error term. We also add a vector of control variables $\mathbf{X}_i$ including age, being male, a set of indicators for the time of the experimental session and dummy indicating whether the participant was hungry or not.

In first instance we present robust standard errors. These are on average more conservative than standard errors that are clustered at the session level. Although the participants could not see or interact with each other there could be a concern that the there is correlation at the session level for a variety of reasons. Given the small number of clusters, however, we therefore perform the wild bootstrapping procedure, clustering at the session level (Cameron et al. (2008)). In addition, we also perform three further corrections to the p-values. First, we perform a randomization inference procedure set out in Young (2019). This involves a test of a sharp null (all participants of a particular treatment have a zero treatment effect rather than an average treatment effect of zero). Second, we take into account of the multiple comparisons problem by using the by using the False Discovery Rate, FDR (the share of significant estimates that are expected to be false positives) of Anderson (2008) as set out in Anderson (2008). We also correct for multiple comparison issue using the more conservative adjustment for the family wise error rate (FWER) as proposed by Romano and Wolf (2005a,b) - this shows us the chance that at least one of our outcomes within the family of outcomes is significant when the null hypothesis of no effect is true. We do not include the proportion spent on unhealthy items in our multiple hypothesis correction as that outcome is a composite measure of the nutrients.

The results in Table 3 show that participants in the generic information treatment made dietary choices that were on average healthier. They chose a basket that had 4.5 percentage points (22.8%) fewer unhealthy items relative to the control group. As previously mentioned in section 4.6, unhealthy items are classified using the UK Food Standards Agencys nutrient profiling system that allocates points for each item on the basis of the nutrient content of 100g of a food or drink. Points are awarded for energy, saturated fat, total sugar and sodium (A-nutrients), and for fruit, vegetables and nut content, fibre and protein (C-nutrients). The points from C-nutrients are then subtracted from the score for A-nutrients to calculate a final score. The unhealthy items are then classified as foods with 4 or more points and drinks with 1 or more points. We

[12] Where $k = 1$ denotes the generic health information treatment, while $k = 2$ denotes tailored health information.

Table 3
Impact of the Information Treatments on Dietary Choices.

	Unhealthy (%)	Calories (kcal)	Fat (g)	Saturated fat (g)	Sugar (g)	Salt (g)	Fibre (g)	Protein (g)	Spend F&V (%)
Generic	-0.0459**	-362.0	-43.81**	-18.92**	-0.415	-3.193**	9.470	-10.23	0.00655
	(0.0231)	(449.1)	(19.08)	(8.960)	(36.29)	(1.401)	(10.06)	(21.78)	(0.0209)
Wild cluster p-val	*0.022*	*0.542*	*0.025*	*0.081*	*0.993*	*0.036*	*0.438*	*0.661*	*0.792*
RI p-val	*0.048*	*0.425*	*0.025*	*0.040*	*0.991*	*0.020*	*0.346*	*0.645*	*0.758*
FDR q-val		*0.674*	*0.094*	*0.095*	*0.991*	*0.094*	*0.674*	*0.852*	*0.862*
FWER p-val		*0.855*	*0.126*	*0.165*	*0.992*	*0.127*	*0.819*	*0.944*	*0.944*
Tailored	-0.0062	-815.2*	-26.97	-9.809	-3.836	-1.284	-7.855	-7.060	0.0146
	(0.0269)	(460.3)	(20.83)	(10.25)	(38.95)	(1.644)	(10.95)	(23.86)	(0.0241)
Wild cluster p-val	*0.849*	*0.090*	*0.229*	*0.402*	*0.934*	*0.511*	*0.353*	*0.749*	*0.582*
RI p-val	*0.814*	*0.079*	*0.202*	*0.341*	*0.920*	*0.446*	*0.473*	*0.766*	*0.536*
FDR q-val		*0.621*	*0.727*	*0.727*	*0.922*	*0.727*	*0.727*	*0.878*	*0.727*
FWER p-val		*0.357*	*0.667*	*0.870*	*0.944*	*0.912*	*0.912*	*0.944*	*0.912*
G = T (p-val)	*0.0574*	*0.283*	*0.239*	*0.167*	*0.922*	*0.279*	*0.069*	*0.881*	*0.684*
G = T = 0 (p-val)	*0.0498*	*0.204*	*0.060*	*0.063*	*0.994*	*0.076*	*0.184*	*0.895*	*0.830*
R-squared	0.087	0.094	0.110	0.097	0.037	0.050	0.020	0.075	0.097
Mean (control)	0.201	10,858	262.3	92.56	645.6	21.55	184.2	481.2	0.346

Note: Observations for all columns equal to 309. The dependent variables are based on the totals of the basket. All regressions include controls, these include age, being male, a set of indicators for the time of the experimental session and a dummy indicating whether the participant was hungry or not. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild clustered bootstrapped p-values are clustered at the session level using the procedure by Cameron et al. (2008). RI p-value refers to the equivalent p-value using a Randomization Inference procedure specifically, the randomization-t p-value from Young (2019). FDR q-val calculated using the method from Benjamini and Hochberg (1995) and Anderson (2008). FWER correct p-value refers to the p-value using the step-down methods of Romano and Wolf (2005a,b). All p-values are calculated using 5000 replications. An item is classified as 'unhealthy' is based on the UK Food Standards Agencys nutrient profiling technique. Points for each item are allocated on the basis of the nutrient content of 100g of a food or drink. Points are awarded for energy, saturated fat, total sugar and sodium (A-nutrients), and for fruit, vegetables and nut content, fibre and protein (C-nutrients). The points from C-nutrients are then subtracted from the score for A-nutrients to calculate a final score. Unhealthy items are foods with 4 or more points and drinks with 1 or more points.

next turn to these other elements that determine whether something is classified as unhealthy or not to understand which nutrients were driving the improvement in the healthiness of the basket.

