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ABSTRACT

Present Bias in Choices over Food and Money*

This paper investigates time inconsistencies in food consumption based on a field experiment at a college canteen where participants repeatedly select and consume lunch menus. The design features a convex non-monetary budget in a natural environment and satisfies the consume-on-receipt assumption. Leveraging 3,666 choices of different food healthiness, we find no time inconsistency at the meal level. Utility weight estimates at the dish level reveal that consumers balance healthiness between food categories. Individuals who exert self-control take up a commitment device as soon as available, while non-committers are present-biased. Dynamic inconsistencies in food and money choices are independent.

JEL Classification: D12, D01, C93, D91, I12

Keywords: field experiment, dynamic inconsistency, commitment, food consumption

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1 Introduction

Not to comply with own intentions seems human. Almost everybody has experienced unfulfilled new years resolutions, failed diet plans, or futile attempts to quit smoking. Most people attempt to eat healthily but fail in practice (Kumanyika et al., 2000). Economists explain such failures with dynamically inconsistent behavior (Akerlof, 1991; Laibson, 1997; Loewenstein & Thaler, 1989; O'Donoghue & Rabin, 1999; Strotz, 1955).[1] A vast literature has documented and tested time inconsistencies (Frederick et al., 2002). Yet, this literature almost exclusively exploits financial decisions and monetary rewards to identify inconsistent behavior. This is a direct consequence of the advantageous features of money (e.g., costless exchangeability); however, some features are less desired and make monetary experiments less suitable to study real-world consumption (e.g., almost infinite storability, one-dimensionality). Recent research has made progress towards modeling consumption decisions more realistically, focusing on goods such as leisure (Augenblick et al., 2015) or food (Cherchye et al., 2020; Sadoff et al., 2020). Understanding whether behavior in monetary rewards proxies well for food choices is pivotal if we are to understand unhealthy eating habits with their associated economic and social costs (Finkelstein et al., 2009). Food choices are not only a matter of taste; the consumption of nutrient-poor foods negatively impacts individual health and labor productivity (Bütikofer et al., 2018; WHO/FAO, 2003).

In this paper we provide a test of dynamically inconsistent behavior for a continuous convex non-monetary budget in a natural environment: food healthiness decisions and consumption in a real canteen set-up. Unlike earlier studies, we not only allow for a continuum of healthy or unhealthy food bundles without choice restrictions, but also explicitly design the often ignored consumption stage to comply with the consume-on-receipt assumption (Cohen et al., 2020). The paper also analyzes consumers' tendency to utilize different types of control devices to commit to personal consumption plans. We compare inconsistent behavior between convex food and convex money choices to understand the applicability of monetary reward studies to natural behavior.

[1] Further explanations for self control problems are summarized in Cobb-Clark et al. (2023).

This paper makes three major contributions. First, we propose a holistic experimental design to measure dynamic inconsistency, thereby addressing four challenges simultaneously: structurally estimating a time inconsistency measure with random shocks; in a natural task and environment; offering a convex choice set; and enforcing true consumption on receipt by design. We join a small list of recent field experiments seeking to operationalize economic theory more directly (Andreoni et al., 2022). Related studies specialize on a subset of the aforementioned dimensions. One strand summarized in Frederick et al. (2002) focuses on measuring a present bias parameter using monetary rewards in the laboratory. While results deliver precise estimates for dynamic inconsistency, a common concern is the limited ecological validity owing to abstract tasks and simulated lab settings. It is also unclear whether monetary rewards are immediately transferred into true consumption. A second strand summarized in Imai et al. (2021) focuses on lab experiments conducted with effort-evoking tasks. These tasks do imply consuming leisure on receipt but in an overly stylized experimental setting: artificial tasks are conducted in front of a computer, potentially limiting the applicability to real world behavior. A third strand focuses on behavior in true field settings by observing snacks choices (Alan & Ertac, 2015; Read & Van Leeuwen, 1998; Sadoff et al., 2020). We add to this literature by introducing fully convex choice sets that contain 25 food items on average and from which subjects can choose without restrictions (except a budget constraint).[2] Throughout the experiment, 135 unique dishes are offered in the canteen. Contrary to previous studies, we ensure and observe the immediate consumption of food.[3] In this respect, our experimental design is more comparable to the work of Belot et al. (2018) who study health behaviors, preferences and educational achievements with real meal consumption.

Second, we add to the understanding of the relation between factual self-control problems and subjective beliefs thereof. The value of public policies for altering economic behavior depends on individuals' responses to interventions, such as commitment devices. The existing evidence on the nexus between time inconsistencies and the demand for commitment is mixed: While Avery et al. (2022), Bai et al.

[2]In fact, designs of earlier studies focus on a limited number of snacks and are implemented with choice restrictions. In Sadoff et al. (2020), subjects must choose 10 out of 20 food items in the advance choice and are allowed to make only up to four changes in the immediate choice.

[3]Most food items in Sadoff et al. (2020) were consumed only within three days after delivery.

(2021), and Kaur et al. (2015) document a positive relation, the studies of Royer et al. (2015) and Sadoff et al. (2020) suggest that present-biased individuals are less likely to take up a commitment device. A related question refers to the psychology of time-consistent individuals: are they immune to temptation or do they exert internal control when external commitment is absent? While this question has not gained much attention Sjåstad and Ekström (2021) show that individuals with high internal trait self-control are more likely to demand commitment in an online experiment. The finding is in line with the work by Benhabib and Bisin (2005) who model active internal self-control mechanisms in dynamic consumption-savings decisions. Our granular data on revealed consumption preferences enable us to analyze the tendency to utilize internal and external control as substitutes.

Third, we compare choices over food with choices over money at the individual level. To make this feasible, we design our experiment for eliciting convex time budgets in money and food and ask whether dynamic inconsistency in real consumption choices is reflected in intertemporal behavior derived from monetary rewards. We contribute to the literature that focuses on comparing money with abstract effort choices: Augenblick et al. (2015) find dynamic inconsistencies in effort but not in money tasks; individual behavior between tasks is not correlated. Alan and Ertac (2015) and Cheung et al. (2022) compare money and (artificial) snack choices. They find evidence for a significant correlation between tasks.

We explore dynamic inconsistency in food consumption choices by conducting a longitudinal field experiment in a college canteen. Over a period of six weeks, we observe 73 subjects making repeated food choices for lunch using tablet computers. Based on different budget endowments subjects construct a food bundle for immediate lunch (after the session) and for advance lunch (one week apart) from the entire available canteen menu. Importantly, every theoretically possible food bundle of the advance choice was really available for consumption one week later. Each subject participates for three sessions with one week spacing. The design constitutes a within-subject experiment with 219 individual-session observations allowing to compare individual food choices over time. Our main analysis is based on 3,666 observations: 73 individuals make on average 25 food item decisions for two different time perspectives (today vs. in one week). Focusing on the item choice level, our study is well-powered to identify small minimal detectable effects. We identify dynamic inconsistencies as deviations in the healthiness of food between advance and immediate choices. In particular, the advance choice of the first week is compared to the immediate choice of the second week (without choice reminder), and so on. Present-biased individuals would, for instance, order a healthy salad in the advance choice but switch to the unhealthy burger meal in the immediate choice. One of the selected lunch bundles is randomly chosen in an incentive compatible way; we collect the food and administer it to subjects for immediate consumption (for free). While waiting for the food delivery, individuals allocate money over time with real stakes. In week 2 we offer a commitment device once participants have made their advance choices for week 3. If they choose to take the device, they disable the possibility to make immediate lunch choices in week 3 and instead receive their advance choice from week 2.

To operationalize a test of dynamically (in)consistent behavior in food consumption, we leverage the psychological insight that consumers tend to mentally separate dish categories, such as main or side dishes and desserts (Flores et al., 2019; Wansink & Hanks, 2013), and keep mental records over nutrients and balance accounts (Bublitz et al., 2010). Initially, we analyze choices at the food item (dish) level. Then, we investigate full meal sets (containing several items) at the aggregate level to test for the use of nutritional accounts and to link our findings to the literature on non-monetary rewards. Finally, we compare inconsistent behavior between convex food and money choices at the individual level.

To estimate dynamic inconsistencies in food choices, we follow Sadoff et al. (2020) and implement a structural approach that accounts for the possibility that *inconsistent* food choices arise under time *consistent* preferences by chance. We apply a random utility model that derives the value of a food item from food characteristics and a random utility shock (Beggs et al., 1981). To assess food healthiness, we collect nutritional information about food items at the dish and meal level. We also calculate the Nutrient Profile Score (NPS) as a holistic healthiness measure taking into account seven different nutrients (Cherchye et al., 2020; Rayner et al., 2009). We analyze money allocation over time by applying four Convex Time Budget (CTB) sets (Andreoni & Sprenger, 2012) and interpreting choices in the β, δ-model (Laibson, 1997; O'Donoghue & Rabin, 1999).

We document three main findings. First, we compare within-individual choices from the natural food consumption task and the standard money allocation task at the individual level. In the choice comparison, we find that the distribution of the food inconsistency measure is more dispersed than the one of the money inconsistency measure ($p < 0.001$). The latter is strongly concentrated around time consistency suggesting that subjects do not behave dynamically inconsistent. We do not find a significant correlation between behaviors in the money allocation and food consumption tasks. Second, our results provide evidence for a balancing of healthiness over dish categories. While unhealthy main dishes are preferred in the advance choice, the opposite is true for desserts. In the immediate choice, subjects shift even further towards unhealthy main dishes and healthy desserts. This finding suggests that subjects treat food items differently depending on the dish category (main dish vs. dessert). Since nutrients are balanced over dish categories, we do not find significant differences in food bundle healthiness between advance and immediate choices in aggregate food baskets (meals). Third, individuals choosing the commitment device show internal self-control in their food choices when commitment is absent. They do so by balancing food healthiness between different dish categories with a systematic tendency to simultaneously pick unhealthier main dishes and healthier desserts in immediate choices. In fact, only (later) committing individuals balance food bundle healthiness in immediate food choices when temptation should be greatest. These subjects seem to be control-enforcing: they apply internal self-control before the commitment is offered and choose the external commitment device as soon as it becomes available. This finding suggests that internal and external commitment strategies are substitutes for committers. Non-committing individuals do not seek control. They neither choose the commitment device nor exercise internal self-control. Comparing food choices over the two rounds of the experiment, this group always displays present-biased behavior over single food categories suggesting stability of dynamic inconsistency.

The remainder of the paper is structured as follows: Section 2 describes the experimental design and theoretical background. Section 3 first analyzes behavior in the food consumption task at the aggregate level before comparing food with money choices at the individual level. We discuss the robustness of our results in Section 3.3 and conclude in Section 4.

2 Empirical Design

2.1 The Experiment

We examine dynamic inconsistencies in real food consumption using a longitudinal framed field experiment[4] at a college canteen in Bavaria, Germany. In three separate sessions participants choose food items from the canteen's menu for immediate and prospective consumption, and subsequently consume their lunch.

2.1.1 Design Details Subjects can choose from the entire canteen menu without choice restrictions, apart from the budget limit which is either €4 or €5. In effect, individuals make choices for both budget constraints before the computer randomly selects one payoff. Time inconsistencies are identified from comparing *advance food choices* that are made in the first week for the second week (advance perspective) with *immediate food choices* that are made in the second week for the second week (immediate perspective). We expect time inconsistent individuals to switch from healthier food items in advance choice to unhealthier food items in immediate choice given the desire to adopt a healthier diet (in the future) (DellaVigna, 2009). The experimental design is summarized in Table 1.

Subjects complete three separate sessions. In each session, they choose lunch menus for the respective day and for the next session one week ahead. Subsequent to the lunch choices, subjects allocate money over time in the second part of the experiment; there is no money allocation in session 3.

To get familiar with the food choice task in session 1, subjects start with making *immediate* lunch choices (t_1t_1 choices) for the same day from the regular canteen menu (which is published each Monday for the entire week). They select twice - one lunch for up to €4 and the other lunch for up to €5. The high budget condition allows high-calorie choices that exceed usual consumption patterns. There are no further restrictions: subjects are allowed to choose food items multiple times, or to choose the same food items for both budget conditions. We inform subjects that one of the two immediate t_1t_1 choices will be randomly selected by the computer

[4] Since we focus on a college context, our natural subject pool are college students. Subjects were aware of taking part in a research study.

with probability 0.5 and delivered to them for free at the end of the session. By randomly selecting one lunch from the choices made by an individual, we incentivize participants to select according to their true preferences.

Table 1: *Summary of experiment*

Session 1 $\equiv t_1$	Session 2 $\equiv t_2$	Session 3 $\equiv t_3$
Lunch choices t_1t_1 for budgets $b = 4$ and $b = 5$ *(immediate)*	Lunch choices t_2t_2 for budgets $b = 4$ and $b = 5$ *(immediate)*	C=0: Lunch choices t_3t_3 for budgets $b = 4$ and $b = 5$ *(immediate)*
Lunch choices t_1t_2 for budgets $b = 4$ and $b = 5$ *(advance)*	Lunch choices t_2t_3 for budgets $b = 4$ and $b = 5$ *(advance)*	C=1: No lunch choices t_3t_3
	Commitment decision for t_3 (C)	
Convex Time Budget sets t_1t_2 and t_1t_3 *(immediate)* and t_2t_3 *(advance)*	Convex Time Budget set t_2t_3 *(immediate)*	

Note: Table 1 summarises the sequences of the experiment between sessions (columns) and within sessions (rows). All participants were present at three consecutive sessions. Within each session, they make choices for the present and the future (one week later). In session 1, participants initially make four lunch choices: they first choose lunches from today's canteen menu for today (t_1t_1). After that, they make advance lunch choices for next week based on next week's canteen menu. For each point in time, they choose food items for a low budget (€4) and a high budget (€5). This implies two lunch choices for $t = 1$ of which one is randomly chosen for implementation with equal probability (p=0.5). In session 2, participants make lunch choices for session 2 from an immediate perspective. This implies four lunch choices for session 2 $t = 2$ (two immediate and two advance choices from the prior week) of which one is randomly chosen for implementation with equal probability (p=0.25). In session 2, after making advance choices for session 3, participants are offered a commitment device. If they commit, they switch off the possibility to make immediate lunch choices in session 3. Participants also make money choices (trading off earlier and later payments) in session 1 and 2 using four CTB sets.

