WORKING PAPER · NO. 2023-128

Time Preferences and Food Choice

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SEPTEMBER 2023

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Thanks to Puja Bhattacharya and participants at the Winter Workshop on the Behavioral and Experimental Economics of Food Consumption for valuable feedback. We sincerely thank the Robert Wood Johnson Foundation for providing funding and valuable feedback. Many thanks to Marilyn Soukup and the team at Field Agent for their incredibly hard work on the program implementation. We also received excellent research assistance from Mohammed Ibrahim. Pre-registration for the project is at AsPredicted: http://aspredicted.org/blind.php?x=u4r8yp. University of Arkansas Internal Review Board approval for this project was obtained prior to any research being conducted.

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JEL No. D03,H20,I12,I39

ABSTRACT

Healthy food choices are a canonical example used to illustrate the importance of time preferences in behavioral economics. However, the literature lacks a direct demonstration that they are well-predicted by incentivized time preference measures. We offer direct evidence by combining a novel, two-question, incentivized time preference measurement with data from a field experiment that includes grocery purchases and consumption. Our present-focus measure is highly predictive of food choice, capturing a number of behaviors consistent with self-control problems, which provides direct evidence for the common assumption that important aspects of nutrition are driven by time preferences.

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A randomized controlled trials registry entry is available at http://aspredicted.org/blind.php?x=u4r8yp

1 Introduction

Diet quality is a key determinant of health (World Health Organization, 2003). Consumption of fruits and vegetables, for example, has been found to have many health benefits, including reducing the risk of cancer and cardiovascular disease (Liu, 2003; Willett, 1994; Woodside et al., 2013). The impact of nutrition extends beyond health: income and food choice are closely associated (Drewnowski and Specter, 2004), raising concerns about nutrition inequality (Drewnowski and Specter, 2004; Rehm et al., 2016). This association is part of a vicious circle where poor nutrition causes poor health outcomes, which exacerbate existing income inequalities (Wolf, 2012). Thus, understanding the motivations behind food-choice decisions is not only central to health policy but to broader public policy regarding opportunity and inequality.

In economics, psychology, and consumer behavior research, nutrition has long been tied to intertemporal choice. Consider the food-choice decision posed by O'Donoghue and Rabin (1999); when deciding whether or not to consume potato chips one has to weigh the utility of consumption against the long-run health consequences. With well-behaved time preferences (and known utility streams), food choices should reveal the intertemporal discount rate. However, as O'Donoghue and Rabin (1999) makes clear, self-control problems complicate this analysis. It is therefore essential to understand both "patience"—in the form of discount rates—and "present-focus"—in the form of decision-making that is inconsistent across time horizons.[1] Food choice appears alongside smoking, going to the gym, and other health behaviors as canonical examples of this issue (e.g. DellaVigna and Malmendier (2006); O'Donoghue and Rabin (1999); Read and van Leeuwen (1998)). However, despite the oft-made assumption that food choice is driven by time preferences, there has been little empirical work to establish a direct link between measures of an individual's patience or present-focus and their nutritional choices—especially in a natural environment.

This paper aims to provide this evidence using food choices made by low-income shoppers in the aisles of their chosen grocery stores. We find a direct link between key food-choice

[1]There is a debate in the literature on whether changes in patience across the time horizon—particularly across earlier versus later time periods—is indicative of a bias or other more standard factors (see discussion in Bernheim and Taubinsky (2018)). Our measures of time preferences do not allow us to distinguish a present-*bias* from a present-*focus*, so we opt for the latter term.

behaviors and incentivized measures of patience and present-focus collected using a novel, portable, two-question elicitation module.

We recruited low-income shoppers from across the country as part of a broader study examining food choice.[2] Shoppers revealed food-choice behaviors across multiple surveys both with and without experimental interventions. As part of the study, shoppers provided grocery receipts for up to six shopping trips, and two sets of food consumption diaries. In addition, shoppers assigned to certain treatments received healthy subsidies for fruits and vegetables or made choices between these healthy subsidies and unhealthy subsidies for baked goods. All grocery shopping occurred at the time and place of the shopper's choosing.

We focus on three food-choice decisions our shoppers made: 1) what foods to purchase and consume, 2) how to change food spending in response to the receipt of a subsidy for healthy food, and 3) whether to select healthy or unhealthy subsidies. We find that behaviors across these three food-choice decisions correlate with incentivized measures of time preferences in the expected direction. While measures of patience and present-focus are both predictive of behaviors, we find that measures of the latter are particularly strong predictors of food-choice decisions. This underscores the importance of identifying present-focus in measures of time preferences when considering their relationship with decisions about nutrition.

We specifically find that more patient shoppers 1) buy and consume a greater amount and larger share of fruits and vegetables, 2) plan their consumption better—displaying fruit and vegetable consumption that is more consistent with their spending, and 3) are more likely to select healthy over unhealthy subsidies. On the other hand, shoppers exhibiting present focus 1) purchase and consume fewer fruits and vegetables, 2) have difficulty planning their consumption—under-consuming fruits and vegetables relative to their spending, 3) are less likely to select healthy subsidies over unhealthy ones, but, 4) they do increase their spending on healthy foods more in response to being given a healthy subsidy.

In contrast to our direct evidence linking time preferences and food choices, the existing literature (presented in Table 1) largely consists of indirect evidence. The literature uses two primary approaches, each with certain limitations. Under the first approach, presented

[2] Brownback et al. (2023) used the same setting to study how behavioral interventions can be leveraged to make nutritional food subsidies more effective.

in Panel A of Table 1, researchers identify the association between measures of patience or present-bias and long-term health outcomes from diet such as body mass index (BMI), obesity, or diabetes. Under the second approach, presented in Panel B of Table 1, researchers use a food-choice decision itself to identify impatience or present-bias. Panel C presents prior research directly linking time preference measures and food choice.