Baskets in the generic treatment were 43g (17%) lower in total fat, 19g (24%) in total saturated fat, and 3.2g (15%) lower in salt.[13] That is, choices became healthier due to the reduction in A-nutrients and not an increase in the C-nutrients.

We find weaker effects of the tailored information treatment. We find a significant and large reduction in calories (a point estimate of 815, significant at 10% level). But we do not have much evidence that the calorie reduction corresponds to healthier choices. Overall, the baskets in the tailored treatment are on average healthier by around 3% however the estimate is very imprecise. Most of the coefficients for the various nutrients are negative and none are statistically significant at conventional levels.[14,15]

To put these results in context, we can compare the results to other similar interventions, such as providing calorie information on menus or receiving a diabetes diagnosis. Wisdom et al. (2010) find a reduced calorific intake by approximately 7% and Bollinger et al. (2011) find an average calories per transaction fell by around 6%. While our calorie reductions were statistically insignificant it is around the impact of our interventions of 3.3% and 7.5% for the generic and tailored information treatments. For a diabetes diagnosis, Oster (2018) finds a 6.4% reduction in calories purchased in the two months around the diagnosis which falls to 2.5% which is statistically insignificant for the long run effects. While the calorie reduction was either small or statistically insignificant, Oster (2018) does find that these reductions reflect some improvements in diet quality for example, she finds a reduction in consumption of non-whole grains, fizzy soft drinks, and whole milk products.

Since there are small differences in covariates across treatment and control, we examine the impact that the inclusion of controls has on the estimates. Fig. 1 shows the impact of the information treatments for a baseline without controlling variables (1), and seven different sets of controls: (2) includes a control for being male, (3) includes addition demographic (an indicator for being white, and one for being married) and controls for body size, (4) includes controls for qualifications and income, (5) includes controls for the experimental conditions of time of day and the front page of the tool, (6) controls

[13] The estimates for fat and salt remain statistically significant at the 5% level when the wild bootstrap and the randomization inference procedures are carried out. Once we correct for multiple hypothesis testing using the FDR approach the coefficients on fat, saturated fat and salt are not longer significant at the 5% level but remain so at the 10% level. However, when the we correct using the more conservative approach correcting for the FWER (Romano and Wolf (2005a,b)) our estimates are no longer statistically significant at the 10% level (the p-values are 0.126, 0.165 and 0.127 respectively on fat, saturated fat and salt).

[14] In the appendix we also present (Appendix Table A.6) the analysis where the dependent variables are the mean amount of the nutrient per 100g. The point estimates in this instance are all in the same direction, however, the estimates of the impact of the generic treatment on the consumption of fat and saturated fat are no long statistically significant in contrast the coefficient on the generic treatment on salt remains statistically significant.

[15] We also interact the tailored treatment with the specific recommendation given by the YDR tool. The estimates of this analysis are presented in the appendix (Appendix Table A.7). We do not find a relationship between the tool's specific recommendations and basket choices.

for measures of pre-experiment diet and health behaviors, and finally (7) includes all control variables. The treatment effects are robust and relatively unaffected by the inclusion or exclusion of controls. The magnitude of both treatment effects is greater (in absolute terms) when time of the experiment and front page of the experiment are controlled for, although these differences are not statistically significant. All treatment effects are of a very similar magnitude and point to the same conclusion: There is an impact of providing generic information on the healthiness of the basket and in particular on the amount of fat, saturated fat and salt in the foods chosen but there is little impact of the tailored information treatment.[16]

Of course the average treatment effect in the tailored information treatment could mask important heterogeneity, depending on whether people received good or bad news.

Good News and Bad News[17] — We next examine the nature of the tailored information that was provided by the YDR tool. In our initial questionnaire we ask the participants to indicate what they think their relative risk of developing a particular disease is along the same scale as the YDR tool – ranging from 'Very Much Below Average' to 'Very Much Above Average'. We then know whether the information provided by the YDR tool gave the respondent good news or not. The information provided by the tool falls into four main categories. First, an individual can receive *good news*, this is when the information is better than the participants' expectations. As we have provided information regarding two diseases, we define good news as getting good news about one disease and at least expected news about the other. The second category is mixed news, this is where the individual receives good news (or expected news) for one disease and bad news for the other. The third group is where in both cases the respondent YDR tools reports the risk that they expected to receive. The final category is bad news where in each case the information provided from the tool suggested a higher relative risk than the responded expected. For the majority of our participants who were in the tailored information group, 71.3%, received good news 14.8% were given mixed news, 6.5% received the news they expected and 7.4% got bad news.

We again estimate the impact of the information treatments, this time breaking up the tailored information into main two categories – receiving good news or not, where not receiving good news is made up of the other three categories described above. The results of this exercise are presented in Table 4. We find some heterogeneity in the response to the tailored health information, but the difference between the two tailored information is not statistically different. The estimates for both the tailored information groups are imprecisely estimated.

As mentioned in the literature Section, the evidence on the effects of good or bad news on subsequent behavior in other domains (such as performance) is not clear cut. There is however little evidence that good news leads to people slacking off as result. Our results fit with this evidence.