After these immediate lunch choices, subjects make *advance* lunch choices (t_1t_2 choices) for the same weekday and time next week (from the prospective canteen menu which is not publicly available until next Monday). Advance choices are stored and retrieved in session 2. In session 2 (denoted by t_2), subjects again make two immediate lunch choices (t_2t_2 choices). The difference between t_1t_2 and t_2t_2 choices is the choice perspective: while t_1t_2 choices are made from an advance perspective for the upcoming week in session 1, t_2t_2 choices are made from an immediate perspective in session 2. We follow Augenblick et al. (2015) and inform subjects in session 1 about the repeated decision making in session 2 to avoid surprise effects. Our strategy has no prior disclosure: subjects in session

2 are not reminded of their session 1 choices. This guarantees that advance and immediate choices are made in isolation, and that subjects do not integrate advance and immediate choices (Halevy, 2015). Reminders of prior choices might also undesirably enforce consistency across time. We advise subjects that the total number of lunch choices for session 2 is four (two choices from session 1 and two choices from session 2) and that they receive one meal based on a random draw with equal probability of 25%. In the main analysis, we focus on the comparison of advance choices from session 1 (t_1t_2 choices) and immediate choices from session 2 (t_2t_2 choices) to identify violations of time consistency.

In Session 2, after making advance lunch choices for session 3 (t_2t_3 choices), we offer subjects an externally enforced commitment device. If they choose to commit, they switch off the possibility to make immediate lunch choices in session 3 (t_3t_3 choices). By choosing the commitment device participants can abstain from choosing again when temptation should be greatest. If they choose not to commit, they make immediate lunch choices in the next session again. In session 3, the computer randomly draws one out of two advance choices for committing individuals ($C = 1$) with probability 0.5, and one out of four advance and immediate choices for non-committing individuals ($C = 0$) with probability 0.25.

In the second part of sessions 1 and 2, subjects allocate money over a one-week and two-week time horizon. Overall, subjects make 28 financial allocation decisions comprising seven different interest rates ranging from 1.00 to 2.00 in four different CTB sets. In addition to the show-up fee paid out at the end of each session, subjects can win up to €20 in this task. As summarized in Table 1, subjects in session 1 allocate money between sessions 1 and 2 (t_1t_2) and between sessions 1 and 3 (t_1t_3) from an immediate choice perspective since the allocation includes the current session date. They additionally allocate money between sessions 2 and 3 (t_2t_3) from an advance perspective. In Session 2, subjects allocate money between sessions 2 and 3 (t_2t_3) from an immediate perspective. There is no money allocation in week three. Subjects are informed that one out of 14 decisions from the t_1t_2 and t_1t_3 set is chosen in session 1 with equal probability (≈ 0.07). They are further informed that in session 2, one out of 14 money decisions from the t_2t_3 (prospective) and the t_2t_3 (immediate) set is chosen.

2.1.2 Setup and Timeline

All college students receive an e-mail invitation for the experiment from the administration.[5] Subjects register via email and are assigned the same session day and (lunch) time for three consecutive weeks, according to their preferences. Subjects are informed about participating in an experiment which involves a free lunch for consumption in all three experimental sessions. We ask them to not eat for at least two hours before the start of each session.

Importantly, we carefully craft the advance information for participants to prevent self-selection of individuals with a particular interest in food topics. The advertisement for the longitudinal research study includes information that participants can earn money by making decisions using a computer and receive a lunch menu worth at least €4 for free. We announce that each slot lasts between 30 to 60 minutes. For completing all three sessions, subjects receive a total show-up fee of €25.50, of which €5 are paid in sessions 1 and 2 and €15.50 in session 3. The large fee in the last session is an attrition penalty. In total, 86 students sign up for the experiment. Since 13 do not show up or drop out, the analysis is based on more than 3,600 single food choices made by 73 subjects in 45 sessions.

The experiment was conducted between Nov. 11 and Dec. 20, 2019, according to the timeline depicted in Figure A2. At the beginning of a session, subjects enter an experimental booth specifically erected in the dining hall for the time of the study. In the experimental space visual covers ensure that all choices are made in private. Subjects begin by making food choices on-screen using tablet computers. Then, they answer short questionnaires about their socio-economic background and consumption routines followed by the allocation of money over time. In the meantime, research assistants collect the computer-selected lunch menus in the canteen and deliver them under a steel tableware cloche to the experimental booth using a cart. By covering the meal, we seek to prevent social eating norms to interfere with individual preferences.[6] Appendix Figure A1 depicts the experimental setup. At the end of each session, participants receive money payments in cash (show-up fee + money task yield) as well as a tray with their lunch choice for free. Subjects leave the experimental booth and consume their

[5] The experiment is also advertised using a roll-up banner at the entry of the college canteen.

[6] There is a large body of literature on the effects of social norms on eating behavior. See for example Prättälä et al., 2007; Robinson et al., 2014; Stok et al., 2016.

dish in the regular seating area of the canteen. The experiment is programmed in Python and executed with the software o-tree (Chen et al., 2016).

By design, we do not observe the eating process to ensure natural behavior and prevent distractions. However, using a unique tray color and identifier system, we collect the trays in the dish-washing area after consumption. This allows us to merge information about eating behavior with the food decisions made during a session. Out of 219 possible tray observations, we have data on 210 trays.[7] In all 210 cases, dishes were consumed (with a varying amount of plate waste).

Participants in the experiment are students at the respective college. They are on average 22 years old, around 44% are female. The majority of students studies business and management (34%) followed by computer sciences (25%) and engineering (19%). Twenty-two percent of participants study business in combination with computer sciences (8%) or engineering (14%). Around 12% of participants state that they primarily follow a vegetarian or vegan diet.

2.1.3 Canteen Menu Around 25 food items are offered in the regular canteen menu on a daily basis: five main dishes, 14 side dishes and six desserts. The canteen menu is highly standardized and offers dish variations on a daily basis. Our canteen setup comprises 135 unique dishes during the experimental period.

By adopting the natural setup, individuals face 2,300 (2,925) possible food choice combinations without (with) replacement assuming a three component meal. While this number seems high, it reflects a real decision scenario in a real-world environment. Given this complexity, eating behaviors often follow certain habits as humans try to minimize cognitive resources spent on everyday tasks (Khare & Inman, 2006; Wood & Neal, 2009). Any disturbance to these routines might result in unusual choice behavior. The studies of Flores et al. (2019) and Wansink and Hanks (2013) for example show that the appearance order of food items matters for food choices: Individuals are influenced by the first item they see and tend to make their subsequent food choices on the basis of this first impression. We thus mimic the natural choice setting as closely as possible by presenting lunch menus in the most familiar way. First, we sort food items into three dish categories: main dishes, side dishes and desserts. Second, we follow canteen dis-

[7] In 9 cases, trays were cleaned by the canteen staff before we could analyze them.

play conventions and show food categories in a fixed order. In the canteen, main dishes are shown at the top of the menu, followed by side dishes and desserts that are displayed last. In the experiment, we fix the order of respective food columns: main dishes are listed first, side dishes and desserts are shown in the second and third column. Within each food category, we randomize the presentation order of food items.

Figure 1 depicts an extract of a sample canteen menu (for €4 t_1t_2 choice made in session 1). Participants select or delete food items by clicking on the green plus or red minus buttons. Prices for food items correspond to regular canteen prices and are displayed in the cell right to the respective food label. The total price of the menu is automatically calculated and displayed at the bottom of the page.[8] If the total price exceeds the price limit, the forward button disappears and the lunch order cannot be submitted until the budget endowment is met.[9] After reading the experimental instructions and before choosing their first lunch, subjects answer several control questions to ensure a good understanding of the food choice task.[10]

To assess dish healthiness, we collect nutritional information such as energy content (calories), saturated fats, sugar, salt, fiber, proteins and the share of fruits/vegetables for all food items. All nutrients are collected for single ingredients, summed up and weighted according to recipes. Most recipes are provided by the canteen operator. In case recipes are not provided, we search for comparable dishes.[11] Nutritional information was hand-collected online and additionally provided by a commercial supplier platform. We follow Cherchye et al. (2020) and compute the Nutrient Profile Score (NPS) for each food item. The score was developed by nutritionists (Arambepola et al., 2008; Rayner et al., 2005, 2009; Scarborough et al., 2007) and converts a multidimensional nutrient profile consisting of the aforementioned seven nutrients into a single score ranging from -15 (most

[8] To circumvent the potential problem of specific food items selling out, participants are also asked to choose replacement alternatives.

[9] As the sample menu only shows a subset of food items, a full canteen menu including all food items is shown in Figure A3 in the Appendix.

[10] After answering each control question the correct answer is displayed to participants independent of the actual answer. Ninety-six per cent of submitted answers are correct.

[11] For example, most desserts are based on products by a large supplier of bake and cake processed products from which we obtain recipes online.

Figure 1: *Example food choice task (translated from German)*

Select the dishes for your canteen lunch that you will receive at the end of the second session on [*date of 'today in one week'*] with a probability of 25%. Your seleced items must not exceed the total value of €4.00. Your chosen budget is indicated below the canteen menu. Click on the plus or minus sign to add an item, discard an item or change the amount.

Note: A large mixed salad has approximately 260 grams. If a dish is offered in the self-serving area, the plate will be fully filled by eye. The portion sizes of all other dishes are set by the canteen operator.

Main Dishes	**€**	**Amount**	**Side Dishes**	**€**	**Amount**	**Desserts**	**€**	**Amount**	**Sides**	**€**	**Amount**
Vegan Thai noodle vegetable pan with peanuts in coconut sauce	1.92	0	Rice	0.70	0	Fresh Fruit	0.50	0	Mayonn aise	0.20	0
Chicken breast with onion cream sauce	2.35	0	Green leaf salad	0.70	0	Fruit quark	0.70	0	Ketchup	0.20	0
Alaska pollock fillet in batter with tomato sauce and rice	2.81	0	Cucumb er salad	0.70	0	Natural yogurt with muesli	0.70	0			
Vegetarian soup of the day large with roll	1.20	0	Spaetzle	0.70	0	Pudding	0.80	0			
Large mixed salad (green leaf lettuce, carrots, tomatoes, cucumber) with dressing	2.21	0	Carotts	0.70	0	Mousse/ Creme	1.10	0			

Sum: 0 Euros

Note: The figure shows an example of the food choice task. Subjects can click on the green plus or red minus to add or delete food items. There are no choice restrictions except that the price of the food basket must not exceed the price limit of €4 or €5, respectively. Following standard procedures in the canteen, we present food items in the main food categories main dishes, side dishes and desserts. Every day, as main dish options the canteen offers at least one vegetarian main dish, a salad buffet, two main dishes containing meat and a vegetarian soup bowl. As dessert options, the canteen always offers pudding, mousse, fruit quark, yoghurt with and without sugar and a fruit (apple or banana). As side dish options, there is always one sort of vegetables and a constant variety of small salads, different sorts of buns, a small vegetarian soup bowl as well as at least one hot side dish such as noodles, rice, potatoes or fries.

healthy) to +40 (most unhealthy).[12] Table 2 shows that the three dish categories differ with respect to average dish size and nutritional content. While desserts are rich in sugar and fat, main and side dishes contain more salt and vegetables. We summarize nutritional information, prices and dish sizes for single food items in Table A1 in the Appendix.

Table 2: *Summary of nutrients: dish categories*

Food Category	Nutrient Profile Score	Calories (Kcal)	Sugar (g)	Saturated Fats (g)	Proteins (g)	Salt (Sodium in mg)	Veg Share (%)	Item Size (g)	Price
Panel A: average weight (in g)									
Main Dish	12.07	482.18	11.03	7.13	21.42	1190.98	45.59	368.18	2.26
Side Dish	-2.16	168.05	3.62	1.23	4.15	382.98	48.16	145.02	0.68
Dessert	9.33	247.39	21.29	5.61	6.77	109.31	16.67	169.83	0.75
Panel B: per 100g									
Main Dish	-0.31	120.98	2.89	1.88	5.60	299.44	45.59	100	0.65
Side Dish	-1.68	142.48	2.36	0.80	3.85	363.78	48.16	100	0.57
Dessert	2.67	149.10	13.01	3.18	3.80	66.00	16.67	100	0.47

Note: The table depicts average nutrient profile scores, average single nutrients, the average size and average price of the three dish categories offered during the experiment at the university canteen. In panel A, all nutrient information are based on the average weight measured in grams. Panel B reports all information per 100 grams. Nutrient profile scores range between -15 (most healthy) and +40 (most unhealthy).

2.2 *Structural Estimation*

We analyze food consumption behavior over time by comparing food choices made from an advance and an immediate choice perspective. By applying an Ordinary Least Squares (OLS) regression framework, we might mistakenly consider inconsistencies in food choices as evidence for inconsistent time preferences. Inconsistencies can, however, result from random shocks to utility under time consistent preferences. To account for such shocks, we follow Beggs et al. (1981) and Sadoff et al. (2020) and apply standard random utility techniques for structural estimation.

In a random utility model (Walker & Ben-Akiva, 2002), the value of each food item is derived from a set of underlying characteristics and a random utility shock:

$$V_j = \mathbf{X}_j \phi + \epsilon_j \quad j \in 1, .., J, \tag{1}$$

where $\mathbf{X}_j$ represents a vector of food characteristics and ϵ_j is a random utility

[12] The NPS system is, for instance, used by governmental authorities in the UK, Australia and New Zealand to regulate health claims in TV advertisements mainly watched by children.

shock drawn from a Type-1 extreme value distribution. The parameter vector ϕ represents the weights of attributes. Food choices can now be summarized by orderings. In a first step, consider the probability that a given food item j is preferred to all alternative food items $1, ..., J-K-1$:

$$F_j[x_1, ..., x_{J-K-1}; x_j; \phi] = \frac{exp(\mathbf{x}_j \phi)}{exp(\mathbf{x}_j \phi) + \Sigma_{i=1}^{J-K-1} exp(\mathbf{x}_i \phi)}. \tag{2}$$

Now consider a subject choosing K unique food items from the choice set. We order all food items and summarize it in a ranking $r \equiv \{1, ..., J\}$. The probability of observing this ranking is

$$Prob(r, \mathbf{x}, \phi) = \prod_{j=J-K}^{J} F_j[x_1, ..., x_{J-K-1}; x_j; \phi]. \tag{3}$$

We calculate the log-likelihood of observing a certain number of rankings N as

$$L(\phi) = \Sigma_{i=1}^{N} log(Prob(r_i, \mathbf{x}_i, \phi)) \tag{4}$$

by applying a rank-ordered logit regression model estimated via maximum likelihood. Standard errors are clustered at the individual level. For $N = 73$ subjects, we construct 73 orderings from advance and 73 orderings from immediate food choices. The coefficients ϕ_A and ϕ_I can be estimated simultaneously and we test the null hypothesis H_0 that $\phi_A = \phi_I$ given a random error structure. When exploiting within-individual switches between healthier and unhealthier food items over time, a rejection of the null provides evidence for violations of time-consistent preferences even in the presence of random shocks to utility.