The advantage of the first approach is the focus on imminently policy-relevant outcomes. For example, Sutter et al. (2013) use incentivized laboratory measures of patience in children and find that more patient children tend to have better health outcomes, including lower BMI. The implicit assumption is that this operates in part through diet; however, this approach does not directly identify this link nor explore whether patience or present-focus influences the relevant outcomes.[3]

The second approach identifies clear preference reversals within the domain of food choice itself. For example, Read and van Leeuwen (1998) find that people make healthier choices when planning their consumption in advance, and that people will often reverse previously made healthy choices when given the opportunity. This relates time preferences to food choice under the assumption the healthy foods have delayed benefits and immediate costs relative to unhealthy foods. There are three shortcomings to this approach. First, research in this vein has not established that a preference reversal over one kind of food choice predicts others. Thus, generalizability may be limited. Second, measuring time preferences from food choices is cumbersome relative to our portable, context-free elicitation. Third, Carrera et al. (2018) highlights that uncertainty (rather than present-bias) can drive similar preference reversals between planned and actual consumption.[4]

Panel C of Table 1 highlights other literature in the "direct" approach category along with our paper. Samek et al. (2021) evaluates the link between time preferences—elicited using the common Multiple Price List (MPL) approach—and food choice—measured through self-

[3]There is additional research taking this theoretical approach, but using proxies for time preferences, making the implied link between time preferences and diet choice even less direct. Examples include research linking savings rates and obesity (Komlos et al., 2004), and linking interest in nutrition labels and health claims to obesity (Cavaliere et al., 2014).

[4]Cheung et al. (2020) identify that time preferences measured in the domains of money, healthy food, and unhealthy food, are all positively correlated with one another, using the modified Convex Time Budget (mCTB) technique of Andreoni et al. (2015). In other words, they find that time preferences appear stable across reward domains, not that time preferences in one domain predict behavior in another.

reports. This study finds no association between these two, though unincentivized measures of time preferences are found to be predictive. Vitt et al. (2021) finds no link between self-assessed patience and healthy or unhealthy snack choices. Additionally, work in psychology considers how survey-measured procrastination and "consideration of future consequences" (CFC) relates to intended healthy-eating behavior (Joireman et al., 2012; Sirois, 2004), and self-reported diet (Piko and Brassai, 2009).[5] Finally, work in psychology and marketing also explores the relationship between unincentivized measures of time-preferences and self-reported healthy eating, finding mixed evidence (Bartels et al., 2023). Our study differentiates itself from this branch of the literature through the type of data used on both sides of the equation. We explore relationships using measures that are closer to what are considered to be the "gold standard" in economics: *incentivized* measures of time preference and consequential, real-world food choices.

[5] There is also research taking this approach, but using an indirect proxy for time preference. For example, Houston and Finke (2003) construct a measure of time preference within the Continuing Survey of Food Intake by Individuals (CSFII) survey (partly relying on food-choice related variables like attention to nutrition labels, and show it predicts an individual's Healthy Eating Index score.

Table 1. Literature on Time-Preferences and Health and Nutrition Metrics

Approach	Citation	Summary
Panel A: Time Preferences and Health Outcomes	Smith et al. (2005)	Proxies for time preferences correlate with BMI in the NLSY.
	Borghans and Golsteyn (2006)	Proxies for time preferences correlate with BMI in cross-sectional analysis.
	Chabris et al. (2008)	Individual patience predicts field behaviors in health (exercise, smoking, BMI, etc.) better than demographic variables.
	Weller et al. (2008)	Obese women tend to be more impatient than matched control women.
	Zhang and Rashad (2008)	Measures of willpower (a proxy for time preferences) correlate with obesity for men.
	Adams and White (2009)	BMI correlates with CFC in cross-sectional survey.
	Daly et al. (2009)	Time preferences correlate with heart rate variability and blood pressure (biomarkers of impulsivity) as well as psychometric measures of future focus.
	Seeyave et al. (2009)	Four-year-olds who do not delay gratification are more likely to be overweight at age 11.
	Sutter et al. (2013)	Impatient adolescents are more likely to drink, smoke, and have high BMI.
	Courtemanche et al. (2015)	Decreases in the prices of unhealthy foods affect impatient people most. Impatience and present-bias predict BMI.
	de Oliveira et al. (2016)	Patience only predicts BMI for risk-averse individuals.
	Ikeda et al. (2010)	Impatience and present-bias predict body weight.
	Bradford et al. (2017)	Impatience and present-bias correlate with health and exercise behaviors.
	Pastore et al. (2020)	Among obese Australians, time preferences do not correlate with BMI.
	Nebout et al. (2023)	Nationwide survey finds that impatience correlates with high-calorie diets.
Panel B: Preference Reversals in Food Choice	Read and van Leeuwen (1998)	Healthier food choices are made when choice is in advance of consumption.
	Milkman et al. (2010)	Online grocery purchases made for delivery further in the future are healthier.
	De Marchi et al. (2016)	CFC scale predicts sensitivity to health claims in a food-choice experiment.
	Sadoff and Samek (2019)	People adopt commitment devices after experience eliminating tempting options.
	Sadoff et al. (2020)	Healthier groceries selected in advance of delivery. Commitment demand for healthier options.
	Cheung et al. (2020)	Measures of present-bias over money are modestly correlated with measures of present-bias in food choices.
Panel C: Time Preferences and Food Choice	Sirois (2004)	Self-efficacy and CFC both predict health behaviors including nutrition quality.
	Joireman et al. (2012)	CFC predicts healthy eating and exercise.
	Vitt et al. (2021)	Self-assessed patience does not predict snack choice in a lab setting.
	Samek et al. (2021)	Time preferences predict BMI and self-reported consumption of fast food, sweets, and soda.
	Bartels et al. (2023)	Unincentivized time preference measures have a mixed relationship with self-reported nutritional choices.