Post Treatment Beliefs — We are also interested in looking at variation in dietary choices according to people's beliefs *after* treatment. This is because post-treatment beliefs would provide a good indicator of whether participants have understood or indeed believe the health information provided and updated their beliefs regarding their own health, which in turn is more likely to influence their dietary choices.[18] In the post-experiment questionnaire we ask: "Having read the information provided in this study, indicate the extent to which you believe that you are leading a healthy life?" which is then followed[1] by a scale from 0 to 100 ranging from 'Very Unhealthy' to 'Very Healthy'. This is directly comparable to the question asked in the initial questionnaire pre-treatment, therefore enabling us to evaluate whether participants have changed their beliefs regarding their own health following treatment. On average, we find that people across all 3 information treatments initially rate themselves at 67, i.e. moderately good health (there is no statistically-significant difference across the 3 treatments in the initial survey period). As described above we also ask respondents, in the initial questionnaire, what they believe their chances are of developing heart disease and diabetes. We ask these questions again after the treatment. In addition, we ask whether the information that was provided was new to them or not.

Table 5 shows the impact of the information treatments on the changes in lifestyle beliefs, changes in the beliefs of disease risks and whether the information that was provided was new. We find that the tailored health information treatment leads people to positively update their beliefs regarding their lifestyle. They report a higher score of living a healthy life after they received the tailored information. There is an increase by around 4.9 percentage points (around 7%) in the extent to which participants in the tailored treatment believe they are living a healthy lifestyle. Given, as described above, that most people received good news from the tailored information treatment then this is what we would expect to see. The difference between the generic and tailored treatments is significantly different along the lifestyle measure.

In the next two columns we examine the change in beliefs of developing heart disease (column 2) and diabetes (column 3). The tailored information results in participants reporting a lower risk for both diseases with a coefficient of -1.1 (heart disease) and -0.5 (diabetes). To put this into context, in the control group prior to being given information the mean of these variables are (3.17 and 3.19 respectively). The reductions we find in the changes in perceived risk are therefore large. This is in line with the information provided and the results on changes in lifestyle and provides context for the lack of statistically significant impact of tailored health information on food choices. Furthermore, Fig. 2 also shows that on average, people in this group received positive news regarding their health, leading to an upward revision in their beliefs, which in turn may not have induced them to select healthier items from the food choice tool. The final column in Table 5 shows

[16] We have also examined heterogeneity of the impact with respect to gender. These results were not part of the pre-analysis plan. Appenidx Tables A.8A and A.8B present the results.

[17] Note that this is additional analysis not specified in the pre-analysis plan in order to further understand our main findings.

[18] In the post-experiment questionnaire, an average of 98% of respondents across the two treatment groups stated that they found the information to be 'credible or trustworthy', and a further 92% found the information to be 'useful'.

Table 4
Impact of Information on Dietary Choices with the Tailored Treatment Separated by Good and Not Good News.

	Unhealthy (%)	Calories (kcal)	Fat (g)	Saturated fat (g)	Sugar (g)	Salt (g)	Fibre (g)	Protein (g)	Spend F&V (%)
Generic	-0.0457**	-358.1	-43.72**	-18.95**	0.204	-3.206**	9.300	-10.06	0.00610
	(0.0231)	(450.1)	(19.10)	(8.955)	(36.36)	(1.410)	(10.07)	(21.83)	(0.0209)
Wild cluster p-val	*0.022*	*0.544*	*0.025*	*0.078*	*0.996*	*0.036*	*0.450*	*0.670*	*0.803*
RI p-val	*0.049*	*0.431*	*0.025*	*0.039*	*0.997*	*0.020*	*0.355*	*0.652*	*0.775*
FDR q-val		*0.684*	*0.094*	*0.094*	*0.996*	*0.094*	*0.684*	*0.860*	*0.882*
FWER p-val		*0.860*	*0.127*	*0.163*	*0.996*	*0.128*	*0.829*	*0.947*	*0.947*
Tailored: Good message	-0.00839	-873.6*	-28.30	-9.419	-13.01	-1.089	-5.338	-9.516	0.0212
	(0.0295)	(485.7)	(22.12)	(11.12)	(41.66)	(1.960)	(11.83)	(25.66)	(0.0265)
Wild cluster p-val	*0.794*	*0.055*	*0.226*	*0.446*	*0.802*	*0.616*	*0.519*	*0.732*	*0.481*
RI p-val	*0.768*	*0.073*	*0.209*	*0.413*	*0.753*	*0.586*	*0.654*	*0.710*	*0.426*
FDR q-val		*0.584*	*0.755*	*0.755*	*0.755*	*0.755*	*0.755*	*0.755*	*0.755*
FWER p-val		*0.343*	*0.685*	*0.918*	*0.951*	*0.951*	*0.951*	*0.951*	*0.918*
Tailored: Not good message	-0.000331	-662.3	-23.48	-10.83	20.21	-1.794	-14.45	-0.625	-0.00278
	(0.0363)	(735.5)	(27.09)	(11.75)	(60.35)	(2.051)	(15.87)	(35.64)	(0.0330)
Wild cluster p-val	*0.993*	*0.536*	*0.310*	*0.276*	*0.733*	*0.457*	*0.417*	*0.981*	*0.902*
RI p-val	*0.994*	*0.379*	*0.399*	*0.370*	*0.736*	*0.409*	*0.376*	*0.986*	*0.938*
FDR p-val		*0.620*	*0.620*	*0.620*	*0.984*	*0.620*	*0.620*	*0.986*	*0.986*
FWER p-val		*0.894*	*0.894*	*0.894*	*0.977*	*0.894*	*0.894*	*0.994*	*0.994*
Gen. vs Good News	*0.116*	*0.259*	*0.333*	*0.210*	*0.731*	*0.325*	*0.166*	*0.982*	*0.506*
Gen. vs Not Good News	*0.168*	*0.663*	*0.373*	*0.388*	*0.722*	*0.471*	*0.112*	*0.775*	*0.766*
Good News vs Not Good News	*0.826*	*0.773*	*0.845*	*0.894*	*0.585*	*0.777*	*0.568*	*0.804*	*0.478*
Joint all	*0.111*	*0.334*	*0.132*	*0.134*	*0.956*	*0.162*	*0.302*	*0.962*	*0.846*
R-squared	0.087	0.095	0.110	0.097	0.039	0.050	0.021	0.076	0.098
Mean (control)	0.201	10,858	262.3	92.56	645.6	21.55	184.2	481.2	0.346