By assumption, any item included in an individual's lunch menu is preferred over all excluded items. Since selected food items are represented by dummy variables, no ordering exists within the sets of included or excluded items. The ranks within both sets are tied and all possible rankings are consistent with observed behavior. We use the method of Efron (1977) to handle ties in rank order data.[13]

[13] Since subjects faced no choice restriction for lunch, the number of included and excluded items can vary within individuals over time implying changes in rank numbers. According to Allison and Christakis (1994), the sum of ranks is not necessarily constant across individuals as long as tied items are assigned the same number. We can therefore apply this setup for all subjects independent of the number of included items.

3 Results

This section provides evidence on dynamic inconsistency in natural food consumption choices (Section 3.1) and compares food consumption with money allocation choices (Section 3.2). Finally, we provide robustness tests (Section 3.3).

3.1 Dynamic Inconsistency in Food Consumption

To assess the extent of dynamic inconsistency in food choices, we follow Ashraf et al. (2006), Augenblick et al. (2015), and Sadoff et al. (2020) and consider choices made prior to offering commitment. Subjects in our experiment make food choices for the lunch in session 2 from an advance perspective in session 1 (t_1t_2) and from an immediate perspective in session 2 (t_2t_2). To evaluate dynamic inconsistency, we compare these two choices with respect to food healthiness. Throughout our analysis, we focus on the share of fruits and vegetables as main outcome variable. In the Appendix, we also summarize the results for calories, saturated fats, and NPS as additional outcomes. All of these measures are established indicators of diet healthiness, with NPS being the most holistic metric.

3.1.1 Food Choices Subjects choose on average 3.1 food items to construct a meal: 2.9 items in the low budget and 3.4 items in the high budget condition[14]. The average price is €3.70 (€4.40) for a low (high) budget choice. Main dishes in the advance choice have an average share of fruits and vegetables of 39.3%. This share decreases to 34.1% in the immediate choice. The fraction of main dishes remains almost constant: 32.1% (31.5%) of all food items are mains in the advance (immediate) choice. As a consequence, main dishes become unhealthier in the immediate choice. The share of fruits and vegetables in desserts is 26.2% in the advance choice and increases to 37.1% in the immediate choice. The fraction of chosen desserts slightly decreases: 18.5% (16.2%) of chosen food items are desserts in the advance (immediate) choice. These numbers suggest that desserts become healthier in the immediate choice.

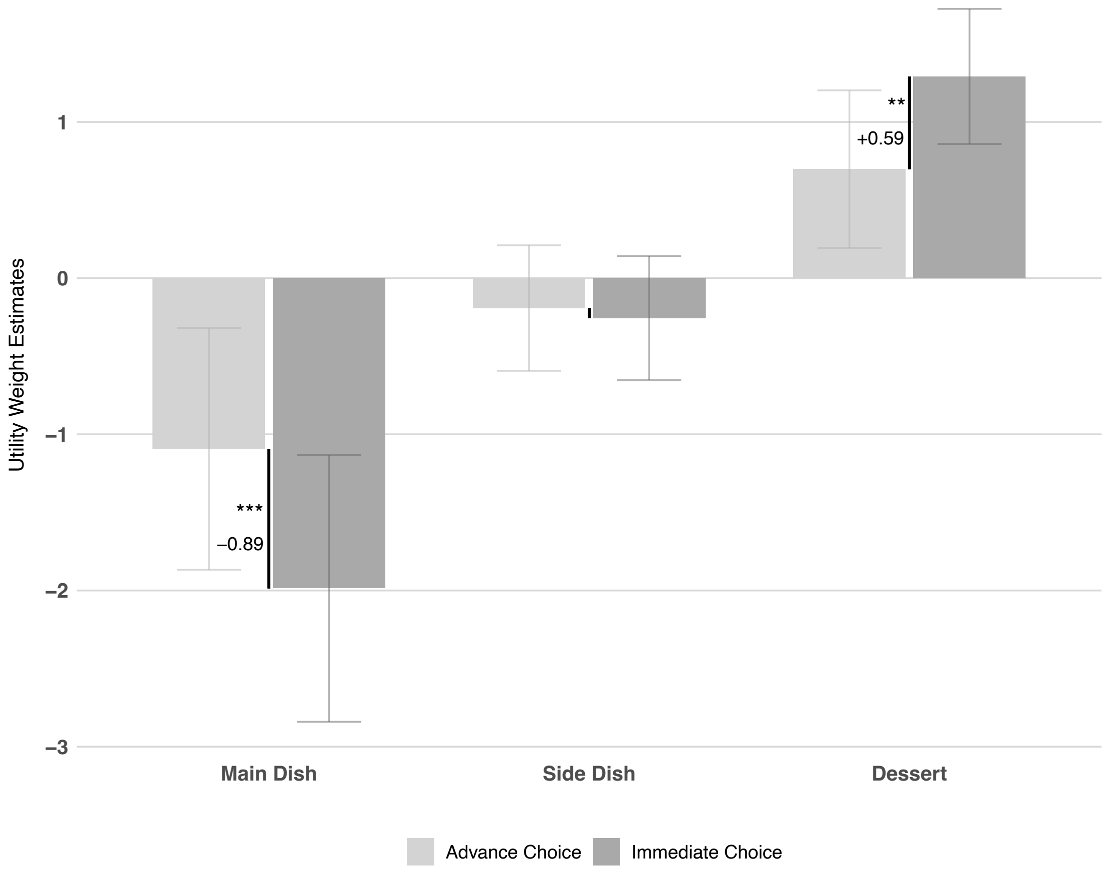
Figure 2 displays results for the structural estimation of the random utility

[14] Add-ons like ketchup or mayonnaise are not considered in these numbers.

model introduced in Section 2.2. The utility driver of interest is the share of fruits and vegetables. The light gray (dark gray) bars depict utility weights from an advance (immediate) choice perspective, separated by the dish categories: main dishes, side dishes and desserts. As Figure 2 reveals, the choice pattern is highly heterogeneous across dish categories. In the advance choice, subjects derive less utility from vegetables in their main dishes. At the same time, they favor healthier desserts with more fruits. These different inclusion probabilities imply that subjects favor unhealthy main dishes but healthy desserts in the advance choice. The pattern suggests a preference for mixed bundles with respect to healthiness. In the immediate choice, the utility weight for healthy main dishes decreases significantly (-0.89, p = 0.003) while the opposite is true for desserts (+0.59, p = 0.035). This choice pattern suggests that subjects value healthiness in main dishes less but healthiness in desserts more when they shift to the immediate choice perspective. They seem to balance the healthiness of food items over dish categories. Therefore, Figure 2 provides evidence in line with subjects mentally separating different dish categories. This finding resonates with the psychological literature (Flores et al., 2019; Knight & Boland, 1989; Wansink & Hanks, 2013) suggesting that consumers use internalized heuristics to facilitate decision making and consider the *food category* rather than the *food item* when selecting meals.

Table 3 summarizes the statistics corresponding to Figure 2. The first three columns differentiate the results by dish category while column 4 reports results for full meals. The first line contains utility weights given to food items in the advance choice, ϕ_A. The interaction term reported in line two calculates the intertemporal difference in utility weights between immediate and advance choice ($\phi_I - \phi_A$). These estimates reflect the difference between the light and dark gray bars in Figure 2. Relating the intertemporal change in utility weights to the advance weight implies large shifts: the utility weight for healthy main dishes decreases by 82% over time, while the utility weight for healthy desserts increases by 85%. These changes are larger than in Sadoff et al. (2020) who document an adjustment of 25% between advance and immediate choice. We attribute this difference to research design features: we shift from a storable and discrete food bundle to perishable, convex and truly immediate consumption. At the full meal level in column 4 of Table 3, we observe no dynamic inconsistency. Featuring enough

Figure 2: *Food Choices over Time: Share of Fruits and Vegetables*



Note: The figure presents results from rank-ordered logit regressions estimated with maximum likelihood. Results are reported for the three dish categories separately: main dishes, side dishes and desserts. Dependent variable: the share of fruits and vegetables of food items. Independent variables: an "Is Chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with the choice perspective (difference between immediate and advance choice). The light grey bars show utility weight estimates based on advance food choices. The dark grey bars depict the utility weight estimates based on immediate food choices. The null hypothesis tests for differences between advance and immediate utility weight estimates. These differences are graphically illustrated by the black line. Significance levels are indicated by asterisks. Standard errors are clustered at individual level. The overall sample size is 3666. Levels of significance: *0.10, **0.05, ***0.01

power to detect an MDE in utility weight change of 0.036, we conclude that the aggregate analysis hides substantial within-meal heterogeneity in choice behavior. In Appendix Table A2, we report estimation results for calories, saturated fats and the NPS. The results are qualitatively similar.

Table 3: *Utility weight estimates*

	Main dish	Side dish	Dessert	Full meal
Share Fruits & Vegetables				
Advance Share ($\hat{\phi}_A$)	-1.093***	-0.192	0.698***	-0.024
	(0.395)	(0.205)	(0.257)	(0.149)
Immediate choice ×	-0.893***	-0.064	0.593**	-0.032
Difference ($\hat{\phi}_I - \hat{\phi}_A$)	(0.296)	(0.226)	(0.281)	(0.126)
Log-likelihood	-332.630	-647.175	-243.514	-2171.461
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 9.082$	$\chi^2(1) = 0.082$	$\chi^2(1) = 4.450$	$\chi^2(1) = 0.066$
	($p = 0.003$)	($p = 0.775$)	($p = 0.035$)	($p = 0.798$)
# Observations	730	1780	864	3666
# Rankings	146	146	146	146
# Clusters	73	73	73	73

Note: The table presents results from rank-ordered logit regressions estimated with maximum likelihood. We report results for the utility driver share of fruits and vegetables. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the respective utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice (ϕ_A). The interaction term indicates a utility weight change between immediate and advance choice. The null hypothesis tests whether the interaction coefficient is different from 0. Results are first reported for the three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Column 4 shows results at the food basket level (looking at all food categories simultaneously. In column 4, the data set comprises 3,666 observations. Levels of significance: *0.10, **0.05, ***0.01

What are potential explanations for this behavioral pattern? While we cannot pin down the exact channel, one mechanism consistent with the data is mental accounting. While Thaler (1999) applies mental accounting to financial activities, Tversky and Kahneman (1981) adopt a broader perspective, leading to an emerging literature that also expands to food choices (Cheema & Soman, 2006; Koch & Nafziger, 2016). According to the mental accounting strategy, subjects set a healthiness goal for lunch. This goal defines a reference point that makes under-performance painful under the assumption of loss-aversion. With narrow bracketing, the lunch choice is assessed in isolation and the loss cannot be compensated by later behavior, e.g., by over-performing at dinner (Koch & Nafziger, 2016). Food items for lunch are, hence, chosen against the background of a given nutritional account or budget. An under-performance in the main (and side dish) category needs to be offset immediately by over-performing in the dessert category.

As a result, nutrients are treated differently across dish categories, while overall meal healthiness does not change between advance and immediate choice.

3.1.2 Commitment Demand To investigate the relation between self-control problems and beliefs thereof, we analyze the demand for a commitment device. Subjects decide in session 2 whether to use a commitment device that ties them to their advance choices from session 2 for session 3.[15] In the experiment, 52% of subjects select the commitment. This number is comparable to Augenblick et al. (2015) and Sadoff et al. (2020) who report a take-up of 53% and 59%, respectively.

For committing individuals, main dishes become marginally unhealthier from t_1t_2 to t_2t_2: The average share of fruits and vegetables is 37.7% (33.4%) in the advance (immediate) choice. The number of selected main dishes does not change between perspectives (both 32.1%). Dessert choices of committing individuals become healthier: the average share of fruits and vegetables increases strongly from 24.4% in the advance choice to 41.2% in the immediate choice. At the same time, committing individuals pick desserts less often: in 18.2% (15.1%) of cases in the advance (immediate) choice. This change implies that the increase in dessert healthiness partly reflects strategies of forgoing desserts (extensive margin) and of switching from unhealthier to healthier desserts (intensive margin).

Non-committing individuals choose substantially unhealthier main dishes in the immediate choice. The share of fruits and vegetables for main dishes decreases from 41% in the advance choice to 34.8% in the immediate choice; and 32% (30.9%) of advance (immediate) choices are main dishes for non-committers, implying that non-committers do not generally reduce main dishes. Regarding desserts, the average share of fruits and vegetables increases very modestly between advance (28.2%) and immediate choice (33.3%). The incidence of consuming a dessert remains almost constant with 18.8% (17.4%) in the advance (immediate) choice. This suggests that the healthiness of desserts hardly changes for non-committers.

To investigate self-selection into the commitment device structurally, we repeat the analysis from Section 3.1 for separate samples based on commitment take-up.

[15] If participants choose to commit, one out of two food choices made from an advance choice perspective in session 2 is randomly chosen and served in session 3. Subjects who choose not to commit make an additional two food choices from an immediate perspective in session 3. In this case, one out of four choices is randomly selected and implemented.

Therefore we analyze choices made *before* the commitment device was offered; consequently, we are comparing behaviors that are not confounded by the availability of the commitment offer. Results are summarized in Table 4.[16] Columns 1-3 show structural estimates for all choices made by individuals who later take up the commitment device. Columns 4-6 report utility weights for individuals who abstain from commitment. Results are reported for food categories separately: main dishes, side dishes and desserts.

Table 4: *Utility weight estimates and commitment demand*

	Committer=1			Committer=0		
	Main dish	Side dish	Dessert	Main dish	Side dish	Dessert
Share Fruits & Vegetables						
Advance share ($\hat{\phi}_A$)	-1.321**	-0.390	0.590	-0.862*	0.023	0.807**
	(0.623)	(0.287)	(0.359)	(0.504)	(0.298)	(0.375)
Immediate choice ×	-0.727*	-0.022	0.916**	-1.060**	-0.108	0.276
Difference ($\hat{\phi}_I - \hat{\phi}_A$)	(0.414)	(0.319)	(0.384)	(0.423)	(0.327)	(0.414)
Log-likelihood	-173.803	-337.902	-119.994	-158.605	-308.372	-123.086
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 3.075$	$\chi^2(1) = 0.005$	$\chi^2(1) = 5.702$	$\chi^2(1) = 6.272$	$\chi^2(1) = 0.110$	$\chi^2(1) = 0.445$
	$(p = 0.080)$	$(p = 0.945)$	$(p = 0.017)$	$(p = 0.012)$	$(p = 0.740)$	$(p = 0.505)$
# Observations	380	934	450	350	846	414
# Rankings	76	76	76	70	70	70
# Clusters	38	38	38	35	35	35

Note: The table presents results from rank-ordered logit regressions applying a random utility model that takes into account random utility shocks. We report results for the utility driver share of fruits and vegetables, and report results for committing and non-committing individuals separately. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the respective utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice. The interaction term indicates a utility weight change from advance to immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to advance choice (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

Focusing on advance food choices, both committing and non-committing subjects prefer unhealthier main dishes but healthier desserts and balance food healthiness over dish categories suggesting a preference for mixed bundles. This result echos the findings from Section 3.1.1.