Beyond the development of a concise, portable time preference elicitation, our primary contribution is to demonstrate that the "now vs. later" paradigm of time preferences—measured in a non-food domain with real incentives—can indeed be applied to the purchase and consumption of healthy food in both naturalistic and experimental settings. With this demonstration, we also establish the importance of non-stationarity time preference (e.g. hyperbolic and quasi-hyperbolic discounting). The associations we identify between time preferences and food-choice behavior offer directions for policies designed to improve diet quality. Specifically, our results show that these policies must confront the same tension between long-run goals and immediate gratification that is present in other "now vs. later" settings. Established policies that promote future-focus include commitment opportunities (e.g. Sadoff and Samek (2019); Sadoff et al. (2020); Trope and Fishbach (2000)), waiting periods (e.g. Brownback et al. (2023), Imas et al. (2018), and DeJarnette (2018)), or planning prompts (e.g. Milkman et al. (2011, 2013)). In addition to verifying the intertemporal-choice framing of nutrition behavior, our results show that targeted subsidies may empower shoppers to make future-focused decisions in this context.

In the following section, we explain the study design. Section 3 describes our data. Section 4 presents our findings about the impact of time preferences on grocery purchases. Section 5 concludes.

2 Study Design

The details of our design and analysis were pre-registered on AsPredicted.org.[6] Data for the present study were collected alongside an experimental study on food subsidies (Brownback et al., 2023). We will refer to relevant aspects of the experimental study as we explain the data used in the present study.

Our data were collected through shoppers' smartphones using Field Agent—a market research platform. This app-based platform is designed for crowd-sourced consumer research that can be conducted anywhere with a specific focus on collecting data inside retail locations across the country. App users complete paid tasks using their smartphones during their typical shopping trips.

[6]Our pre-registration includes the present analysis as well as analyses included in Brownback et al. (2023).

Shoppers were paid to complete surveys and upload pictures of their grocery shopping receipts. The distributed nature of the Field Agent platform allowed us to collect grocery shopping data within a natural environment—at the grocery store of the shopper's choice, at the time of the shopper's choosing—without requiring that shoppers give us advanced notification.

Field Agent validated each completed shopping trip after submission to ensure that it complied with our protocols. In particular, they used submitted pictures of the receipts, timestamps, and smartphone location tags to ensure (i) all decisions made as part of the experiment were made prior to checkout, (ii) surveys were taken while physically present at the grocery store when required by protocols, and (iii) all receipt submissions were unique. Shoppers who violated these procedures were given one warning and removed from the study after a second offense. The researchers had no input in this process.

2.1 Recruitment

Recruitment began in March 2018 and all data collection was completed by July 2018. We recruited shoppers in eight separate recruitment waves and study participation lasted several weeks. In total, we recruited 807 shoppers for the study.

We recruited exclusively low-income shoppers from Field Agent's pool of over 1 million registered users in the U.S.[7] Before enrolling in the study, all shoppers first completed an income-screening survey. Shoppers qualified if they reported a gross household income less than 185% of the federal poverty line. This ensured that all of our shoppers would at least meet the income qualification for WIC subsidies. We then invited qualifying shoppers to finish their enrollment in the study by completing our baseline survey.

Shoppers completed all procedures, including the baseline survey and all shopping trips, at their desired pace. Lagging shoppers were regularly encouraged to continue with the study. However, we could not enforce completion and our study did feature some attrition. We test for differential attrition in Appendix Section A.2, and find no evidence thereof.

[7] Since over 67% of Americans with incomes less than $30,000 own smartphones (Pew Research Center: www.pewinternet.org/fact-sheet/mobile), we do not believe this platform substantially distorts our selection of shoppers.

2.2 Experimental Procedures

All shoppers in our study were enrolled in the aforementioned study on food subsidies (Brownback et al., 2023). In this experimental study, treated shoppers received either "healthy" subsidies for 30% off of purchases of fruits and vegetables or "unhealthy" subsidies for 30% off of purchases of baked goods.[8] Subsidy payments were capped at $10 per shopping trip and shopping trips were required to be at least five days apart.

To enroll in the study, shoppers completed a baseline survey. The baseline survey collected characteristics of each shopper's food household including income, household size, SNAP participation, a recent shopping receipt, and a 24-hour food diary. Next, each shopper participated in the experiment for up to four distinct shopping trips with the same treatment each trip. In the experiment, shoppers were randomized into either an unsubsidized control group or a subsidized group. Within the subsidized group, shoppers were randomized into a group restricted to receive the healthy subsidy or a group endowed with choice between the healthy and unhealthy subsidies.

Of the 807 shoppers recruited to the study, 239 only responded to the baseline survey and did not continue to receive their treatment assignment. 105 shoppers were assigned to the unsubsidized control group. 463 shoppers were assigned to receive subsidies. Among these subsidized shoppers, 356 were endowed with a choice between the healthy and unhealthy subsidies each trip. The other 107 subsidized shoppers were restricted to always receive the healthy subsidy.

All shoppers uploaded grocery shopping receipts on the same timeline regardless of their subsidy assignment. Shoppers earned $1 for each survey they submitted in addition to any payments from subsidies. There was a $30 completion bonus for finishing the entire study. Five days after the fourth and final shopping trip, shoppers completed an endline survey. The endline survey repeated many of the baseline data points, including a grocery shopping receipt and a 24-hour food diary.

[8]Fruits and vegetables include fresh, canned, or frozen fruits or vegetables without added salt or sugar. Baked goods include bread, biscuits and rolls, muffins, cakes and cupcakes, pies and tarts.