Note: Observations for all columns equal to 309. All regressions include controls that are described in the notes to Table 3. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild clustered bootstrapped p-values are clustered at the session level using the procedure by Cameron et al. (2008). RI p-value refers to the equivalent p-value using a Randomization Inference procedure specifically, the randomization-t p-value from Young (2019). FDR q-val calculated using the method from Benjamini and Hochberg (1995) and Anderson (2008). FWER correct p-value refers to the p-value using the step-down methods of Romano and Wolf (2005a,b). All p-values are calculated using 5000 replications. Good, and not good are messages based on tailored health information that was provided by the your disease risk tool and the prior beliefs of developing the diseases. A good heart disease message is one where the tool provided a lower risk than the individual selected in the survey before using the health information tool. We categorise "Good" news (71.3%) for those who were given good news for both heart disease and diabetes, or received good news for one disease and expected news (the individual's prior about their health risk was the same as the risk provided by the tool) for the other. The "not good" news is made up of "Mixed" news (14.8%) which includes those who received good news and bad news, or expected and bad news. "Expected" (6.5%) and "Bad" (7.4%) news are where both pieces of news were in the respective category. See notes to Table 3 for classification of unhealthy items.

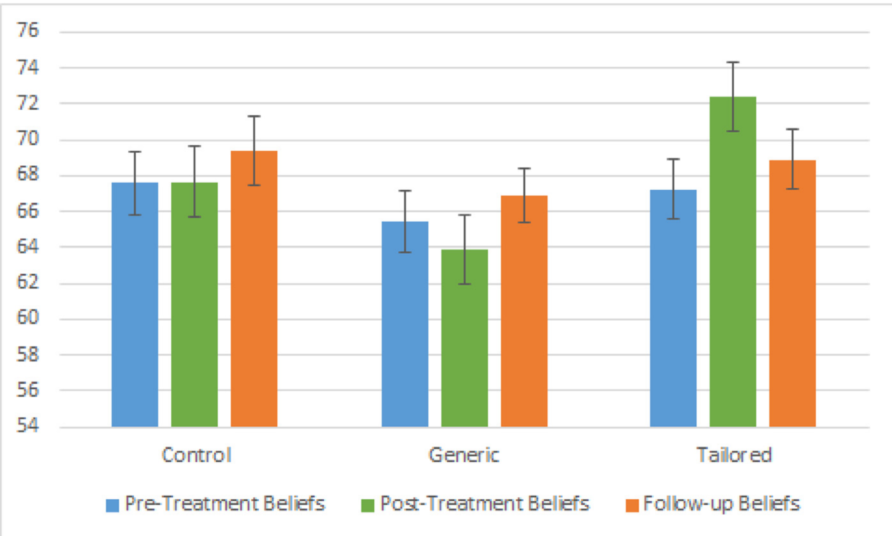

Fig. 2. Comparison of Pre-Treatment, Post-Treatment and Long-Run Beliefs of Living a Healthy Lifestyle by Information Group *Note*: The measurement is based on the participants indicating the extent to which they believe that they are leading a healthy life? on a scale from 0 to 100 ranging from 'Very Unhealthy' to 'Very Healthy'. Pre-treatment is taken from the first session before the participants in the tailored health information treatment received any information. Post-treatment was elicited after the information at the end of the session and follow-up was measured in the laboratory sessions three months after the first session.

Table 5
Impact of Information Treatments on Changes in Lifestyle Rating & Changes in Risk Beliefs.

	Δ Lifestyle	Δ Heart Risk	Δ Diabetes Risk	New Information
Generic	-2.078	-0.0807	-0.150	0.0601
	(1.773)	(0.130)	(0.152)	(0.0574)
Wild cluster p-val	*0.184*	*0.598*	*0.292*	*0.363*
RI p-val	*0.241*	*0.536*	*0.320*	*0.301*
FDR q-val	*0.384*	*0.513*	*0.384*	*0.384*
FWER p-val	*0.633*	*0.633*	*0.633*	*0.633*
Tailored	4.885***	-1.099***	-0.486**	0.105*
	(1.706)	(0.149)	(0.193)	(0.0604)
Wild cluster p-val	*0.005*	*0.000*	*0.026*	*0.208*
RI p-val	*0.004*	*0.000*	*0.013*	*0.088*
FDR q-val	*0.002*	*0.001*	*0.034*	*0.126*
FWER p-val	*0.012*	*0.000*	*0.028*	*0.083*
G = T (p-val)	*0.000*	*0.000*	*0.087*	*0.421*
G = T = 0 (p-val)	*0.000*	*0.000*	*0.044*	*0.222*
R-squared	0.065	0.210	0.038	0.046
Mean (control)	68.2	3.17	3.19	0.167

Note: Observations for all columns equal to 309. All regressions include controls that are described in the notes to Table 3. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild clustered bootstrapped p-values are clustered at the session level using the procedure by Cameron et al. (2008). RI p-value refers to the equivalent p-value using a Randomization Inference procedure specifically, the randomization-t p-value from Young (2019). FDR q-val calculated using the method from Benjamini and Hochberg (1995) and Anderson (2008). FWER correct p-value refers to the p-value using the step-down methods of Romano and Wolf (2005a,b). All p-values are calculated using 5000 replications. All p-values are calculated using 5000 replications. The dependent variable in columns (1) - (3) are the change in lifestyle, heart risk and diabetes risk after the information treatment compared to before the information treatment. Column (4) is a dummy variable that takes a one if the participant indicated that the information provided was new, and zero if they indicated it was not new. The row G vs T is the *p-value* of the test of the difference of the parameters of generic info and tailored info. Mean (control) shows the mean of variable prior to the information being given (or reading the architecture article in the case of the control group) for the lifestyle, heart risk and diabetes risk variables. For "new info" mean (control) is just the mean of the dependent variable of the control group.

that the tailored information participants were more likely to report the information provided was new. This is a large but imprecisely estimated effect.