Regarding the comparison of immediate and advance choices ($\phi_I - \phi_A$), we observe differences in behavior between committing and non-committing individuals. Committers show a preference for unhealthier main dishes ($\phi_I - \phi_A = -0.73$, $p = 0.08$), while they give more weight to healthier desserts ($\phi_I - \phi_A = 0.92$, $p = 0.02$) in the immediate choice. The weight for healthy food decreases significantly by 55% for main dishes between advance and immediate choice, while it

[16] The full analysis with results for all utility drivers is summarized in Appendix Table A3.

increases by 155% for desserts. Committing individuals offset unhealthier main dishes against healthier desserts. They balance food basket healthiness over food categories not only in the advance, but also in the immediate choice when temptation should be greatest. This suggests that committers follow an internal self-control strategy when external commitment is absent. The observed behavior is in line with theoretical considerations by Benhabib and Bisin (2005) who account for self-control mechanisms in modeling dynamic consumption-savings choices, and echos the findings by Sjåstad and Ekström (2021) who study internal and external commitment in a more stylized lab setting. The result implies that internal and external commitment mechanisms are substitutes; and that committing individuals actively regulate their behavior when external devices are absent. A plausible internal self-control mechanism is mental accounting as described in Section 3.1.1.

To the contrary, non-committing individuals show an elevated preference for unhealthy main dishes in the immediate choice that is not offset by picking healthier desserts. Between choice perspectives, the utility weight for healthy main dishes decreases significantly by 123% ($\phi_I - \phi_A = -1.06$, $p = 0.01$) while there is no significant difference for desserts ($p = 0.51$). This finding reveals dynamically inconsistent choice behavior for non-committing individuals. Since they neither choose the external commitment device nor enforce self-control when commitment is absent, the results suggest that non-committers are at least partially naive about their inconsistency (O'Donoghue & Rabin, 2001).

Choice patterns are similar for all four utility drivers (see Appendix Table A3) implying that present-biased individuals are less likely to take up a commitment device. This finding is in line with studies by Royer et al. (2015) and Sadoff et al. (2020) who also detect a negative relation between self-control problems and beliefs thereof. Yet, it stands in contrast to results by Avery et al. (2022), Bai et al. (2021), and Kaur et al. (2015) who find a positive correlation. A negative association like ours limits the scope for policy interventions that offer such devices.

3.2 Comparison of Food Consumption and Money Allocation Choices

How does our novel food choice task compare to a money allocation task? To benchmark our results, we elicit dynamic inconsistency in a standard monetary approach. We provide details on the money allocation task and analyze the associated discounting behavior in Section 3.2.2. Thereafter, we examine the correlation between the food and the money tasks at the individual level in Section 3.2.3.

3.2.1 Money Allocation Task In sessions 1 and 2, participants allocate money to a sooner and later point in time by choosing allocations in Convex Time Budget (CTB) sets. The task is summarized in Table 5. Subjects decide on financial trade-offs in four separate CTB sets that differ with respect to delay length k (one vs. two weeks) and choice perspective (advance vs. immediate choice). In the first set, they allocate money between session 1 (today) and session 2 (in one week). In the second set, money is allocated between sessions 1 and 3 (in two weeks). In the third set, all allocation choices are made for the future: the trade-off is between in one week and in two weeks. CTB set 4 is identical to set 3 except for the choice perspective: in session 2, money is allocated from an immediate choice perspective involving today (session 2) and the next week (session 3).

Table 5: *Money allocation task: CTB sets*

Experimental Session	CTB set	Sooner payment (c_t)	Later payment (c_{t+k})	Delay (k)
1	1: $t_1 \rightarrow t_1t_2$	Today	In 1 week	1 week
1	2: $t_1 \rightarrow t_1t_3$	Today	In 2 weeks	2 weeks
1	3: $t_1 \rightarrow t_2t_3$	In 1 Week	In 2 weeks	1 week
2	4: $t_2 \rightarrow t_2t_3$	Today	In 1 week	1 week

Note: The figure depicts an exemplary CTB set with a delay length of one week and immediate choice perspective (set 1 or 4 in Table 5). Subjects are informed to choose exactly one allocation in each row. In fact, they can only proceed if exactly one allocation per row is chosen. In each row, a different interest rate is implemented. Overall, the interest rates are given by $(1+r) \in \{1.00, 1.05, 1.11, 1.18, 1.33, 1.43, 2.00\}$. By choosing the rightmost allocation, subjects will always receive €10 at the future payment date.

In each CTB sheet, subjects make seven decisions with the following interest rates $(1+r)$: $1.00, 1.05, 1.11, 1.18, 1.33, 1.43, 2.00$. Interest rates are chosen according to prior work (Andreoni et al., 2015; Augenblick et al., 2015; Lührmann et al., 2018). The intertemporal budget constraint is always given by

$$(1+r)c_t + c_{t+k} = m \tag{5}$$

with the budget m being set to €10. While c_t is the payment delivered immediately, c_{t+k} is a future payment delivered with delay k. In each row, a different interest rate is implemented. Figure A4 in the Appendix depicts an example CTB sheet. Higher interest rates imply that the implicit penalty for receiving money sooner than later increases, hence diminishing the amount of money that can be allocated to the sooner payment date. In session 1, CTB sets 1 and 2 are displayed in random order. Before starting the money allocation task, subjects receive instructions (see Appendix B), see an example screen and answer several control questions to ensure a proper understanding of the task. After participants submit answers to control questions, the correct solutions are displayed.

In designing our experiment, we implement a number of features to reduce potential confounders for measuring present bias in money. First, to alleviate the concern of *pay-out uncertainty*, we follow Andreoni and Sprenger (2012) and explicitly guarantee all money payments by the university in the instructions. Second, we rule out *pay-out delay* as Augenblick (2018) and Balakrishnan et al. (2020) find that a delay of the initial payment by even a few hours reduces present bias significantly. In our experiment, each draw is paid directly at the end of the respective session. Third, since subjects receive a show-up fee anyways, there are no additional *transaction costs* for collecting pay-outs from the money task that could potentially influence allocation behavior. Fourth, we reduce *task interference* by explicitly stating in the instructions that the food consumption and the money allocation tasks are independent of each other.

3.2.2 Monetary Discounting To estimate dynamic inconsistencies in choices over money, we apply the quasi-hyperbolic discounting framework (β, δ-model) of Laibson (1997) and O'Donoghue and Rabin (1999) and adopt the parametric approach of Andreoni and Sprenger (2012) by assuming constant relative risk aversion (CRRA) with Stone-Geary background consumption parameters. Following Augenblick et al. (2015), we fix the minimum amount of background consumption at the level of the show-up fee that subjects receive at the end of each experimental session. Hence, the quasi-hyperbolic discounted utility from experimental payments at two payment dates, c_t, and c_{t+k}, is given by

$$U(c_t, c_{t+k}) = (c_t + \omega)^\alpha + \beta^{\mathbf{1}_{t=0}} \delta^k (c_{t+k} + \omega)^\alpha. \tag{6}$$

A risk-averse individual maximizes utility from two payments over time. Because c_{t+k} is a future payment delivered with delay k, it will be discounted. The parameter δ captures long-run discounting, while β captures the degree of dynamic inconsistency. For $\beta = 1$, the quasi-hyperbolic discounting model nests the exponential discounting model. The variable $\mathbf{1}_{t=0}$ is an indicator that takes on the value of one if the earlier payment date, t, is the present, and zero otherwise. Background consumption is captured by ω. Maximizing equation 6 given the intertemporal budget constraint in equation 5 yields the intertemporal Euler equation that can be rearranged to obtain:

$$ln(\frac{c_t + \omega}{c_{t+k} + \omega}) = \frac{ln(\beta)}{\alpha - 1} \mathbf{1}_{t=0} + \frac{ln(\delta)}{\alpha - 1} k + ln(P). \tag{7}$$

Assuming an additive error, the Euler equation can be estimated at the aggregate or individual level:

$$ln(\frac{c_t + \omega}{c_{t+k} + \omega})_i = \eta_0 \times k + \eta_1 \times (\mathbf{1}_{t=0}) + \eta_2 \times ln(P) + \epsilon_i. \tag{8}$$

Discounting and utility function parameters can be estimated as nonlinear combinations of regression coefficients with standard errors based on the delta method:

$$\hat{\beta} = exp(\hat{\eta}_1/\hat{\eta}_2), \hat{\delta} = exp(\hat{\eta}_0/\hat{\eta}_2) \text{ and } \hat{\alpha} = 1 + 1/\hat{\eta}_2.$$

In each CTB set, subjects can only pick one out of six different allocation options. They allocate either 100 percent, 80 percent, 60 percent, 40 percent, 20 percent or 0 percent to the sooner payment date. Other allocations to the sooner payment date are not possible by design. This restriction leads to interval censoring of the data and requires to adapt the estimation method. To account for censoring, we follow Andreoni et al. (2015) and Lührmann et al. (2018) and estimate utility function parameters applying an interval-censored tobit regression model using maximum likelihood.

The realized money choices reflect the law of demand (Appendix Figure A5). As $(1 + r)$ increases, the average money allocation to the sooner payment date decreases. In fact, 96% of choices are monotonically decreasing in $(1 + r)$ at the individual level and no participant exhibits more than three deviations.[17]

Table 6 shows the results of the structural estimation, with standard errors clustered at the individual level. Column 1 reports estimates of the present bias parameter β, the long-run discount factor δ and the degree of risk aversion α. The estimation is based on 2,044 observations: 73 subjects allocate money in four separate CTB sets with seven allocation choices each. In column 2, we additionally consider an error parameter in the estimation: Like Lührmann et al. (2018) we allow subjects to make Fechner errors, which are misjudgments of the distance between optimal and available choices. Since our college students face this money allocation task probably for the first time, they might not select the available money ratio that is closest to their optimal ratio. With Fechner errors, less weight is given to this distance evaluation implying more decision errors (von Gaudecker et al., 2011). Column 2 reports the resultant stochastic decision making term τ.

The present bias parameter without Fechner errors is estimated at $\beta = 1.105$ (Table 6, column 1). A Wald test reveals that $\hat{\beta}$ is not statistically different from 1 ($H_0 : \beta = 1$, $p = 0.375$). By considering Fechner errors (column 2), we estimate $\beta = 1.018$ that is again not statistically distinguishable from 1 ($p = 0.302$). Since the results are insensitive to including errors in decision making, we will in the following focus on the first specification. Our results do not suggest dynamic inconsistency in money choices. This conclusion is consistent with findings by Augenblick et al. (2015) and Imai et al. (2021) who also find no evidence for dynamically inconsistent behavior in allocating money over time.

3.2.3 Individual Analysis At the aggregate level, we find evidence for dynamic inconsistency in the food consumption but not in the money allocation task. We now turn to the comparison of individual behaviors to assess whether dynamic inconsistency in real consumption choices is reflected in intertemporal choices de-

[17]Subjects have 24 opportunities to violate monotonicity comparing two adjacent values of $(1+r)$ in their 28 total CTB choices. 54 of 73 subjects have no identified nonmonotonicities. Of those 19 participants violating monotonicity, 10 participants only have one nonmonotonicity, six individuals have up to three nonmonotonicities.

Table 6: *Utility parameter estimates*

	Interval-Censored Tobit	Interval-Censored Tobit with Fechner error
	(1)	(2)
Utility parameters		
Present bias parameter ($\hat{\beta}$)	1.015	1.018
	(0.017)	(0.017)
Discount factor ($\hat{\delta}$)	1.023	1.022
	(0.005)	(0.005)
Curvature ($\hat{\alpha}$)	0.816	0.827
	(0.031)	(0.039)
Error parameter		
Fechner error ($\hat{\tau}$)		1.102
		(0.133)
# Observations	2044	2044
# Clusters	73	73
$H_0 : \hat{\beta} = 1$	$\chi^2(1) = 0.79$	$\chi^2(1) = 1.07$
	$p = 0.375$	$p = 0.302$

Note: The table shows results from an interval-censored tobit regression. In the maximum likelihood estimation, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm is applied. Estimates are structurally based on the Euler equation $ln(\frac{c_t+\omega}{c_{t+k}+\omega}) = \frac{ln(\beta)}{\alpha-1}\mathbf{1}_{t=0} + \frac{ln(\delta)}{\alpha-1}k + ln(P)$, and a minimum amount of background consumption is considered by including the show-up fee paid at the end of each experimental session in the estimation. Parameters are computed as nonlinear combinations of regression coefficients. Standard errors are clustered at individual level and recovered via the delta method. For each column, results of a Wald-test are reported. The underlying hypothesis H_0 is: $\hat{\beta} = 1$.

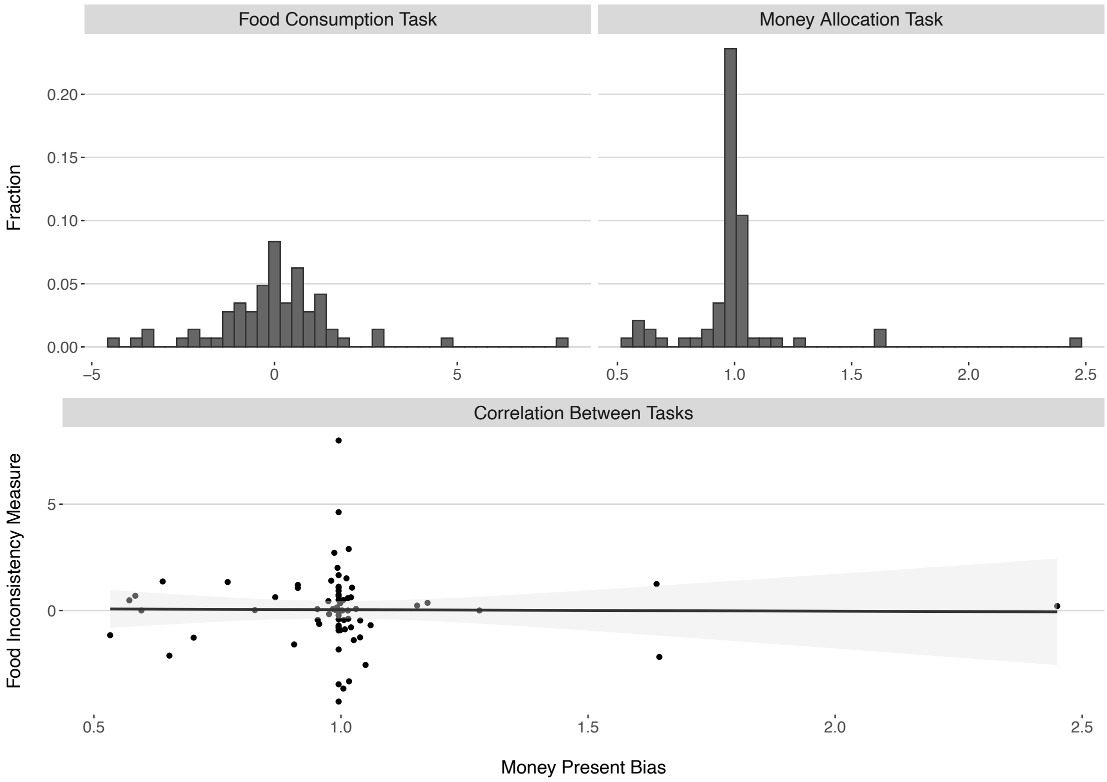
rived from monetary rewards. To operationalize this comparison, we re-run the structural estimation approaches at the individual level. More precisely, we apply the random utility approach introduced in Section 2.2 and perform rank-ordered logit regressions for each individual to obtain a measure of dynamic inconsistency over food choices. In a similar way, we apply the β, δ-model introduced in Section 3.2.2 and estimate interval-censored tobit regressions for each individual to derive the present bias parameter β for choices over money. In the money allocation task, we follow Lührmann et al. (2018) and exclude extreme observations with values for β_i below 0.01 or above 9.6. We exclude one observation with $\beta_i = 22.83$ and focus on the 99% subsample.