2.3 Measures of Time Preferences

During the baseline survey, we elicited shoppers' monetary time discounting using incentivized intertemporal choices. In this elicitation, we endow shoppers with an asset worth $50 if redeemed at the earliest possible date after the survey, but the asset's value grows through delayed redemption. There are twelve redemption options. As the options progress, the gap in redemption times weakly increases while the growth rate of the asset weakly decreases to capture finer differences in discounting in the range of common market rates. Question 1 includes a front-end delay on the first redemption date while Question 2 does not.[9] Each question was randomly chosen to be implemented with an independent 1-in-50 chance.[10]

In Question 1 the options presented were *(dollars, weeks of delay)*: ($50, 1 week); ($53, 2 weeks); ($54, 3 weeks); ($55, 5 weeks); ($56, 7 weeks); ($57, 9 weeks); ($58, 11 weeks); ($59, 13 weeks); ($60, 16 weeks); ($61, 19 weeks); ($62, 23 weeks); and ($63, 27 weeks). Question 2 was identical except moved one week forward so that the first option was to receive $50 immediately. The reward schedule was calibrated such that heterogeneity in the selected option corresponds to discount-rate heterogeneity over the range of interest. For example, an individual with an annual discount rate of 25% would just prefer to maximize their utility at option 11 over option 12, and an individual with an annual discount rate of 100% would maximize their utility at option 3.[11]

Our two measures of discounting are identified through shoppers' responses to Questions 1 and 2. Our first measure, "patience," is a measure of general discounting in the absence of an option for immediate gratification. We derive patience from standardized responses to Question 1 that have mean of zero and a standard deviation of 1. Our second measure, "hyperbolicity," captures non-stationary discounting behavior. Specifically, hyperbolicity measures how much an individual's patience is reduced in the presence of an option for immediate gratification is introduced. We derive hyperbolicity by subtracting the selected option (1 through 12) on Question 2 from the selected option (1 through 12) on Question 1

[9] At the end of the survey, we re-asked Question 2 to see if respondents changed their answer from their initial impulse. There was very little deviation from initial choices, so we omit the discussion of this question.

[10] Subject instructions are in Appendix Section A.1.

[11] These calculations assume no utility concavity but can easily be adjusted to account for concavity. For example, assuming a utility function of $U(x) = x^{0.75}$ implies an individual with an annual discount rate of 25% would now maximize their utility at option 8 rather than option 11.

and standardizing this difference to also have a mean of zero and a standard deviation of 1. This hyperbolicity measure is distinct from quasi-hyperbolic present focus (i.e. the $\beta - \delta$ model (Laibson, 1997; O'Donoghue and Rabin, 1999)), which is often the standard approach in this literature because our metric captures hyperbolic discounting more generically. For example, if a respondent moves from Option 10 on Question 1 to Option 8 on Question 2, this cannot be attributed to $\beta - \delta$ discounting.[12]

Utility curvature is a key concern in the literature on time preference elicitation (see Andersen et al. (2008); Andreoni et al. (2015); Andreoni and Sprenger (2012a,b)). However, our simple survey design required that we abstract from considerations of curvature. We note four reasons why variation in the level of utility curvature should not impact inference from our measure of discounting. First, we had the simple objective of producing an ordinal ranking of patience and present bias rather than cardinal estimates of the annual discount rate based on assumptions about utility curvature. Second, we selected our shoppers to be exclusively low-income. Thus, any utility curvature based on background wealth will be relatively consistent across shoppers. Third, our primary measure of interest is calculated based on a within-individual difference between responses to Questions 1 and 2, thus differencing out the influence of utility curvature. Finally, the prizes are valued between \$50 and \$63 with none in the neighborhood of zero. Utility should be linear for such small values (in terms of lifetime wealth), and marginal utility is unlikely to shift rapidly within this narrow range.

2.4 Measures of Healthy Eating

We measure both healthy food purchases and healthy food consumption to study the relationship between time preferences and each margin of food choice.

Grocery choices: Our primary grocery-choice variable is the amount of money spent on fruits and vegetables during an observed shopping trip (in 2018 USD). These spending amounts were tabulated by workers on Amazon's Mechanical Turk website based on

[12] We can observe a coarse measure of $\beta - \delta$ discounting by looking for subjects that selected any option other than 1 on Question 1, and then switch to Option 1 for Question 2. But, this measure has the significant disadvantage that the amount of present focus required to trigger it dramatically increases as the discount rate decreases. See Section 3 for rates of quasi-hyperbolicity in our sample.

submitted photos of shopping receipts. We consider fruit and vegetable spending both in absolute terms and in terms of its share of total food spending.[13]

We consider two different kinds of grocery choices in our study: unsubsidized and subsidized. We observe unsubsidized grocery purchases from all shoppers on their baseline shopping trips. We then observe five additional unsubsidized shopping trips from shoppers in the control group—one for each of their four shopping trips and one for the endline survey. We observe subsidized grocery purchases only from treated shoppers and only during their four shopping trips.

We estimate the association of time preference with unsubsidized spending on fruits and vegetables in Section 4.1. We then estimate how time preferences predict heterogeneity in the impact of subsidies on fruit and vegetable spending in Section 4.2.[14]

Dietary choices: We collected self-reported 24-hour food consumption diaries from all shoppers on the baseline and endline surveys. Shoppers were instructed to describe each meal in a 24-hour period including every item and its quantity (e.g. "two slices of pizza"). Workers on Amazon's Mechanical Turk website tabulated these food diaries by separately adding up (1) the number of fruits and vegetables listed on the diary, and (2) the total number of food items. We again report results for fruits and vegetables as both an absolute number and a share of total items.[15]

We use baseline and endline data from the control group along with baseline data from the treated group to explore the association between time preferences and unsubsidized food choices in Section 4.1.

Subsidy selection: A subset of subsidized shoppers were endowed with a choice between healthy and unhealthy subsidies that we captured on each shopping survey. In Section 4.3,

[13]Mechanical Turk workers tabulated: total food spending, spending on fruits and vegetables, and spending on baked goods. Healthy spending shares are calculated as fruit and vegetable spending divided by total food spending. However, anytime a receipt was tabulated as having less total food spending than the sum of the two sub-categories, we replace total food spending with the sum. If both total food spending and total spending on fruits and vegetables are $0, we record the share as zero.