In Table A.9 we examine belief updating further by splitting those in the tailored information into two groups – those receiving good news, or not – as was carried out in Table 4. Those who received good news reported a precisely estimated increase by 6 percentage points in the extent to which participants believe they are living a healthy lifestyle, compared to 1.75 percentage points for those who did not get good news, although this point estimate is not statistically significant. Similarly for heart disease, those who receive good news updated their beliefs whereas those who did not get good news did not update. For diabetes, both groups update their beliefs in the opposite direction. On average, we find that those who received good news were more likely to update than those who did not receive good news - this is in line with Sharot et al. (2011).

The perceptions of health risks in the generic group were largely unaffected by the treatment. This result, along with participants revising down their lifestyle rating, points to generic information not influencing food choices by virtue of novelty, but rather due to salience, by reminding participants of the risk of heart disease and diabetes and the dietary changes required to lower this risk, as mentioned in the previous section.[19]

5.3. Time availability treatment

We now evaluate the second experimental variation, related to the amount of time available for participants to select their food and drink items from the food choice tool. The basic specification is a linear model which can be described as follows:

$$Y_i = \rho A_i + \mathbf{X}_i'\alpha + \upsilon_i \tag{2}$$

[19] In the Appendix we present additional evidence for salience as being the most likely mechanism at work. Appendix Table A.10 shows that the significant effects are particularly present for the sample for which the information was not new. These results suggest that the mechanism is salience rather than belief updating following new information.

Table 6
The Impact of the Time Availability treatment on Dietary Choices.

	Unhealthy (%)	Calories (kcal)	Fat (g)	Saturated fat (g)	Sugar (g)	Salt (g)	Fibre (g)	Protein (g)	Spend F&V (%)
Long time	-0.00886	-52.23	-4.273	-3.284	30.81	0.271	1.393	2.409	0.00466
	(0.0202)	(394.1)	(15.02)	(6.894)	(32.43)	(1.430)	(8.801)	(18.37)	(0.0182)
Wild cluster p-val	*0.674*	*0.915*	*0.769*	*0.622*	*0.220*	*0.878*	*0.909*	*0.900*	*0.780*
RI p-val	*0.662*	*0.906*	*0.781*	*0.645*	*0.341*	*0.845*	*0.878*	*0.896*	*0.797*
FDR p-val		*0.896*	*0.896*	*0.896*	*0.896*	*0.896*	*0.896*	*0.896*	*0.896*
FWER p-val		*0.999*	*0.999*	*0.992*	*0.892*	*0.999*	*0.999*	*0.999*	*0.999*
Mean (short time)	0.193	10,679	246	86.13	631.4	20.27	183.6	482.9	0.346
R-squared	0.073	0.084	0.092	0.082	0.040	0.038	0.010	0.075	0.096

Note: Observations for all columns equal to 309. All regressions include controls, these include age, being male, a set of indicators for the time of the experimental session and a dummy indicating whether the participant was hungry or not. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild clustered bootstrapped p-values are clustered at the session level using the procedure by Cameron et al. (2008). RI p-value refers to the equivalent p-value using a Randomization Inference procedure specifically, the randomization-t p-value from Young (2019). FDR q-val calculated using the method from Benjamini and Hochberg (1995) and Anderson (2008). FWER correct p-value refers to the p-value using the step-down methods of Romano and Wolf (2005a,b). All p-values are calculated using 5000 replications. An item is classified as 'unhealthy' is based on the UK Food Standards Agencys nutrient profiling technique. Points for each item are allocated on the basis of the nutrient content of 100g of a food or drink. Points are awarded for energy, saturated fat, total sugar and sodium (A-nutrients), and for fruit, vegetables and nut content, fibre and protein (C-nutrients). The points from C-nutrients are then subtracted from the score for A-nutrients to calculate a final score. Unhealthy items are foods with 4 or more points and drinks with 1 or more points.

where Y_i is the nutritional content of participant i's chosen food basket, A_i is a dummy variable denoting whether the participant was part of the long-time treatment group, ρ is our parameter of interest and υ_i is an idiosyncratic error term.

We do not have precise records on the time spent on the task, but we included a question in the end survey asking whether participants felt they had enough time to shop. For those in the Long Time (10 minutes) treatment 80% reported that the time they had was just right, and 20% reported they had too much time to spend the £30. None reported that they had too little time. In contrast, 22% of those in the Short Time (3 minutes) treatment reported that they had too little time with 3.9% still reporting they had too much time - the remaining 73.9% reported that the time was just right.

The results in Table 6 show that there is no statistically-significant difference between the two time treatments in terms of the nutritional content of the food choice baskets selected by participants in either group. We do observe coefficients on our high time dummy that go in the direction of healthier purchases (except for sugar), but all of these estimates are imprecise. For comparison, the point estimates for all the outcomes, except sugar which is almost three times as large, are a fraction of the estimates of the generic information. These results are not consistent with the hypothesis that people choose unhealthy foods because of time constraints.[20]

One concern is that we may be underpowered to detect significant effects. As indicated earlier, our sample size should have been sufficient to detect effect sizes of 15% in nutrient content with at least 80% power. We find estimated coefficients that tend to be small and none of the estimates are significant, so overall it does not seem that the null results are due to lack of power.