The top panel of Figure 3 presents the distribution of individual dynamic inconsistency estimates for food (left) and money (right). For the money allocation task, a parameter estimate $\hat{\beta}$ below 1 indicates present-biased behavior, while for food, a negative value indicates unhealthier or more present-biased behavior. Table A4 in the Appendix summarizes the distribution of estimated parameters for both tasks (for the full sample). The figure reveals a greater dispersion of the inconsistency measure for the food compared to the money allocation task (Kolmogorov-Smirnoff test: $p < 0.001$). This result does not change when we look at the other healthiness criteria (calories, saturated fats, NPS)[18] in Appendix Figures A6, A7 and A8. The bottom panel of Figure 3 shows the (zero) correlation between the individual measures from the two domains.

We follow Augenblick et al. (2015) and construct two dummy variables indicating that individuals exhibit dynamically inconsistent behavior: choosing unhealthier food or impatiently allocating more money to the sooner payment date in the immediate choice, respectively. For the money allocation task, we mimic the approach of the correlational studies by Ashraf et al. (2006) and Meier and Sprenger (2010) and define the dummy to take the value of one if the individual estimate lies strictly below 0.99 (present bias), zero otherwise. For the food consumption task, we define the dummy to take the value of one if the individual estimate $(\phi_I - \phi_A)$ lies strictly below 0.00 (consistency), zero otherwise. Considering the

[18]Note that we invert the difference in utility weights $(\phi_I - \phi_A)$ for calories, saturated fats and nutrient profile scores for better comparability: a negative difference indicates a higher inclusion probability of unhealthier food items in the immediate compared to the advance choice.

Figure 3: *Individual estimates: quota of fruits and vegetables*



Note: The figure summarises estimates of dynamic inconsistency at individual level for a 99% subsample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming the quota of fruits and vegetables as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the correlation of measures between tasks: behavior is not correlated.

food choice task, we find that 44% of individuals show dynamic inconsistency in the expected direction (choosing unhealthier food), while in the money allocation task only 31% show present-biased behavior (allocating more money to the sooner payment date). While the reported result considers the share of fruits and vegetables, the findings for the remaining criteria are qualitatively similar (57% for calories, 53% for fat and 54% for nutrient profile scores). These differences are significant in two-sample z-tests: $z = 1.73$ with $p = 0.08$ for the share of fruits and vegetables, $z = 3.29$ with $p = 0.00$ for calories, $z = 2.76$ with $p = 0.01$ for saturated fats and $z = 2.93$ with $p = 0.00$ for nutrient profile scores.[19]

We now investigate the correlation between individual estimates. As the linear estimation in Figure 3 (bottom part) reveals, there is no significant association between the money allocation and food consumption tasks. The coefficient from a linear regression is -0.07 ($p = 0.93$). The estimated Spearman's correlation coefficient for the share of fruits and vegetables is $\rho = -0.15$ with $p = 0.20$. The corresponding correlation coefficients for the remaining nutrients are: $\rho = 0.19$ ($p = 0.11$) for calories, $\rho = 0.06$ ($p = 0.60$) for saturated fats and $\rho = 0.18$ ($p = 0.13$) for nutrient profile scores. Note that while correlation coefficients for calories and nutrient profile scores seem to be only marginally insignificant, this is mainly driven by one very high observation for money present bias (β_i=2.45). Excluding this one observation diminishes the correlation coefficients $\rho = 0.16$ ($p = 0.18$) for calories and $\rho = 0.15$ ($p = 0.21$) for nutrient profile scores.[20] The correlation between the two binary measures yields comparable results. We estimate a correlation coefficient of $\rho = -0.169$ ($p = 0.16$) for the share of fruits and vegetables as well as $\rho = 0.03$ ($p = 0.81$) for calories, $\rho = 0.02$ ($p = 0.84$) for

[19] In an alternative specification, we define the dynamic inconsistency dummy from the food consumption task to take the value of one if the individual estimate lies strictly below -0.01. In this case, 40% of individuals show dynamic inconsistency in the expected direction for the share of fruits and vegetables (47% for calories, 43% for fat and 40% for nutrient profile scores). Applying two-sample z-tests, these differences between the food consumption and money allocation task are no longer significant, except for calories: $z = 1.22$ with $p = 0.22$ for the share of fruits and vegetables, $z = 2.07$ with $p = 0.04$ for calories, $z = 1.56$ with $p = 0.12$ for saturated fats and $z = 1.22$ with $p = 0.22$ for nutrient profile scores.

[20] Graphical representations of linear regression results for the three remaining criteria are shown in Figures A6, A7 and A8 in the Appendix. Note that the significant correlation for calories is again driven by the highest individual estimate for money present bias (β_i=2.45). When excluding this observation, the correlation turns insignificant with a slope of 0.08 ($p = 0.24$). For saturated fats and nutrient profile scores, the slopes are not statistically different from zero.

saturated fats and $\rho = 0.07$ ($p = 0.58$) for nutrient profile scores.[21]

We conclude from this exercise that the behavior in the two tasks is not correlated within individuals. Our results are in line with Augenblick et al. (2015) who find no correlation between an effort and a money allocation task as well as a much more dispersed parameter distribution for the effort task. We follow Augenblick et al. (2015) and investigate whether subjects who take up the commitment device in the food consumption task show a different allocation behavior in the money task. The analysis is documented in Appendix **??**. In line with Augenblick et al. (2015), we find no systematic differences emphasizing that the money allocation and food consumption tasks entail different inconsistency patterns.

3.3 Robustness Tests

In our food choice analysis, we interpret dynamically inconsistent behavior as evidence for dynamically inconsistent preferences. In this subsection, we provide evidence in support of the idea that behavioral patterns directly reflect preferences rather than noise, changes in the decision environment, or arbitrage opportunities.

3.3.1 Stability of Inconsistency So far, our analysis has focused on food choices made in session 1 (advance choices) and session 2 (immediate choices) to identify violations of time consistency. To investigate the stability of dynamic inconsistency, we now focus on food consumption choices of non-committing individuals after commitment has been offered in session 2. More precisely, we compare food choices made from an advance perspective in session 2 with food choices made from an immediate perspective in session 3, and structurally estimate utility weights for immediate and advance choices applying the random utility techniques introduced in Section 2.2. The comparison between the new second round results (Table A5) and the first round results (Table A3) reveals similar behavioral patterns over time. First, non-committing individuals show a preference for mixed bundles from the advance perspective in both rounds. Sec-

[21] With the alternative specification for the inconsistency dummy over food choices (threshold -0.01), results remain qualitatively similar: $\rho = -0.11$ ($p = 0.34$) for the share of fruits and vegetables, $\rho = -0.02$ ($p = 0.84$) for calories, $\rho = 0.09$ ($p = 0.44$) for saturated fats and $\rho = 0.01$ ($p = 0.94$) for nutrient profile scores.

ond, they favor unhealthier items within specific food categories in the immediate choice in both rounds. In the first choice comparison (Table A3), non-committing individuals derive greater utility from including unhealthy savory food items from the main or side dish category in their immediate choice bundles. In the second comparison (Table A5), more utility stems from unhealthy sweet food items from the dessert category in the immediate choice. Non-committing individuals show dynamically inconsistent behavior in both rounds.

3.3.2 Subjective Healthiness Perception Since we provide no nutritional information about dishes in the experiment, concerns might arise that subjects apply heterogeneous beliefs regarding the healthiness of canteen food items. To alleviate this concern, we investigate the level of experience and knowledge among canteen consumers. First, we ask subjects about the frequency of canteen visits last week. Subjects provide this information at the beginning of each session before making food choices. Participants visit the canteen on average 1.8 times per week (out of five possible days). Regarding the anticipation of the food offer, note that lunch menus are highly standardized at the canteen. Every day, the canteen serves at least one vegetarian and two non-vegetarian main dishes as well as a big salad and a vegetarian soup bowl. As side dishes, the operator always supplies vegetables, a variety of small salads, different sorts of buns, a small vegetarian soup bowl as well as at least one hot side dish (noodles, rice, potatoes or fries). As dessert options, the canteen daily offers pudding, mousse and fruit quark with different flavors, plain yogurt and fruits. We conclude that customers of the canteen are experienced consumers.

Second, we elicit subjective beliefs about the healthiness of all food items and subsequently investigate the correlation between individual healthiness perception and nutritional content. We elicit subjective beliefs after the food choice task on an 11-point Likert-scale. The correlations between the subjective score and the objective nutritional measures all go in the expected direction and are highly statistically significant.[22] We conclude that health perceptions among customers are in line with objective measures.

[22] $\rho = 0.66$ with ($p < 0.00$) for the share of fruits and vegetables, $\rho = -0.40$ with ($p < 0.00$) for calories, $\rho = -0.25$ with ($p < 0.00$) for fat and $\rho = -0.52$ with ($p < 0.00$) for NPS.

Third, we re-run the random utility analysis from Section 3.1.2 by applying the subjective health score. While the resulting coefficients are less precisely estimated (Table A6), they are similar to objective measures (Table A3). We also repeat the analysis regarding second round choices for non-committing individuals (Table A7). The results are again very comparable to the estimates reported in Table A5.

3.3.3 Decision Environment We further investigate the influence of the decision environment on food choices over time. In five tests we show that environmental conditions cannot explain our results (Table A8): First, we analyze individual hunger levels since being more hungry in week 2 might spuriously result in unhealthier food consumption in the immediate choice. Besides requesting and reminding subjects to not eat for at least two hours before the start of the experiment, respondents rate their hunger level at the beginning of each session. The average hunger level on a 11-point Likert scale ranging from 0 (not at all hungry) to 10 (very hungry) is 6.9 in session 1 and 7.0 in session 2 and the hunger level is not correlated with nutritional choices. Second, subjects might adapt their immediate food choices if they visually inspected the dishes in the canteen on session day. Since canteen food is standardized, uncertainty about the appearance of dishes should be relatively low. Still, we ask subjects whether they inspected today's dishes: This was true for 22% of participants in session 1 and 29% in session 2. Overall, 54 out of 73 (74%) participants do not change their inspection behavior over time and food inspection is not correlated with food choices. Third, personal lunch purchases on the day before experimental sessions might influence food choice behavior. We find no correlation between purchases on the day before the experiment and experimental food selection. Fourth, environmental stimuli might influence individual food choices over time, as summarized under the notion of ambience (Stroebele & De Castro, 2004). In the study design, we fix all controllable session settings such as group composition or the protocol. Yet, we cannot control for day-specific outdoor weather. Therefore, we collect city-day-specific temperature, sunshine and rainfall data from the German Weather Service, but find no correlation between weather and selected foods. A final change in the decision environment over time might pertain to resource constraints: while subjects do not need to pay for the experimental canteen lunches, differences in disposable income can influence general food choices over time. We therefore ask subjects in each session whether they expected an inflow of income between the last session and today. This can serve as a simple measure of relative income over time. We observe no correlation between our income proxy and dynamic inconsistency.

3.3.4 Arbitrage Opportunities One common concern about monetary allocation experiments is the high fungibility of money, allowing to easily exchange it outside the experiment. Consequently, money allocation choices in the experiment might simply reflect a person's lending and borrowing opportunities outside the lab (Cubitt & Read, 2007). This can explain time consistent behavior in money allocations over time (Augenblick et al., 2015). Similarly, arbitrage opportunities in food choices might indicate subjects' opportunities to trade food items outside the experiment rather than their true preferences. The original choice would no longer reflect consumption preferences. Yet, arbitrage opportunities are unlikely in our setting: First, prices and sizes of food items in the experiment are identical to regular canteen prices and sizes. Second, the perishability of food items puts a tight time constraint on trades. Third, finding individuals interested in food trades is practically impossible because all members of the college community can purchase food at the canteen without quantity restrictions.

Although trade opportunities seem unrealistic *during* the experiment, arbitrage might prevail if subjects complement healthier eating during the session with unhealthier eating thereafter, e.g., by purchasing a chocolate bar instead of an apple from the campus cafe in the afternoon. Yet, the evidence does not indicate large-scale extra-lab consumption of potentially confounding food items. The average selected meal during the experiment contains 1,200 kilo calories (kcal). With a recommended daily calorie intake of 2,000 for women and 2,500 for men (National Health Service, 2023), these lunches cover 50-60% of the daily energy requirement. As our subjects take (nutritional) high-stake decisions, they should reliably choose according to their true preferences. We also collect data on the universe of subjects' on-campus food transactions by investigating their food purchases using unique campus card numbers. Campus cards are the only eligible payment method on campus (at both the canteen and cafe).[23] Across all days of session 1 and 2, we

[23] At the time of the experiment, there were no other food places available on campus. The

observe 15 out of 73 (21%) subjects making 23 on-campus food transactions.We calculate the correlation between purchasing food items on session days outside the experiment (dummy) and nutrients chosen during a session as well as between the nutrients purchased *outside* and *inside* the experiment. None of these estimates is close to significant (Table A8).[24]

4 Discussion and Conclusion

We implement a longitudinal, framed field experiment to examine dynamically inconsistent preferences for a continuous and convex non-monetary budget in food choices: College students repeatedly select lunches that are immediately consumed in the college canteen. We document three main findings: First, we contrast individual food consumption and money allocation choices to examine the fundamental question whether dynamic inconsistencies in real consumption choices are reflected in intertemporal behavior derived from monetary rewards. We find that the distribution of food inconsistency measures is much more dispersed than the inconsistency distribution of money, which is tightly centered around consistency. We also observe no significant correlation between the money allocation and food consumption behaviors. These findings suggest a limited applicability of monetary reward studies to real food consumption behavior. Second, subjects treat food categories (main, side, dessert) differently and balance food healthiness across categories. This balancing implies dynamically consistent behavior at the overall meal level. Complex behavioral patters seem to navigate human decision making in a true natural consumption task. Third, more than half of participants choose voluntary restraint when a commitment device is offered. We examine control mechanisms for committing and non-committing subjects and document a negative relation between self-control problems and beliefs thereof: subjects choosing our (external) commitment device already enforce internal self-control before commitment is offered, while non-committing subjects are present-biased. These results

campus canteen is rather isolated with the next fast food possibility being 5 mins and the city center being 10 mins away.