[14]In Brownback et al. (2023), we explore the effect of three additional treatments on healthy food choices, in conjunction with the impact of subsidies (called Agency, Waiting Period, and Early Choice). We find no heterogeneous treatment effects of any of these treatments by time preference, and as such we largely pool over all of the subsidy treatments for simplicity in this paper (one exception is described in Section 4.2).

[15]Food consumption percentages are calculated similarly to those of food spending.

we treat subsidy choice as a form of nutrition planning and estimate its association with our time preference measures.

3 Data

807 shoppers successfully completed the baseline survey—from which we capture time preferences, shopping behaviors for all shoppers, and food diaries. Of these 807 shoppers, 568 persisted into the active study period—from which we capture shopping behaviors. We observe 1,936 unique shopping trips from these shoppers during this active study period. 431 shoppers completed all surveys through the endline—from which we capture shopping behaviors and consumption behaviors for the control group.[16] Table 2 summarizes the data we collected from our shoppers.

Panel A of Table 2 presents time preferences elicited from our shoppers on the baseline survey. First, we report responses to Question 1 from the time preference elicitation: the weeks until redemption when all rewards are in the future. In order to create our measure of "patience," we subtract one so that we measure the delay after the first possible redemption and standardize this variable such that larger values correspond to a longer willingness to wait. We next report responses to Question 2: the weeks until redemption when the first reward is immediate. In order to create our measure of "hyperbolicity," we first find the difference between the two measures: Question 1 minus Question 2 (minus one, such that identical selected *delays beyond the soonest possible date* yield a zero). For example, a shopper who elects to wait 9 weeks on Question 1 and 2 weeks on Question 2 will yield a value of 6 because they chose to wait 6 weeks longer after the first possible redemption date. This difference represents the acceleration of redemption when immediate gratification becomes possible. We standardize this difference to finalize our "hyperbolicity" metric. This variable has a mode of zero (three-quarters of the sample), indicating that most shoppers are time-stationary in our task. We find that roughly 9% of the sample show present focus, while roughly 16% of the sample show future focus. Recall, however, that our objective is not to identify present focus in this elicitation, but to use the responses to predict present-focused

[16]We do not use endline shopping or consumption behaviors for shoppers in an incentivized treatment as they are likely influenced by the treatment they experienced in the preceding weeks.

behaviors elsewhere.

Panel B of Table 2 presents baseline food choices derived from receipts and food diaries submitted on the baseline survey. Prior to any interventions, shoppers spend \$4.95 on fruits and vegetables or approximately 11% of their total food spending. Baseline food diaries reveal that our shoppers consume an average of nearly 2.5 servings of fruits and vegetables, approximately 20% of their total consumption.

Panel C of Table 2 presents food choices from shopping trips during the active study period. During these shopping trips, the unsubsidized control group spends \$4.03, on average, on fruits and vegetables, similar to baseline spending. We then pool all shoppers assigned to any of the subsidized groups and find that they spend an average of \$10.12 on fruits and vegetables, more than twice as much as the control group.

Finally, we report the selection rate of the healthy subsidies. Across all experimental treatments that endowed shoppers with subsidy choice, the selection rate of healthy subsidies is 78%, revealing food planning behaviors that overwhelmingly favor healthier spending.

Table 2. Food and Subsidy Choice Data

	Mean	SD	Obs
Panel A: Time Preferences			
No immediate gratification: Weeks waiting to redeem	6.96	10.42	807
Possible immediate gratification: Weeks waiting to redeem	6.55	10.04	807
Panel B: Baseline Food Choice			
Baseline total fruit & vegetable spending (\$)	\$4.95	9.05	807
Baseline % fruit & vegetable spending	10.75%	18.45	807
Baseline fruit & vegetable consumption from diary	2.48	2.09	761
Baseline % fruit & vegetable consumption from diary	19.55%	14.34	761
Panel C: Food Choice			
Total fruit & vegetable spending with no subsidies (\$)	\$4.03	6.71	388
Percent of fruit & vegetable spending with no subsidies	12.76%	21.55	388
Total fruit & vegetable spending with subsidies (\$)	\$10.12	10.80	1548
Percent of fruit & vegetable spending with subsidies	27.31%	28.92	1548
Healthy subsidy selection rate	0.78	0.41	1188

We have fewer observations for percentages because we drop any case with a denominator of zero.

4 Results

In this section, we estimate associations between measured time preferences and multiple margins of food choice. We begin by testing the predictive power of time preference measures over purchase and consumption of healthy food. Next, we demonstrate that time preferences predict heterogeneity in the impacts of healthy food subsidies. Finally, we estimate the influence of time preferences on the likelihood of selecting a healthy subsidy over an unhealthy one.

4.1 Time preferences and food choice

The first two margins of food choice that we consider are grocery purchases and self-reported consumption. We observe these choices for all shoppers on the baseline survey and for the control group on up to six total surveys (one baseline survey, four surveys during the active study period, and one endline survey).

Table 3 shows the associations between our time preference measures and fruit and vegetable spending and consumption.[17] While columns (1) and (2) show there is no significant correlation between patience and fruit and vegetable spending, there is a significant negative relationship between hyperbolicity and fruit and vegetable spending. A one standard deviation (SD) increase in hyperbolicity predicts a $0.50 decrease fruit and vegetable spending per shopping trip, equivalent to 10% of the mean. As a share of total food spending, column (2) shows that this is a decline from 12% to 10% of the shopper's basket. Columns (3) and (4) report the association between time preferences and fruit and vegetable consumption. In this case, we find significant impacts of both patience and hyperbolicity in the expected directions. A one SD increase in patience predicts 0.24 more servings of fruits and vegetables consumed per day—more than 10% above the mean—whereas a one SD increase in hyperbolicity predicts 0.23 fewer servings of fruits and vegetables consumed. Fruit and vegetable consumption as a share of total consumption shows only a marginally significant positive correlation with patience ($p = 0.067$) and no significant correlation with hyperbolicity.