Another concern is that participation in the study made health concerns salient and lead to healthier choices than in real life. As described in the experimental design, the study involved a series of questionnaires related to health, lifestyle and nutrition, quite apart from the health information treatment(s). Thus, matters related to health and nutrition were already quite salient in the minds of participants when reaching the food choice stage. Those in the long time treatment were able to ponder their choices, while participants in the short time treatment may have had to rely on simple heuristics when selecting food items. It is possible that the context of the experiment triggered a "healthy" heuristic. This is a key consideration since our theoretical predictions depend on the type of decision-rule people use when making their dietary choices. In both tailored and generic treatments participants received recommendations that were relatively easy to apply immediately. It appears that, when possessing such information, being nudged to spend more time on decisions has little effect.[21]

5.0.12. The long-Term impact of information on dietary choices

The follow-up experiment was held 3 months after the initial experiment, from Monday 12th September to Friday 16th September 2016. In total 265 participated, representing over 83% of the original sample. Appendix Table A.13 compares the sample characteristics of the initial participants to those who showed up for the follow-up session in September. The two samples are statistically very similar to one another, with none of the characteristics exhibiting any significant changes across the two samples, which is unsurprising given the low dropout rate. Therefore, this similarity across samples helps to

[20] Appendix Table A.11 presents the estimates by gender. We do not find a statistically significant impact for either male or female participants.

[21] We also estimate the interaction of the time and information treatments. This is shown in Appendix Table A.12. We only find those in the long time group who also received tailored information chose food baskets higher in sugar, none of the other interactions between the two different treatments were statistically significant.

Table 7
The Impact of the Information Treatments on Dietary Choices 3 Months Later.

	Unhealthy (%)	Calories (kcal)	Fat (g)	Saturated fat (g)	Sugar (g)	Salt (g)	Fibre (g)	Protein (g)	Spend F&V (%)
Generic	-0.00493	-464.4	-6.880	-5.776	-41.64	-1.394	-13.07	14.03	-0.00250
	(0.0230)	(445.3)	(16.39)	(7.390)	(39.53)	(1.354)	(10.07)	(22.73)	(0.0270)
Wild cluster p-val	*0.790*	*0.282*	*0.602*	*0.303*	*0.293*	*0.217*	*0.232*	*0.542*	*0.927*
RI p-val	*0.825*	*0.300*	*0.685*	*0.440*	*0.305*	*0.319*	*0.198*	*0.546*	*0.925*
FDR q-val		*0.608*	*0.772*	*0.696*	*0.608*	*0.608*	*0.608*	*0.718*	*0.926*
FWER p-val		*0.791*	*0.851*	*0.791*	*0.851*	*0.791*	*0.791*	*0.851*	*0.911*
Tailored	0.00216	-1,214***	-11.50	-5.149	-40.93	-1.954	-24.27**	-5.307	0.00758
	(0.0251)	(460.2)	(16.59)	(7.081)	(42.15)	(1.439)	(10.00)	(24.81)	(0.0263)
Wild cluster p-val	*0.919*	*0.017*	*0.465*	*0.439*	*0.148*	*0.202*	*0.015*	*0.842*	*0.774*
RI p-val	*0.929*	*0.009*	*0.486*	*0.471*	*0.334*	*0.176*	*0.017*	*0.832*	*0.766*
FDR q-val		*0.064*	*0.652*	*0.652*	*0.652*	*0.470*	*0.064*	*0.831*	*0.831*
FWER p-val		*0.053*	*0.742*	*0.765*	*0.838*	*0.520*	*0.140*	*0.900*	*0.900*
G = T (p-val)	*0.741*	*0.0748*	*0.762*	*0.922*	*0.985*	*0.655*	*0.259*	*0.405*	*0.672*
G = T = 0 (p-val)	*0.942*	*0.0276*	*0.786*	*0.702*	*0.522*	*0.385*	*0.0545*	*0.676*	*0.908*
R-squared	0.078	0.090	0.078	0.087	0.042	0.056	0.046	0.050	0.078

Note: Observations for all columns equal to 256. All regressions include controls, these include age, being male, a set of indicators for the time of the experimental session and a dummy indicating whether the participant was hungry or not. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild clustered bootstrapped p-values are clustered at the session level using the procedure by Cameron et al. (2008). RI p-value refers to the equivalent p-value using a Randomization Inference procedure specifically, the randomization-t p-value from Young (2019). FDR q-val calculated using the method from Benjamini and Hochberg (1995) and Anderson (2008). FWER correct p-value refers to the p-value using the step-down methods of Romano and Wolf (2005a,b). All p-values are calculated using 5000 replications. An item is classified as 'unhealthy' is based on the UK Food Standards Agencys nutrient profiling technique. Points for each item are allocated on the basis of the nutrient content of 100g of a food or drink. Points are awarded for energy, saturated fat, total sugar and sodium (A-nutrients), and for fruit, vegetables and nut content, fibre and protein (C-nutrients). The points from C-nutrients are then subtracted from the score for A-nutrients to calculate a final score. Unhealthy items are foods with 4 or more points and drinks with 1 or more points.

allay concerns regarding attrition bias, which may limit the validity of any analysis of long-term impacts resulting from our information treatments.

Once again, participants were paid £50 compensation for attending, and in total we had 4 sessions a day with a maximum of 18 participants per session. Upon arrival, participants' weight and waist size were measured. The first stage of the follow-up consisted of a survey where the main aim was to gauge any dietary or lifestyle changes that had occurred since June, while the second stage was the same food frequency questionnaire undertaken 3 months earlier. The third stage was a 24-hour dietary recall, using the computer-based INTAKE24, and the experiment concluded with the food choice tool from the previous session, albeit with no variation in time availability. One participant was again picked from each session at random in order to receive his/her chosen food and drinks basket.