[24] While our data comprise all on-campus food purchases we cannot completely preclude that subjects supplement healthy eating during the experiment with unhealthy eating at home. This would bias our results towards time consistency.

suggest that non-committing participants are at least partially naive about their self-control problem while those demanding commitment show dynamically consistent behavior. This implies that internal and external commitment strategies are substitutes and that committing individuals actively enforce internal self-control when external commitment is absent. When external commitment is offered, which is at least in our design costless, they replace their internal control which is costly in terms of psychological resources (Hofmann et al., 2008).

Our results may attenuate the hopes associated with policy interventions targeting self-control problems. One prominent example is the large-scale roll-out of an online purchasing pilot program by the US Department of Agriculture that allows online pre-ordering of food for low-income communities under the Supplemental Nutrition Assistance Program (SNAP).[25] The aim of this policy is to foster healthier nutrition by committing individuals to their advance food choices. Our findings suggest that those who would benefit most from commitment do not take it up. Potential committers apply other self-control strategies instead.

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[25] https://www.ers.usda.gov/amber-waves/2021/july/online-supplemental-nutrition-assistance-program-snap-purchasing-grew-substantially-in-2020/

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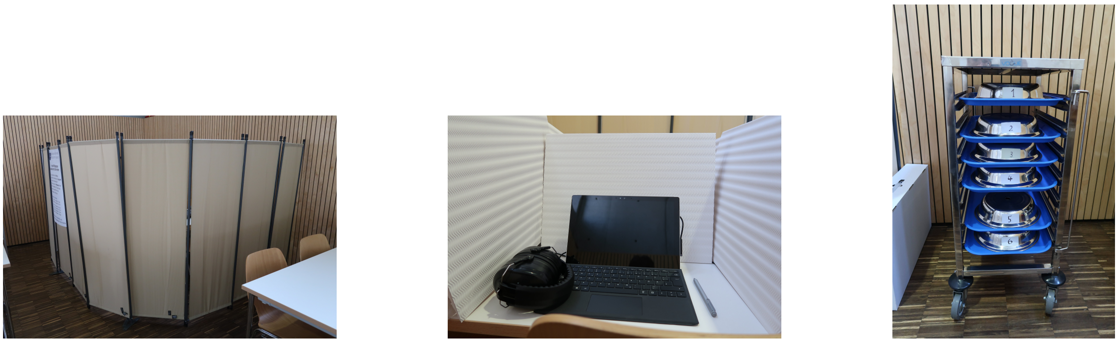
Online Appendix A

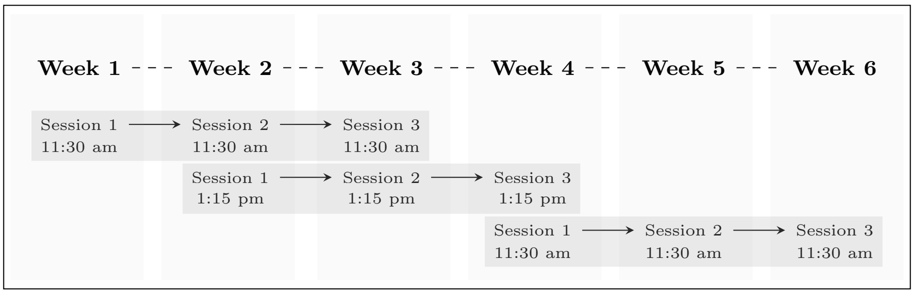
Figure A1: *Experimental setup*



(a) Booth (b) Desk (c) Serving Cart

Note: The figure depicts the experimental setup. Panel a) shows the experimental booth that was built in the dining hall. Participants enter the booth to make food and money choices. Panel b) shows an example desk participants were located to in order to make their choices using a table computer. Panel c) depicts the serving cart that was used to purchase the randomly selected food choice of each participant in the university canteen and serve it at the end of each session.

Figure A2: *Experimental timeline*



Note: The figure summarises the timeline of the experiment. Th experiment was conducted rollingly over a time span of six weeks. Participants went through three consecutive sessions with one week spacing in between. They were allocated to the same time and day for all three sessions. Participants could either start in week 1, week 2 or week 4. Subjects entering the experiment in week 1 and 4 start their sessions at 11:30am. Subjects entering in week 2 start at 1:15pm. Both slots were scheduled to fit the timetable of students during regular canteen opening hours.

Figure A3: *Example of a canteen menu (translated from German)*

Select the dishes for your canteen lunch that you will receive at the end of the second session on [*date of 'today in one week'*] with a probability of 25%. Your seleced items must not exceed the total value of €4.00. Your chosen budget is indicated below the canteen menu. Click on the plus or minus sign to add an item, discard an item or change the amount.

Note: A large mixed salad has approximately 260 grams. If a dish is offered in the self-serving area, the plate will be fully filled by eye. The portion sizes of all other dishes are set by the canteen operator.

Main Dishes	**€**	**Amount**	**Side Dishes**	**€**	**Amount**	**Desserts**	**€**	**Amount**	**Sides**	**€**	**Amount**
Vegan Thai noodle vegetable pan with peanuts in coconut sauce	1.92	0	Rice	0.70	0	Fresh Fruit	0.50	0	Mayonnaise	0.20	0
Chicken breast with onion cream sauce	2.35	0	Green leaf salad	0.70	0	Fruit quark	0.70	0	Ketchup	0.20	0
Alaska pollock fillet in batter with tomato sauce and rice	2.81	0	Cucumber salad	0.70	0	Natural yogurt with muesli	0.70	0			
Vegetarian soup of the day large with roll	1.20	0	Spaetzle	0.70	0	Pudding	0.80	0			
Large mixed salad (green leaf lettuce, carrots, tomatoes, cucumber) with dressing	2.21	0	Carotts	0.70	0	Mousse/ Creme	1.10	0			
			Potatos	0.90	0	Sweetened yogurt with muesli	0.70	0			
			Bell pepper salad	0.70	0						
			Potato salad	0.90	0						
			Whole wheat roll	0.55	0						
			Tomato salad	0.70	0						
			Colorful mixed salad	0.70	0						
			Vegetarian soup of the day small	0.60	0						
			Pretzel/ Lye bar	0.60	0						
			Kaiser bun	0.35	0						

Note: The figure shows an example menu offered in the university canteen. Students can click on the green plus or the red minus button to select or discard a food item. Items are categorized into food categories: main dishes, side dishes, desserts and sides. There are no restrictions posed on participants' choices except for the budget condition. Participants make two food choices: for a €4 and a €5 condition.

Table A1: *Summary of nutrients: food items*

Food Category	Food Label	Nutrient Profile Score	Calories (Kcal)	Sugar (g)	Saturated Fats (g)	Proteins (g)	Salt (Sodium in mg)	Veg Share (%)	Item Size (g)	Price
	Panel A: average weight (in g)									
Main dishes	Main dish heavy	24.9	828.02	16.80	11.97	39.21	2351.46	22.08	477.44	3.05
	Main dish light	17.9	583.01	7.72	7.71	37.56	1568.99	21.18	359.34	2.62
	Main dish veg	19.1	690.52	17.74	7.84	20.46	1479.14	44.52	449.49	2.23
	Big salad veg	-9.0	92.35	6.88	0.45	3.23	174.00	96.15	260.00	2.21
	Big soup bowl veg	7.0	201.89	5.47	7.49	6.62	345.60	44.00	288.00	1.20
Side dishes	Bun "kaiser"	1.00	131.39	1.58	0.20	4.59	367.20	0	51.00	0.35
	Pretzel	3.00	327.93	0.68	1.02	7.74	510.00	0	85.00	0.60
	Wholegrain bun	-4.00	174.12	0.63	0.11	6.27	319.20	0	57.00	0.55
	Fries	25.00	1135.80	4.40	17.42	7.16	1575.60	0	196.00	1.00
	Rice	2.00	50.17	0.04	0.04	1.07	205.24	0	39.47	0.70
	Potatoes	-6.00	258.28	2.22	0.00	6.35	0.00	0	317.30	0.90
	Vegetable	-10.31	105.76	8.78	0.40	7.71	81.09	100	225.97	0.70
	Small salad veg	-6.4	66.03	4.51	0.35	1.42	135.6	91.34	143	0.7
	Small soup bowl veg	-1.00	101.64	2.76	3.77	3.34	174.0	53.00	145	0.6
Desserts	Fruit	-3	106.72	19.44	0.07	0.95	0.00	100	135	0.5
	Fruit quark	15	243.65	28.67	5.83	10.63	96.80	0	220	0.7
	Yoghurt with cereals	7	234.00	15.70	5.38	10.32	152.00	0	200	0.7
	Yoghurt with cereals (sugared)	15	366.30	23.40	12.98	8.52	120.00	0	200	0.7
	Mousse	17	266.69	27.90	7.33	6.59	107.52	0	128	1.1
	Pudding	5	267.00	12.65	2.04	3.64	179.52	0	136	0.8
	Panel B: per 100g									
Main dishes	Main dish heavy	3.94	174.41	3.60	2.67	8.81	496.13	22.08	100	0.67
	Main dish light	2.03	161.07	2.10	2.22	11.16	455.82	21.18	100	0.78
	Main dish veg	0.39	161.98	4.10	1.72	4.61	355.15	44.52	100	0.54
	Big salad	-7.00	35.52	2.65	0.17	1.24	66.92	96.15	100	0.85
	Big soup bowl	-1.00	70.10	1.90	2.60	2.30	120.00	44.00	100	0.42
Side dishes	Bun "kaiser"	1.00	257.62	3.10	0.40	9.00	720.00	0	100	0.69
	Pretzel	7.00	385.80	0.80	1.20	9.10	600.00	0	100	0.71
	Wholegrain bun	-1.00	305.48	1.10	0.20	11.00	560.00	0	100	0.96
	Fries	21.00	579.49	2.24	8.89	3.65	803.88	0	100	0.51
	Rice	4.00	127.10	0.10	0.10	2.70	519.99	0	100	1.77
	Potatoes	-3.00	81.40	0.70	0.00	2.00	0.00	0	100	0.28
	Vegetable	-10.16	46.80	3.85	0.18	3.44	34.65	100	100	0.31
	Small salad	-5.8	46.27	3.02	0.25	1.02	98.24	91.34	100	0.51
	Small soup bowl	-1.0	70.10	1.90	2.60	2.30	120.00	53.00	100	0.41
Desserts	Fruit	-4	79.05	14.40	0.05	0.70	0	100	100	0.37
	Fruit quark	2	110.75	13.03	2.65	4.83	44	0	100	0.32
	Yoghurt with cereals	-1	117.00	7.85	2.69	5.16	76	0	100	0.35
	Yoghurt with cereals (sugared)	3	183.15	11.70	6.49	4.26	60	0	100	0.35
	Mousse	11	208.35	21.80	5.73	5.15	84	0	100	0.86
	Pudding	5	196.32	9.30	1.50	2.68	132	0	100	0.59

Note: Panel A depicts nutrient profile scores, single nutrients, the size and price of food items offered during the experiment at the university canteen. All nutrient information are based on the average weight measured in grams. In the first part of panel A, values for all main dish categories are shown. For heavy, light and vegetarian main dishes, we calculate mean values since main dish items change on a daily basis. The second part of panel A shows the range of side dishes most often offered during the time we conducted the experiment. We calculate mean values for vegetable since the sort of vegetables changes on a daily basis. Part three of panel A shows the nutritional information for desserts. All desserts were constantly offered with only slight variations (vanilla vs. chocolate pudding). Panel B shows information per 100 grams of a food item.

Table A2: *Utility weight estimates*

	Main dish	Side dish	Dessert	Full meal
A: Vegetables/Fruit Quota				
Veg Quota ($\hat{\phi}_A$)	-1.093***	-0.192	0.698***	-0.024
	(0.395)	(0.205)	(0.257)	(0.149)
Immediate choice ×	-0.893***	-0.064	0.593**	-0.032
Veg Quota ($\hat{\phi}_I - \hat{\phi}_A$)	(0.296)	(0.226)	(0.281)	(0.126)
Log-likelihood	-332.630	-647.175	-243.514	-2171.461
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 9.082$	$\chi^2(1) = 0.082$	$\chi^2(1) = 4.450$	$\chi^2(1) = 0.066$
	($p = 0.003$)	($p = 0.775$)	($p = 0.035$)	($p = 0.798$)
B: Calories				
Calories ($\hat{\phi}_A$)	0.110***	0.180***	-0.409***	0.142***
	(0.025)	(0.031)	(0.142)	(0.015)
Immediate choice ×	0.031*	0.025	-0.333*	0.018
Calories ($\hat{\phi}_I - \hat{\phi}_A$)	(0.016)	(0.023)	(0.172)	(0.011)
Log-likelihood	-327.004	-618.033	-242.415	-2087.843
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 3.709$	$\chi^2(1) = 1.175$	$\chi^2(1) = 3.746$	$\chi^2(1) = 2.368$
	($p = 0.054$)	($p = 0.278$)	($p = 0.053$)	($p = 0.124$)
C: Fat				
Fat ($\hat{\phi}_A$)	0.008	0.120***	-0.069**	0.045***
	(0.015)	(0.017)	(0.029)	(0.007)
Immediate choice ×	0.028***	0.009	-0.082**	0.003
Fat ($\hat{\phi}_I - \hat{\phi}_A$)	(0.011)	(0.015)	(0.041)	(0.006)
Log-likelihood	-349.825	-612.403	-244.886	-2146.090
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 6.668$	$\chi^2(1) = 0.393$	$\chi^2(1) = 3.954$	$\chi^2(1) = 0.192$
	($p = 0.010$)	($p = 0.531$)	($p = 0.047$)	($p = 0.661$)
D: Nutrient Profile Score				
Nutrient Profile Score ($\hat{\phi}_A$)	0.034***	0.054***	-0.026*	0.038***
	(0.010)	(0.010)	(0.016)	(0.005)
Immediate choice ×	0.016**	0.003	-0.034*	0.003
Nutrient Profile Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.007)	(0.009)	(0.019)	(0.004)
Log-likelihood	-325.927	-620.344	-250.213	-2105.038
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 4.655$	$\chi^2(1) = 0.165$	$\chi^2(1) = 3.189$	$\chi^2(1) = 0.477$
	($p = 0.031$)	($p = 0.685$)	($p = 0.074$)	($p = 0.490$)
# Observations	730	1780	864	3666
# Rankings	146	146	146	146
# Clusters	73	73	73	73