[17] We use OLS regressions with recruitment wave fixed effects and standard errors clustered at the shopper level. In this specification, the clustering matters only for control-group shoppers, as treated-group shoppers only appear in these data once via their baseline surveys.

Columns (5) and (6) measure planning failures in food choice: the gap between consumption and expenditures. In column (5), we standardize both fruit and vegetable consumption and expenditures and take their difference. In column (6), we take the difference between the shares of consumption and expenditures occupied by fruits and vegetables. In both cases, negative values indicate under-consumption relative to spending. Column (5) shows that this planning failure correlates strongly with our measures of patience ($p = 0.042$) and hyperbolicity ($p = 0.026$). In column (6), the associations retain the same signs but lose significance.

Table 3. Association between Time Preferences and Fruit & Vegetable Spending and Consumption

Behavior:	Expenditure		Consumption		Cons. - Exp.	
Dependent variable:	Amount (1)	Share (2)	Amount (3)	Share (4)	Std. amount (5)	Share (6)
Patience	0.002	0.009	0.243***	0.010*	0.104**	0.056
	(0.270)	(0.006)	(0.085)	(0.006)	(0.051)	(0.042)
Hyperbolicity	-0.503**	-0.019***	-0.230***	-0.007	-0.075**	-0.010
	(0.208)	(0.007)	(0.066)	(0.006)	(0.034)	(0.040)
Constant	4.980	0.122	2.019	0.175	-0.110	0.016
	(0.563)	(0.010)	(0.131)	(0.010)	(0.065)	(0.073)
Shoppers (clusters)	807	807	766	766	766	766
Observations	1283	1283	848	848	848	848

* $\Rightarrow p < 0.10$, ** $\Rightarrow p < 0.05$, *** $\Rightarrow p < 0.01$. All estimates are from OLS regressions. Standard errors in parentheses are clustered at the shopper level. Columns (1) & (2) measure fruit and vegetable spending in USD. Columns (3) & (4) measure fruit and vegetable consumption as the number of items listed on the food diary. For columns (2) & (4), the "share" is fruit and vegetable spending or consumption as a percent of total food spending or consumption. Columns (5) & (6) measure the difference between consumption and expenditure. Column (5) uses standardized amounts and column (6) uses the difference in shares. All specifications include fixed effects for the recruitment wave. The sample includes all observations for the control group and only the baseline observations for treated groups. Consumption data were only collected on the baseline and endline, thus columns (3)–(6) have at most two observations for control shoppers and one observation for all other shoppers.

4.2 Time preferences and subsidy impact

A subset of shoppers were randomly assigned to receive food subsidies. This allows us to identify the causal impact of these subsidies on grocery shopping behavior. Here, we demonstrate how time preferences can predict a third margin of food choice: heterogeneous impacts of subsidies.

We estimate the impact of subsidies by comparing subsidy recipients to the control group on otherwise equivalent shopping trips. To accomplish this, we restrict our sample to shopping trips 1-4 of the active study portion, dropping the universally unsubsidized baseline and endline surveys. Recall that, in our experimental study, some shoppers were restricted to receive only "healthy" subsidies for fruits and vegetables. We compare the control group to these restricted subsidy recipients in columns (1) and (2) of Table 4. Other shoppers in our experimental study were endowed with choice between the healthy subsidies and "unhealthy" subsidies for baked goods. As mentioned in Section 3, the vast majority (78%) of shoppers with subsidy choice chose the healthy subsidy. In columns (3) and (4), we pool all subsidized shoppers and compare them to the control group.

Following our pre-registration, we estimate these relationships using a linear random effects specification due to the panel nature of these data. Standard errors are clustered at the shopper level. All models feature recruitment-wave fixed effects.

The interaction terms of Table 4 reveal the heterogeneous impact of subsidies based on a shopper's time preferences. All specifications find large positive interactions between hyperbolicity and the subsidy impact suggesting that subsidies promote healthy spending more among present-focused shoppers. While this interaction is imprecisely estimated in column (1) ($p = 0.121$), it is statistically significant in all other specifications. Indeed, this interaction is large enough to fully counteract the negative effect of hyperbolicity on fruit and vegetable spending in the control group. We also estimate a large but imprecise ($p = 0.127$) positive interaction between patience and the subsidy effect in column (1). However, this association is not robust across models.

This is a similar test to Courtemanche et al. (2015), who find that impatient people respond the most to decreases in the price of unhealthy foods. Our results are directionally consistent with the idea that patient people respond the most to decreases in the price of healthy foods, but our results are not significant. Our approach includes present focus as one additional margin by which time preferences can predict responses to changes in the price of foods and we find that this interaction is the most robust.

The large and significant subsidy effect across all models is a subject of Brownback et al.

Table 4. Treatment Effects of Subsidies by Time Preference

Sample:	Restricted healthy subsidy		All subsidies	
Fruit & vegetable spending:	Amount (1)	Share (2)	Amount (3)	Share (4)
Subsidy	4.500***	0.141***	6.325***	0.149***
	(0.764)	(0.023)	(0.618)	(0.015)
Patience	0.274	0.026**	0.146	0.023*
	(0.378)	(0.013)	(0.365)	(0.012)
Hyperbolicity	-1.155***	-0.046***	-1.146***	-0.044***
	(0.422)	(0.015)	(0.418)	(0.016)
Subsidy × Patience	1.197	-0.004	0.437	0.007
	(0.772)	(0.020)	(0.527)	(0.015)
Subsidy × Hyperbolicity	1.212	0.072**	1.948***	0.052***
	(0.793)	(0.031)	(0.596)	(0.020)
Constant	4.775	0.145	5.230	0.152
	(0.869)	(0.020)	(0.709)	(0.016)
Shoppers (clusters)	212	212	568	568
Shopping Trips (N)	748	748	1936	1936

* $\Rightarrow p < 0.10$, ** $\Rightarrow p < 0.05$, *** $\Rightarrow p < 0.01$. All estimates are from linear random effect regressions. Standard errors in parentheses are clustered at the shopper level. Fruit and vegetable spending is measured in USD. The fruit and vegetable share is fruit and vegetable spending as a percent of total food spending. All specifications include fixed effects for the recruitment wave. The sample includes up to four treated shopping trips per individual. Columns (1) and (2) include only control group and shoppers restricted to the healthy subsidy. Columns (3) and (4) add all other treatments.