In the follow-up session we are mainly interested in analyzing whether exposure to health information has a long-term impact on people's food choices. Therefore, we shall once again be estimating equation (1), with the only difference being that for the follow-up session we are interested in different dependent variables. These are:

- Nutritional composition of the participants' food/drink basket in the follow-up session;
- The difference in participants' biometric measures: BMI and waist size (in inches);
- The participants' reported dietary and/or lifestyle changes as reported in the follow-up session questionnaire.

Food Choices — We start with participants' food choices as elicited from the supermarket tool. The aim here is to check whether the results observed in the initial experiment still hold now, namely in relation to the reduced fat and saturated fat content, as well as lower proportion spent on unhealthy items, observed among the generic information treatment relative to the control group. We therefore focus on the same outcome variables that were analyzed in the previous section. We will also use the same set of controls used before.

The results are presented in Table 7. We do not find participants chose healthier baskets in either the generic or tailored treatment in the follow up session three months later. None of the coefficients on the generic treatment are statistically significant. In the tailored treatment, in contrast, the baskets are statistically significantly lower in calories. The initial impact of the treatment led to a reduction of around 800 calories so the effect has increased. However, this is somewhat offset by the basket being significantly lower in fibre - leaving the overall (un)healthiness of the basket unchanged.

Returning to Fig. 2 we again examine participants' subjective beliefs regarding their health status in September. All participants were asked to rate their current health status during the follow-up session on a scale from 0 to 100, ranging from 'Very Unhealthy' to 'Very Healthy'. We can thus trace the evolution of participants' health beliefs both before and after treatment (in June), as well as 3 months later in September. These health beliefs are shown in the final column of the figure. We can see that for both the control and generic information groups, subjective health beliefs have stayed largely constant over time, with no statistically-significant changes across the three periods for both groups. In contrast, participants in the tailored information group, who had become more optimistic after receiving the information, are no longer so in the follow up, which suggests that the positive effect generated by the good news has somewhat worn off over time.

Table 8
The Impact of the Information Treatments on Self-Reported Health Behaviours and Health Measurements 3 Months Later.

	Any	Stop Smoking	More Exercise	Reduce Alcohol	Lose weight	Take vitamin	More Fish	More F&V	More Grains	Reduced Sat. Fat	Reduced Transfat	% Δ BMI	% Δ waist
Generic	0.108*	-0.00319	0.00203	0.0701	0.0184	0.00336	-0.0620	-0.0202	-0.105*	0.0831	0.0193	0.00284	-0.00917
	(0.0583)	(0.0349)	(0.0795)	(0.0796)	(0.0706)	(0.0622)	(0.0721)	(0.0741)	(0.0620)	(0.0760)	(0.0815)	(0.0111)	(0.0224)
Wild cluster p-val	*0.0298*	*0.904*	*0.976*	*0.260*	*0.842*	*0.938*	*0.174*	*0.836*	*0.106*	*0.188*	*0.825*	*0.827*	*0.735*
RI p-val	*0.0712*	*0.934*	*0.977*	*0.384*	*0.791*	*0.953*	*0.375*	*0.782*	*0.0942*	*0.277*	*0.805*	*0.800*	*0.723*
FDR q-val		*0.980*	*0.980*	*0.978*	*0.980*	*0.980*	*0.978*	*0.980*	*0.905*	*0.978*	*0.980*		
FWER p-val		*0.995*	*0.995*	*0.991*	*0.993*	*0.995*	*0.995*	*0.995*	*0.433*	*0.963*	*0.993*		
Tailored	0.0239	-0.0177	-0.0978	0.0652	-0.0351	0.00137	-0.120*	-0.0443	-0.0760	0.0317	-0.0731	0.00650	0.000508
	(0.0643)	(0.0328)	(0.0774)	(0.0760)	(0.0663)	(0.0598)	(0.0702)	(0.0721)	(0.0588)	(0.0742)	(0.0787)	(0.0105)	(0.0253)
Wild cluster p-val	*0.580*	*0.384*	*0.153*	*0.413*	*0.536*	*0.981*	*0.0600*	*0.606*	*0.135*	*0.679*	*0.443*	*0.630*	*0.987*
RI p-val	*0.706*	*0.609*	*0.195*	*0.387*	*0.612*	*0.979*	*0.0844*	*0.536*	*0.193*	*0.663*	*0.343*	*0.548*	*0.987*
FDR q-val		*0.744*	*0.69*	*0.744*	*0.744*	*0.982*	*0.69*	*0.744*	*0.69*	*0.744*	*0.744*		
FWER p-val		*0.993*	*0.767*	*0.983*	*0.993*	*0.993*	*0.837*	*0.983*	*0.837*	*0.993*	*0.981*		
G = T (p-val)	*0.0860*	*0.623*	*0.168*	*0.948*	*0.396*	*0.973*	*0.368*	*0.729*	*0.568*	*0.483*	*0.221*	*0.561*	*0.530*
G = T = 0 (p-val)	*0.0852*	*0.823*	*0.296*	*0.613*	*0.682*	*0.999*	*0.229*	*0.825*	*0.230*	*0.543*	*0.431*	*0.742*	*0.779*
R-squared	0.033	0.073	0.026	0.023	0.012	0.008	0.043	0.013	0.023	0.019	0.016	0.048	0.020