Note: The table presents results from rank-ordered logit regressions estimated with maximum likelihood. We report results for all utility drivers: share of fruits and vegetables (A), calories (B), saturated fats (C) and nutrient profile scores (D). We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the respective utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice (ϕ_A). The interaction term indicates a utility weight change between immediate and advance choice. The null hypothesis tests whether the interaction coefficient is different from 0. Results are first reported for the three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Column 4 shows results at the food basket level (looking at all food categories simultaneously. In column 4, the data set comprises 3,666 observations. Levels of significance: *0.10, **0.05, ***0.01

Table A3: *Utility weight estimates and commitment demand*

	Committer=1			Committer=0		
	Main dish	Side dish	Dessert	Main dish	Side dish	Dessert
A: Vegetables/Fruit Quota						
Veg/Fruit Quota ($\hat{\phi}_A$)	-1.321**	-0.390	0.590	-0.862*	0.023	0.807**
	(0.623)	(0.287)	(0.359)	(0.504)	(0.298)	(0.375)
Immediate choice ×	-0.727*	-0.022	0.916**	-1.060**	-0.108	0.276
Veg/Fruit Quota ($\hat{\phi}_I - \hat{\phi}_A$)	(0.414)	(0.319)	(0.384)	(0.423)	(0.327)	(0.414)
Log-likelihood	-173.803	-337.902	-119.994	-158.605	-308.372	-123.086
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 3.075$	$\chi^2(1) = 0.005$	$\chi^2(1) = 5.702$	$\chi^2(1) = 6.272$	$\chi^2(1) = 0.110$	$\chi^2(1) = 0.445$
	($p = 0.080$)	($p = 0.945$)	($p = 0.017$)	($p = 0.012$)	($p = 0.740$)	($p = 0.505$)
B: Calories						
Calories ($\hat{\phi}_A$)	0.130***	0.199***	-0.449**	0.091**	0.143**	-0.365
	(0.028)	(0.036)	(0.180)	(0.039)	(0.059)	(0.225)
Immediate choice ×	0.010	0.013	-0.542***	0.051*	0.049	-0.143
Calories ($\hat{\phi}_I - \hat{\phi}_A$)	(0.013)	(0.031)	(0.200)	(0.028)	(0.031)	(0.283)
Log-likelihood	-171.145	-317.113	-116.207	-155.559	-300.512	-124.920
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.634$	$\chi^2(1) = 0.170$	$\chi^2(1) = 7.372$	$\chi^2(1) = 3.381$	$\chi^2(1) = 2.531$	$\chi^2(1) = 0.257$
	($p = 0.426$)	($p = 0.680$)	($p = 0.007$)	($p = 0.066$)	($p = 0.112$)	($p = 0.612$)
C: Fat						
Fat ($\hat{\phi}_A$)	-0.003	0.124***	-0.081**	0.020	0.113***	-0.056
	(0.023)	(0.021)	(0.039)	(0.019)	(0.030)	(0.043)
Immediate choice ×	0.028**	-0.002	-0.131**	0.030	0.030*	-0.046
Fat ($\hat{\phi}_I - \hat{\phi}_A$)	(0.012)	(0.021)	(0.054)	(0.019)	(0.018)	(0.060)
Log-likelihood	-185.092	-317.520	-117.944	-164.126	-294.694	-125.684
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 4.941$	$\chi^2(1) = 0.007$	$\chi^2(1) = 5.975$	$\chi^2(1) = 2.498$	$\chi^2(1) = 2.965$	$\chi^2(1) = 0.590$
	($p = 0.026$)	($p = 0.934$)	($p = 0.015$)	($p = 0.114$)	($p = 0.085$)	($p = 0.442$)
D: Nutrient Profile Score						
Nutrient Profile Score ($\hat{\phi}_A$)	0.042***	0.068***	-0.014	0.028**	0.033**	-0.038*
	(0.015)	(0.012)	(0.023)	(0.013)	(0.017)	(0.022)
Immediate choice ×	0.012	-0.004	-0.056**	0.020	0.015	-0.012
Nutrient Profile Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.008)	(0.012)	(0.028)	(0.012)	(0.014)	(0.027)
Log-likelihood	-169.567	-316.219	-124.332	-155.997	-302.265	-125.409
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 2.274$	$\chi^2(1) = 0.145$	$\chi^2(1) = 4.182$	$\chi^2(1) = 2.631$	$\chi^2(1) = 1.226$	$\chi^2(1) = 0.213$
	($p = 0.132$)	($p = 0.704$)	($p = 0.041$)	($p = 0.105$)	($p = 0.268$)	($p = 0.645$)
# Observations	380	934	450	350	846	414
# Rankings	76	76	76	70	70	70
# Clusters	38	38	38	35	35	35

Note: The table presents results from rank-ordered logit regressions applying a random utility model that takes into account random utility shocks. We report results for all utility drivers: the share of fruits and vegetables, calories, saturated fats and nutrient profile scores, and report results for committing and non-committing individuals separately. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the respective utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice. The interaction term indicates a utility weight change from advance to immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to advance choice (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

Figure A4: *Example CTB decision sheet (translated from German)*

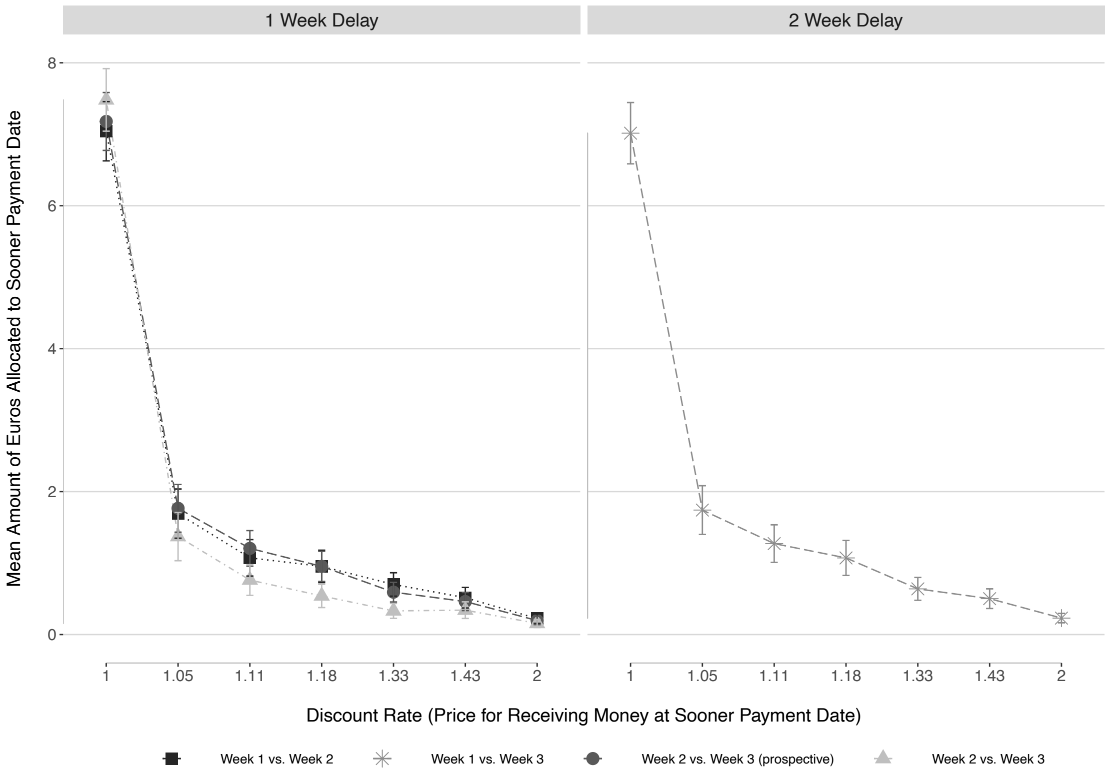
Choose an allocation:

Please allocate money between **today** and **today in one week**. In each row, choose the amount of money you would like to receive today and on [*date of 'today plus one week'*] at the end of the respective session.

1	**Amount today**	**€10.00**	**€8.00**	**€6.00**	**€4.00**	**€2.00**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○
2	**Amount today**	**€9.50**	**€7.60**	**€5.70**	**€3.80**	**€1.90**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○
3	**Amount today**	**€9.00**	**€7.20**	**€5.40**	**€3.60**	**€1.80**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○
4	**Amount today**	**€8.50**	**€6.80**	**€5.10**	**€3.40**	**€1.70**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○
5	**Amount today**	**€7.50**	**€6.00**	**€4.50**	**€3.00**	**€1.50**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○
6	**Amount today**	**€7.00**	**€5.60**	**€4.20**	**€2.80**	**€1.40**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○
7	**Amount today**	**€5.00**	**€4.00**	**€3.00**	**€2.00**	**€1.00**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
		○	○	○	○	○	○

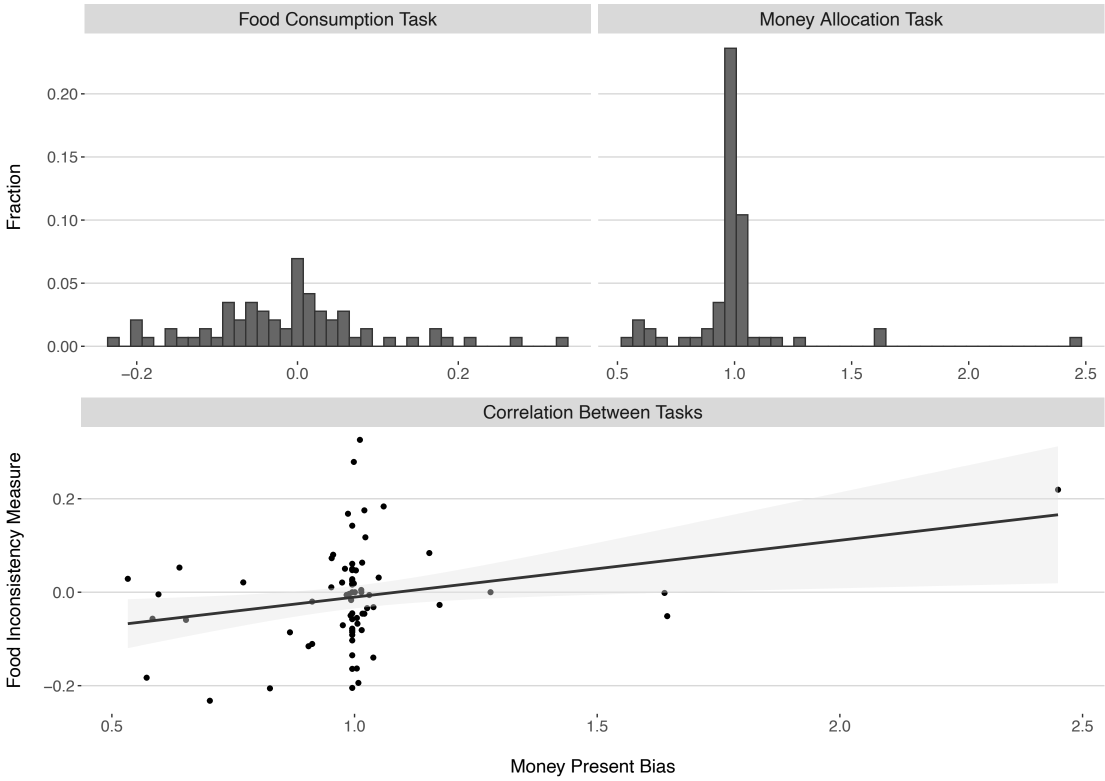
Note: The figure shows an example of one out of four Convex Time Budget sets. Participants make seven allocation decisions choosing a monetary amount paid out earlier and later after an experimental session. In each row, subjects face a different discount rate increasing the price for allocating money to the earlier payment date. In this sheet, subjects allocate €10 between today and today in one week. All amounts are paid out cash to participants at the end of each session.

Figure A5: *Monetary discounting behavior*



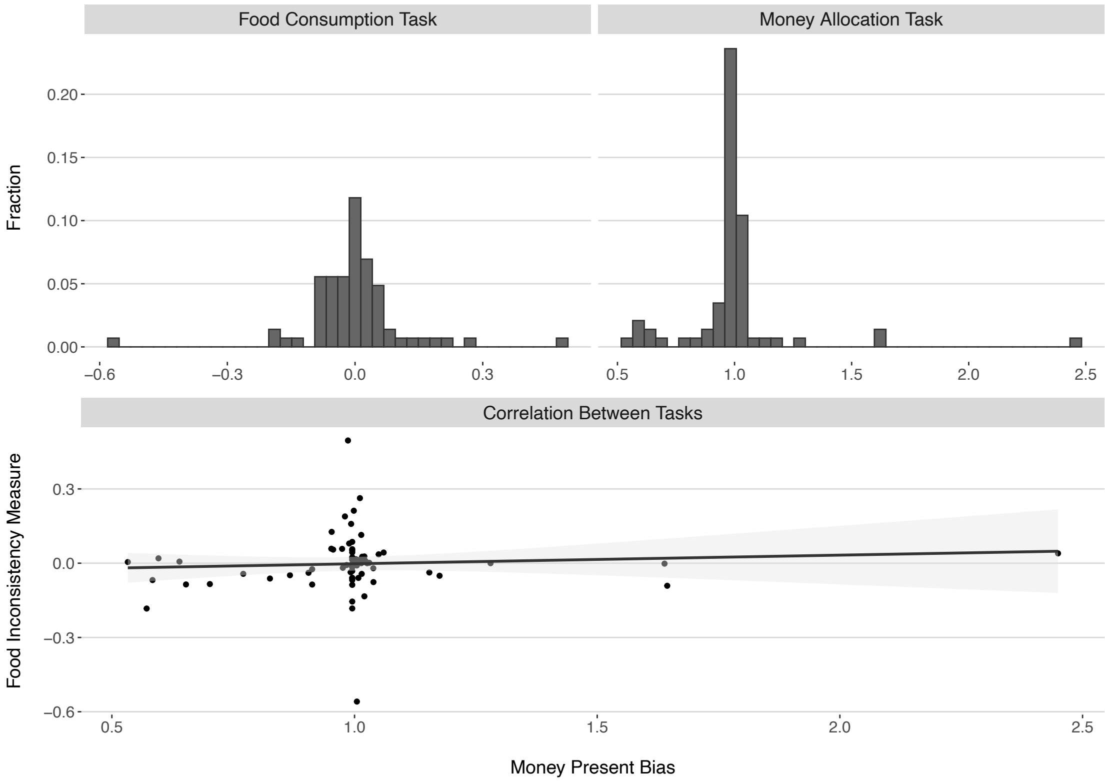
Note: The figure depicts the mean amount of money that subjects allocate to the sooner payment date for all seven different interest rates. The left panel displays all allocation choices with one-week delay while the right panel depicts allocations for a two-week delay. As the discount rate increases, allocating money to the sooner payment date becomes more expensive. The behavior follows the law of demand: as the price increases, the amount of money allocated to the sooner payment date decreases.