(2023). These results confirm that the subsidy effects are not driven by shoppers with unusually extreme measures of patience or hyperbolicity. Instead, the subsidy effect holds for shoppers at the mean of both measures. The coefficients for patience and hyperbolicity replicate our findings from Table 3, although with a different sample that includes only the control group during shopping trips 1-4 of the study without baseline or endline data. In this sample, the association between hyperbolicity and fruit and vegetable spending grows and a new association between patience and fruit and vegetable spending appears when considering the share of spending on fruits and vegetables.

4.3 Time preferences and subsidy choice

A subset of the subsidized shoppers were randomly endowed with an active choice between the healthy and unhealthy subsidies on each of their shopping trips. By observing this type of nutrition planning behavior, we can explore the influence of time preferences over one final margin of food choice—the desire to shift relative prices towards healthier options.

Table 5 presents estimates of the association between time preference and the choice of healthy subsidies.[18] Consistent with our previous results, we find that patience increases healthy food choice behaviors while hyperbolicity decreases them. A one SD increase in patience increases the probability of selecting the healthy subsidy by 3.7 percentage points. Meanwhile, a one SD increase in hyperbolicity decreases the probability of selecting the healthy subsidy by 3.6 percentage points.

Table 5. Effect of Time Preferences on Healthy Subsidy Choice

Model:	Linear probability random effects (1)	Probit marginal effects (2)
Patience	0.037^{**}	0.036^{*}
	(0.017)	(0.019)
Hyperbolicity	-0.036^{**}	-0.037^{**}
	(0.017)	(0.016)
Constant	0.791	0.780
	(0.026)	(0.016)
Shoppers (clusters)	356	356
Shopping Trips (N)	1,862	1,862

$^{*} \Rightarrow p < 0.10$, $^{**} \Rightarrow p < 0.05$, $^{***} \Rightarrow p < 0.01$. Standard errors in parentheses are clustered at the shopper level. The dependent variable is an indicator for selection of the fruit and vegetable subsidy. All specifications include fixed effects for the recruitment wave. Probit marginal effects are local to average patience and hyperbolicity (both equal to zero post-standardization) and the average across recruitment waves.

5 Conclusion

It is commonly assumed that food choice is driven at least partly by individuals' time preferences—namely the extent of their patience and present-focus. Previous research either examines this relationship indirectly or uses unincentivized measures for one of the outcomes (or both); this literature has mostly found mixed support for the predicted relationship. Using a novel tool that allows us to measure two dimensions of time preference

[18] We use a random effects linear probability model of subsidy selection in column (1), and a pooled probit model in column (2). Standard errors are clustered at the shopper level, and we include recruitment-wave fixed effects.

using a simple and portable questionnaire, we fill this gap in the literature and find clear associations between our incentivized measures of time preferences and real-world food choices such as grocery purchases and at-home consumption. We find that present-focused shoppers spend less on healthy foods and consume fewer servings of them, they under-consume healthy foods compared to the purchases they do make, and they are less likely to select healthy subsidies. We find that healthy subsidies can counteract these impulses and are increasingly effective as present focus grows. Interestingly, the association between our measure of general discounting ("patience") and these variables is more limited, though we do find that more patient shoppers are more likely to consume healthy foods, plan better and consume more healthy foods relative to their purchases, and are more likely to subsidize healthy foods when given the choice.

As policymakers continue to experiment with nutrition assistance policies and specifically consider subsidizing healthy foods (Bartlett et al., 2014), it will be important that they are able to anticipate the necessary conditions for success. Collecting measures of time preferences will allow policymakers to better anticipate potential hurdles such as impatience or present focus. Moreover, such measures will open the door to better targeting these programs as they are deployed. For example, our results may be relevant for forecasting the potentially heterogeneous effects of increases in SNAP benefits on the food choices of individuals. More hyperbolic shoppers may be more likely to want to put the marginal dollar toward unhealthy options, and a targeted outreach could be used to prevent such a perverse effect on their diet quality. A similar analysis may help predict the heterogeneous impact of incentives for healthier grocery purchases.

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A Online Appendix

A.1 Time preference elicitation instructions

As a bonus for completing this study, we have included three "Bonus Questions" that offer you a chance to earn additional money. We will randomly choose agents to receive this bonus money, so payment for this question is NOT guaranteed.

For these Bonus Questions, we are going to show you 3 different scenarios (2 now, and 1 at the end of this survey) and ask you to select your preferred option in each scenario.

For each Bonus Question you answer today, you will have about a 1 in 50 chance of winning the amount determined by your selection. So, treat each Bonus Question as if it will determine your actual bonus payment.

Additional money earned from any Bonus Question will be deposited directly into your Field Agent account. However, you will have a choice about when to receive this bonus.

As a reminder, you will be paid the full $30 for successfully completing the full study no matter your answers to the bonus questions and whether or not you are selected for bonus payment.

Bonus Question #1: In this question, your bonus grows larger the longer you wait for it.