Note: Observations for all columns equal to 256. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions include controls that are described in the notes to Table 3. All regressions include controls that are described in the notes to Table 3. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Wild clustered bootstrapped p-values are clustered at the session level using the procedure by Cameron et al. (2008). RI p-value refers to the equivalent p-value using a Randomization Inference procedure specifically, the randomization-t p-value from Young (2019). FDR q-val calculated using the method from Benjamini and Hochberg (1995) and Anderson (2008). FWER correct p-value refers to the p-value using the step-down methods of Romano and Wolf (2005a,b). All p-values are calculated using 5000 replications. All p-values are calculated using 5000 replications. The dependent variables are based on answers to the following question: Which, if any, of the following changes have you made over the last 3 months (i.e. since the initial session)? i) Stop smoking (Stop Smoking), ii) Do some form of moderate physical exercise for at least 30 minutes on most days (More Exercise), iii) Cut down the amount of alcohol I drink (Reduce Alcohol), iv) Lose some weight (Lose weight), v) Take a multivitamin - like a B complex vitamin (Take vitamin), vi) Eat 2 or more servings of fish per week (More Fish), vii) Eat 5 or more servings of fruit and veg per day (More F&V), viii) Eat 3 or more servings of whole grains on most days (More Grains), ix) Reduce consumption of saturated fats like red meat, cheese and whole milk (Reduced Sat. Fat), x) Reduce consumption of trans-saturated fats like cookies, pies, chips, crisps and deep-fried food (Reduced Transfat).

Changes in Body Measurements, Self-Reported Diet and Lifestyle Changes — We now analyze whether the health information had any impact in terms of participants' body measurement and whether participants reported any changes to their diet or lifestyle in the 3 months since the original experiment.

As part of the first stage of the follow-up experiment, participants were asked to indicate whether they had undertaken any dietary or lifestyle changes over the 3-month period since the initial session. They were given a list of options to select from that included:

- Do some form of moderate physical exercise for at least 30 minutes on most days
- Stop smoking
- Cut down the amount of alcohol I drink
- Lose some weight
- Take a multivitamin (like a B complex vitamin)
- Eat 2 or more servings of fish per week
- Eat 5 or more servings of fruit and veg per day
- Eat 3 or more servings of whole grains on most days
- Reduce consumption of saturated fats like red meat, cheese and whole milk
- Reduce consumption of trans-saturated fats like cookies, pies, chips, crisps and deep-fried food

We use these responses as outcome variables, using the same regressors as in Table 7. The results are shown in Table 8. We do not find any statistically-significant differences in the self-reported changes of either the generic or tailored health information groups relative to the no information (control) group. In the final two columns we analyze two new outcome variables representing the relative change in BMI and waist size from the initial measurement to the follow-up. We then use the same regressors used in Table 7 to analyze these changes across our information treatments. We observe no statistically significant difference in either BMI or waist size in either information treatment. Our sample's initial average BMI and waist size in June was 25.27 and 33.31 in. respectively, with these figures barely changing 3 months later (25.30 and 33.34 in. respectively). Furthermore, the BMI average is just on the borderline between healthy and overweight as prescribed by nutritionists, while the waist average is below the recommended limit of 37 in. for men and just above the 31.5 in. for women. Hence, there may have been limited scope for our participants to lose any weight given that their starting point was already relatively healthy to begin with.

6. Conclusion

In this paper we sought to analyze the extent to which it is possible to nudge people into re-optimizing their dietary choices. We introduce two sources of experimental variation, one where we provide easy-to-digest health information, generalized (generic) and personalized (tailored); and a second where we vary the time available to shop for a basket of food.

The results show that participants in the generic health information group selected food baskets that, on average, contained less total fat and less saturated fat (approximately 20% less) relative to the no information group, and spent 34% less on unhealthy items. We also find a (weaker) effect of providing tailored information on the foods chosen, although the picture is less clear. We find a significant effect on the amount of calories chosen, but no significant effect on other measures of the nutrient profile of the baskets. Further analysis suggests that the majority of tailored health participants received *positive* news from the health assessment tool regarding their relative risk of developing both heart disease and diabetes (i.e. below average). However, we find no difference in responses to whether the news was good or bad. That is, beliefs do not appear to play a significant role on choices.

Our second result is that nudging people into spending more time on their dietary choices has little impact on how healthy those choices were.

Our findings indicate that the majority of generic information participants were already familiar with the material presented, since they did not alter their own health perceptions after reading this information. These results support the idea that generic health information influenced people's choices via salience by reminding them of how to reduce their heart disease and diabetes risk, rather than due to the novelty of the details presented. In fact, we find that on average people are not too optimistic about their health, and the tailored treatment does not reveal information that should trigger an improvement in dietary choices.

Finally, we analyze the long-term impact of our health information intervention on people's food choices, any dietary or lifestyle changes undertaken since the experiment, as well as their body measurements. In most cases, we found no significant difference in food choices across all three treatment groups, suggesting that the impact of generic health information is largely instantaneous with no longer-term effects. We did find that tailored information participants picked lower calorie baskets on average relative to the control group, although this was mainly driven by the healthier participants in our sample. Similarly, we also find no statistically-significant differences with regards to any lifestyle or dietary changes, and no difference in BMI or waist size.

Overall, the results presented in this paper have important implications for the design of future health information campaigns. There is now a growing trend towards providing tailored health recommendations. Here we find that participants have relatively pessimistic beliefs about their health and likelihood of developing diabetes or heart disease. As a consequence, these tailored tools may not have the effects intended by their designers, although here we find no evidence of a backfiring effect. Perhaps surprisingly, we find that generic information does affect choices in the short run. These results are in line with recent evidence on the effectiveness of salient information made available at the time of purchase, such as calorie information on product labels (see for example Wisdom et al., 2010 and Bollinger et al. (2011))

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2020.103550.

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