Figure A6: *Individual estimates: calories*



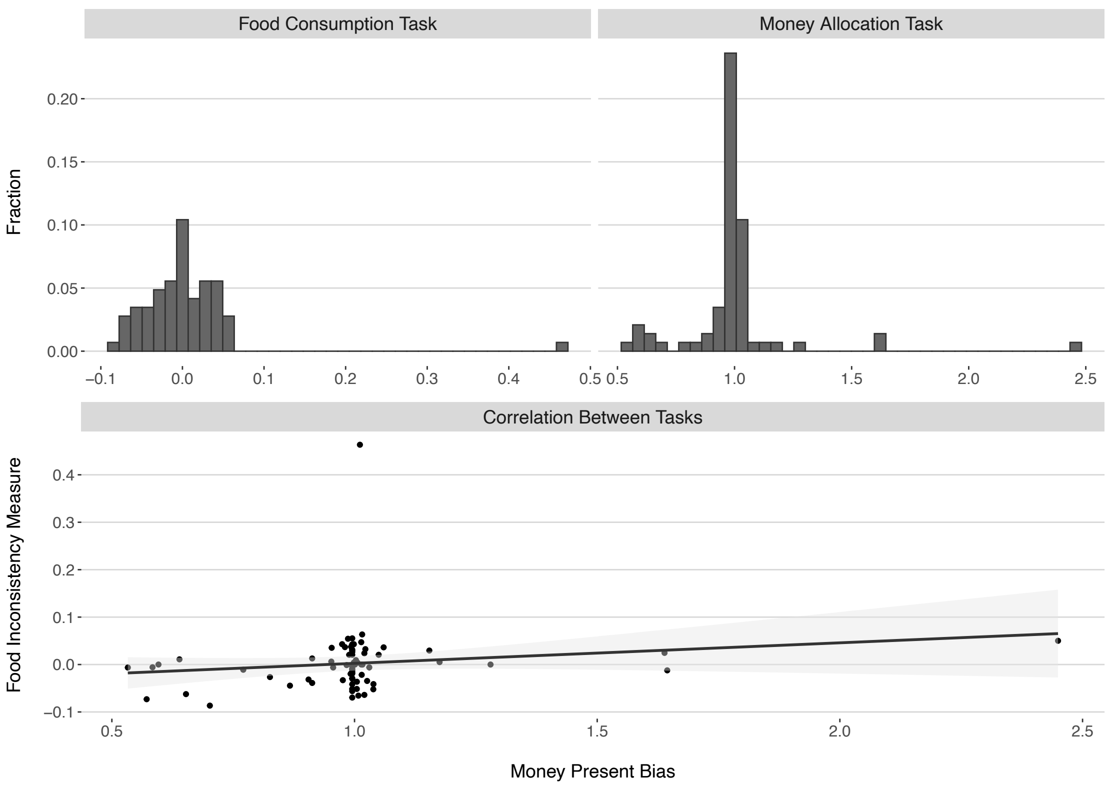
Note: The figure summarises estimates of dynamic inconsistency in at individual level for a 99% subsample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming calories as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

Figure A7: *Individual estimates: fat*



Note: The figure summarises estimates of dynamic inconsistency in at individual level for a 99% subsample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming saturated fats as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

Figure A8: *Individual estimates: nutrient profile score*



Note: The figure summarises estimates of dynamic inconsistency in at individual level for a 99% subsample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming nutrient profile scores as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

Table A4: *Individual parameter estimates*

	Median	5th Percentile	25th Percentile	75th Percentile	95th Percentile
Money Allocation Task					
Present bias parameter ($\hat{\beta}_i$)	0.995	0.622	0.980	1.015	1.424
Discount factor ($\hat{\delta}_i$)	1.000	0.991	0.998	1.016	1.140
Curvature ($\hat{\alpha}_i$)	0.991	-0.099	0.861	0.996	0.996
Food Consumption Task					
Inconsistency measure ($\hat{\phi}_I - \hat{\phi}_A$):					
Quota of Fruits and Vegetables	0.018	-2.87	-0.736	0.693	2.29
Calories ($\times -1$)	-0.005	-0.187	-0.071	0.047	0.179
Fats ($\times -1$)	0	-0.142	-0.049	0.036	0.177
Nutrient Profile Scores ($\times -1$)	0	-0.065	-0.03	0.029	0.053

Table shows descriptive statistics for all utility parameters structurally estimated from the money allocation and food consumption task. We estimate parameters for the full sample of 73 individuals. To facilitate comparison, we convert the utility drivers calories, fat and nutrient profile scores by multiplying with -1: the lower a value is, the unhealthier the choice becomes.

Table A5: *Utility weight estimates: second round choices for non-committers*

	Main dish	Side dish	Dessert
A: Vegetables/Fruit Quota			
Veg Quota ($\hat{\phi}_A$)	-1.913***	-0.462**	1.050***
	(0.631)	(0.226)	(0.293)
Immediate choice ×	0.429	0.348	-0.329
Veg Quota ($\hat{\phi}_I - \hat{\phi}_A$)	(0.683)	(0.238)	(0.265)
Log-likelihood	-142.390	-349.731	-134.537
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.395$	$\chi^2(1) = 2.140$	$\chi^2(1) = 1.540$
	$(p = 0.530)$	$(p = 0.144)$	$(p = 0.215)$
B: Calories			
Calories ($\hat{\phi}_A$)	0.161***	0.216***	-0.716***
	(0.038)	(0.040)	(0.145)
Immediate choice ×	-0.036	-0.013	0.535***
Calories ($\hat{\phi}_I - \hat{\phi}_A$)	(0.044)	(0.026)	(0.184)
Log-likelihood	-142.135	-336.615	-133.484
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.660$	$\chi^2(1) = 0.256$	$\chi^2(1) = 8.464$
	$(p = 0.417)$	$(p = 0.613)$	$(p = 0.004)$
C: Fat			
Fat ($\hat{\phi}_A$)	0.032	0.129***	-0.186***
	(0.028)	(0.021)	(0.043)
Immediate choice ×	0.006	0.030	0.169***
Fat ($\hat{\phi}_I - \hat{\phi}_A$)	(0.030)	(0.022)	(0.035)
Log-likelihood	-151.208	-329.276	-131.367
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.046$	$\chi^2(1) = 1.841$	$\chi^2(1) = 23.415$
	$(p = 0.830)$	$(p = 0.175)$	$(p = 0.000)$
D: Nutrient Profile Score			
Nutrient Profile Score ($\hat{\phi}_A$)	0.051***	0.051***	-0.081***
	(0.014)	(0.014)	(0.020)
Immediate choice ×	-0.009	0.003	0.067***
Nutrient Profile Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.017)	(0.014)	(0.018)
Log-likelihood	-139.696	-339.217	-133.060
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.262$	$\chi^2(1) = 0.047$	$\chi^2(1) = 14.147$
	$(p = 0.609)$	$(p = 0.829)$	$(p = 0.000)$
# Observations	354	908	420
# Rankings	70	70	70
# Clusters	35	35	35

Note: The table presents results from rank-ordered logit regressions for non-committing subjects after commitment has been offered. We regress an "Is chosen" dummy that equals 1 if a food item is chosen by an individual on the respective nutrient (panels A to D) and an interaction term between nutrient and immediate choice dummy. The advance choice coefficient in each panel represents the utility weight in advance choice. The interaction term coefficient indicates a utility weight change in immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to the utility weight from the advance choice perspective (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered on individual level. Levels of significance: *0.10, **0.05, ***0.01

Table A6: *Robustness: Utility weight estimates and commitment demand*

	Committer=1			Committer=0		
	Main dish	Side dish	Dessert	Main dish	Side dish	Dessert
Subjective Health Score ($\hat{\phi}_A$)	-0.177***	-0.071	0.070	-0.005	0.036	0.176***
	(0.067)	(0.054)	(0.057)	(0.063)	(0.085)	(0.068)
Immediate choice ×	-0.038	-0.009	0.137**	-0.057	-0.008	-0.088
Subjective Health Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.035)	(0.038)	(0.062)	(0.042)	(0.082)	(0.096)
Log-likelihood	-173.783	-337.568	-122.148	-166.455	-308.116	-123.429
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 1$	$\chi^2(1) = 1.177$	$\chi^2(1) = 0.053$	$\chi^2(1) = 4.901$	$\chi^2(1) = 1.847$	$\chi^2(1) = 0.008$	$\chi^2(1) = 0.853$
	($p = 0.278$)	($p = 0.818$)	($p = 0.027$)	($p = 0.174$)	($p = 0.927$)	($p = 0.356$)
# Observations	380	934	450	350	846	414
# Clusters	76	76	76	70	70	70

Note: The table presents results from rank-ordered logit regressions applying a random utility model that takes into account random utility shocks. We report results for the subjective health score elicited after making advance food choices in session 1: a subjective healthiness measure on an 11-point Likert scale ranging from 0 (very unhealthy) to 10 (very healthy), and report results for committing and non-committing individuals separately. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice. The interaction term indicates a utility weight change from advance to immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to advance choice (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

Table A7: *Robustness: Utility weight estimates: second round choices for non-committers*

	Main dish	Side dish	Dessert
Subjective Health Score ($\hat{\phi}_A$)	-0.088	-0.028	0.174***
	(0.066)	(0.049)	(0.057)
Immediate choice ×	0.047	0.006	-0.120***
Subjective Health Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.042)	(0.047)	(0.044)
Log-likelihood	-151.529	-350.993	-135.610
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 1.259$	$\chi^2(1) = 0.016$	$\chi^2(1) = 7.464$
	($p = 0.262$)	($p = 0.900$)	($p = 0.006$)
# Observations	354	908	420
# Rankings	70	70	70
# Clusters	35	35	35

Note: The table presents results from rank-ordered logit regressions for non-committing subjects after commitment has been offered. We report results for the subjective health score that is a subjective healthiness measure on an 11-point Likert scale ranging from 0 (very unhealthy) to 10 (very healthy). We elicit scores after making advance food choices in session 2. We regress an "Is chosen" dummy that equals 1 if a food item is chosen by an individual on the subjective health score and an interaction term between health score and immediate choice dummy. The advance choice coefficient in each panel represents the utility weight in advance choice. The interaction term coefficient indicates a utility weight change in immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to the utility weight from the advance choice perspective (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

Table A8: *Robustness: Utility weight estimates: environmental factors and arbitrage opportunities*

	Share of fruits and vegetables	Calories	Saturated fats	NPS
Environmental factors				
Shift to very hungry	-0.16	-0.03	-0.11	-0.13
	(0.18)	(0.80)	(0.34)	(0.26)
Food inspected	0.12	0.04	-0.03	-0.05
	(0.29)	(0.77)	(0.81)	(0.68)
Purchase on day before session	-0.03	-0.05	-0.03	-0.07
	(0.81)	(0.69)	(0.83)	(0.53)
Declining temperatures	-0.06	-0.13	-0.08	0.02
	(0.60)	(0.26)	(0.50)	(0.90)
Income gain	-0.02	-0.15	-0.12	-0.15
	(0.89)	(0.20)	(0.33)	(0.20)
Arbitrage opportunities				
Dummy for purchases outside experiment	0.03	0.00	0.02	0.02
	(0.66)	(0.96)	(0.72)	(0.75)
Nutrients purchased outside experiment	0.01	-0.00	0.02	0.03
	(0.93)	(0.99)	(0.78)	(0.66)

Note: The table presents results from OLS regressions at the individual level. Explanatory measures are dummy variables reflecting changes in the decision environment between t_1 and t_2 based on 146 observations. Results are reported for four nutrient indicators: the share of fruits and vegetables, calories, saturated fats and the nutrient profile score (NPS). Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

Online Appendix B

Experimental instructions before selecting food items for lunch in one week (displayed to subjects in session 1). To facilitate understanding and reduce complexity, all lunch choices are assigned an alphabetic letter starting from A for choices made in session 1 for session 1 in the low budget condition (t_1t_1, €4) to J for immediate lunch choices made in session 3 in the high budget condition (t_3t_3, €5). Before making lunch choices, subjects were always informed about the contextual details.

> Your canteen menu in one week:
>
> On the following pages, you will make decisions and set options C and D. In doing so, you will consider the canteen menu that will be in effect one week from today on [date of 'today in one week']. For both options, you will choose today the components for your canteen menu that you would like to receive on [date of 'today in one week']. You may choose from a variety of components - there will be a variety of main dishes, side dishes, desserts and add-ons. For Option C, the chosen components must not exceed the total value of €4, for Option D they must not exceed the total value of €5. For each option, you may select menu components more than once or not at all. You may select the same or different menu components for both options. You alone decide which components you select.
>
> At the next meeting on [date of 'today in one week'], you will again select the menu components for the canteen meal on [date of 'today in one week'] to determine options E and F. Thus, at the end of the next session on [date of 'today in one week'], you will have determined 4 options - you will determine options C and D today, and you will determine options E and F a week from today. For all 4 options, you can choose the same or different components for your canteen meal.
>
> You will receive one of the 4 options for free at the end of the next session. Which option you will get is randomly determined by the computer. All options are equally likely, that is, the probability of receiving option C, D, E or F for actual consumption is 25% each. Thus, it is in your interest to set each option as if it were the one that will be chosen.

Experimental instructions before allocating money over time:

> On the following pages we ask you to choose between different amounts of money. You will make 14 choices about how to divide money between

an earlier time (e.g. today) and a later time (e.g. in two weeks). One of these 14 decisions will certainly be paid out to you in cash at the end of the first, second or third session by the experiment leader. The payout of the selected decision is guaranteed to you by the Chair of Microeconomics of the Catholic University of Eichstaett-Ingolstadt.

In which session the payout will be made depends on your decisions. All decisions you make in this part of the session are treated by the computer as completely independent decisions. This means that all decisions you will make now will be paid out independently of all previous decisions. Consequently, when the computer selects a decision, it does not matter what components you have previously selected for food options A, B, C, and D.

Which decision is paid out to you is determined randomly by the computer. All decisions can be chosen with the same probability. You are informed about the decision that is chosen at the end of the session.