The earliest you can choose to receive your bonus is 1 week from today. If you choose to receive it 1 week from today, it will be $50. *If you choose to wait longer to receive your bonus—up to a maximum of 27 weeks from today—it will grow by some amount.*

Below, there are a number of combinations of waiting times and bonus amounts that you can choose.
Which is your preferred option?

a. Receive $50 in 1 week
b. Wait 2 weeks, receive $53
c. Wait 3 weeks, receive $54
d. Wait 5 weeks, receive $55
e. Wait 7 weeks, receive $56
f. Wait 9 weeks, receive $57
g. Wait 11 weeks, receive $58
h. Wait 13 weeks, receive $59
i. Wait 16 weeks, receive $60
j. Wait 19 weeks, receive $61
k. Wait 23 weeks, receive $62
l. Wait 27 weeks, receive $63

Bonus Question #2: This question is similar to Bonus Question #1, except shifted by a week.

Here, you have the option of receiving the bonus today. Below are the combinations of waiting times and bonus amounts that you can choose from. **Which is your preferred option?**

a. Receive $50 right away
b. Wait 1 week, receive $53
c. Wait 2 weeks, receive $54
d. Wait 4 weeks, receive $55
e. Wait 6 weeks, receive $56
f. Wait 8 weeks, receive $57
g. Wait 10 weeks, receive $58
h. Wait 12 weeks, receive $59
i. Wait 15 weeks, receive $60
j. Wait 18 weeks, receive $61
k. Wait 22 weeks, receive $62
l. Wait 26 weeks, receive $63

(baseline survey from Brownback et al. (2023) here)

This is the third and final Bonus Question. Again, these questions ask about when you would like to receive the bonus.
Bonus Question #3: Now that you've had a little more time to think about Bonus Question #2, you have another chance to make a selection from the same set of options in Bonus Question #2. This will not replace your answer to Bonus Question #2: it is a different question and your choice from it may count separately from Bonus Question #2.

Recall that, for this question, a $50 bonus is available today. *Also recall that if you wait to receive your bonus—up to a maximum of 26 weeks from today—it will increase as you wait longer.*

Below are your options with different waiting times and bonus amounts that you can choose.
Taking time to think about it, which is your preferred option?

a. Receive $50 right away
b. Wait 1 week, receive $53
c. Wait 2 weeks, receive $54
d. Wait 4 weeks, receive $55
e. Wait 6 weeks, receive $56
f. Wait 8 weeks, receive $57
g. Wait 10 weeks, receive $58
h. Wait 12 weeks, receive $59
i. Wait 15 weeks, receive $60
j. Wait 18 weeks, receive $61
k. Wait 22 weeks, receive $62
l. Wait 26 weeks, receive $63

A.2 Attrition Tests

There are multiple margins at which shoppers can exit our study. While attrition is no threat to the validity of our cross-sectional results such as those from Table 3, it can threaten to confound to any of our results that involve dynamic responses. Specifically, our interpretation of the impact of the subsidies across multiple shopping trips and the choice of subsidies could be affected by differential attrition based on shopper preferences for fruits and vegetables.

Table A.1 tests for selective attrition based on our three key outcome variables: baseline spending, consumption of fruits and vegetables, and the selection rate of the healthy subsidy (among shoppers endowed with choice over their subsidies). The dependent variable in this analysis is the number of shopping trips a shopper completes in the study. Recall that shoppers could complete up to four shopping trips, so this variable takes values from zero to four.

Across all three key outcome variables, we do not find any differential attrition. This suggests that shoppers leaving the study are not systematically biasing our results. Column 1 finds that attrition is not significantly correlated with baseline purchases of fruits and vegetables. Column 2 finds that attrition is not significantly correlated with baseline consumption of fruits and vegetables. Column 3 finds that attrition is not significantly correlated with the selection rate of the healthy subsidy. The lack of association we find between attrition and our key outcome variables, reassures us that our results are not driven by certain types of shoppers selectively leaving the study.

Table A.1. Total Completed Shopping Trips Based on Shopper Characteristics

	Completed Shopping Trips		
	(1)	(2)	(3)
Baseline total FV spending	0.004		
	(0.007)		
Baseline FV consumption from diary		0.025	
		(0.031)	
Selection rate of healthy subsidy			0.193
			(0.228)
Observations	807	761	356

Heteroskedasticity-robust standard errors in parentheses. All specifications are ordinary least squares models. The sample size in Column 2 is smaller because of missing baseline consumption data. The sample size in Column 3 is smaller because it is restricted to only shoppers endowed with a choice of subsidies.

A.3 Commitment Demand

- Commitment Amount: The amount of reimbursement foregone by a shopper from selecting the healthy subsidy. Bounded at $0 for those selecting the unhealthy subsidy.
- Commitment Amount (if FV Selected): The amount of reimbursement foregone by a shopper from selecting the healthy subsidy. Restricted to only those selecting the healthy subsidy.
- Gain from Hypothetical FV Selection: The difference in reimbursements between the healthy and unhealthy subsidies for any agent with subsidy choice regardless of the subsidy they actually selected.
- Gain from Actual Selection: The difference in reimbursements between the selected subsidy and the alternative subsidy for any agent with subsidy choice.

Table A.2. Time Preferences and Gains from Subsidy Selection

	(1) Commitment Amount	(2) Commitment Amount (if FV Selected)	(3) Gain from Hypothetical FV Selection	(4) Gain from Actual Selection
Patience	0.00	0.07	0.10	-0.10
	(0.14)	(0.17)	(0.16)	(0.15)
Hyperbolicity	-0.27*	-0.39**	0.22	0.33**
	(0.15)	(0.17)	(0.17)	(0.14)
Constant	-1.79***	-2.25***	1.21***	2.36***
	(0.25)	(0.29)	(0.30)	(0.25)
Shoppers (Clusters)	356	332	356	356
Shopping Trips (Observations)	1188	926	1188	1188

* $\Rightarrow p < 0.1$ ** $\Rightarrow p < 0.05$ *** $\Rightarrow p < 0.01$. All estimates are from OLS regressions with recruitment-wave fixed effects. Standard errors in parentheses are clustered at the shopper level. All samples are limited to Shopping Trips in which a shopper was endowed with subsidy choice. The sample in Column 2 is limited to shoppers endowed with subsidy choice who selected the FV subsidy.