Impatience and present bias do not determine weight loss in obesity: Evidence from lab-in-field and nationally representative data

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Abstract

Behavioral economic theory attributes the inability to lose weight to impatience and present bias, assuming they lead to excessive food consumption and inadequate exercise. We use data from a large-scale lab-in-field study that tracks 293 participants with obesity who attempted to improve their health as part of a 12-month randomized controlled trial conducted in a clinical setting. Consistent with behavioral economic theory, we find that trial participants who are less impatient are more likely to complete the trial. However, there is no evidence that participants who are less impatient or less present-biased are more successful in reducing body fat or weight. We replicate that a person's impatience does not predict their intended weight change over a period of one year using a nationally representative data of 6,118 adults with obesity. Our results suggest that obesity is not just a behavioral condition. Treatments that focus on correcting individual's impatience or self-control alone may not be the right approach for weight loss in clinically-relevant populations.

Keywords: obesity, impatience, self-control, experiment

JEL codes: I12, C93, D91,

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1. Introduction

Obesity is a common health condition characterized by excessive body fat. It affects over a quarter of adults in OECD countries (OECD, 2023). The prevalence of obesity is even greater in the United States (41.9% of adults) and Australia (31% of adults) (Australian Institute of Health and Welfare, 2023; National Institute of Diabetes and Digestive and Kidney Diseases, 2017). The World Health Organization estimates that over 890 million adults and 160 million children and adolescents are currently classified as living with obesity (World Health Organization, 2024), highlighting the scale of this global health crisis. Obesity is still on the rise, particularly among children and in low-income countries (World Health Organization, 2024). People with obesity face several long-term health problems, including an increased risk of type 2 diabetes, cardiovascular disease, chronic respiratory disease, and several types of cancer. In Australia, adults with obesity and severe obesity (aged 20-29) are predicted to lose 5.6–10.3 years of their life expectancy (Lung et al., 2019). In men and women, excess BMI in the Australian adult population is responsible for over 30 million years of life lost (Lung et al., 2019). The economic cost of obesity is significant, encompassing not only increased healthcare expenditures but also indirect costs associated with reduced productivity. Global costs of overweight and obesity are predicted to reach US$ 4 trillion per year by 2035, a cost equivalent to that of the Covid-19 pandemic (World Obesity Federation, 2023).

People with obesity experience stigma across all facets of their lives: family, peers, coworkers, and medical professionals. It has been widely documented that patients with obesity experience a lower quality of care, including less respect and time spent on education with a physician (Puhl & Heuer, 2010). This is probably because it is generally and widely assumed that they should be able to control their weight through changes to their behavior and diet. Weight loss programs and mainstream media often emphasize the importance of patience and self-control for weight loss and weight maintenance. In the behavioral economics literature, one of the flagship examples of the consequences of lack of self-control is weight gain. However, the message that is often missing is that several other key factors contribute to weight gain: genetics, cultural background, medical conditions (e.g. endocrine diseases, mental health issues, etc.), disability, medication, eating disorders, inadequate sleep, and the environment where people work or live.

Despite the widely held belief that people should be able to lose weight if they control their behavior, eat less, and exercise more, solid empirical evidence is lacking. We found nine studies that assessed the link between concepts closely related to economic risk and/or time preferences, but these nine studies revealed how little we know about the link between self-control (or patience) and success in losing weight. None of the studies were speaking to the (behavioral) economics literature; none used incentivized choice experiments to elicit preferences, the gold standard in the literature. Almost all of them relied exclusively on (self-reported) BMI as health measure, a measure prone to misclassifications of overweight and obesity.[1] Only three of these studies found statistical links between preferences and weight loss[2] (Table A1). This knowledge gap undermines efforts to meaningfully inform the design of treatments for obesity from the lens of behavioral economics.

In this project, we fill this gap using gold standard methods to measure preferences and unhealthy weight in a clinical setting with a medically-relevant population of at risk adults. We use health and economic preferences data that we collected (Pastore et al. 2023) for 293 participants of a 12-month randomized controlled trial that was conducted in one of Australia's leading teaching hospitals based in Sydney (Bessell et al. (2019), Bessell et al. (2020)).[3] All participants have unhealthy body fat percentages and BMI, classifying them as being affected by obesity and at risk of developing diabetes. In addition to receiving a dietary supplement, all participants regularly met with a dietician who provided individualized diet and exercise advice. Moreover, participants attended regular appointments at the hospital (monthly in the first six months) during which their body measurements were taken. Importantly, during three of these visits – at the start, at six months, and at 12 months, participants' body fat percentage was measured by trained medical staff using the Dual-Energy X-ray Absorptiometry (DXA) scan. Body fat percentage is more reliable than BMI in capturing a person's health status because it distinguishes between fat and muscle tissue. We therefore rely on this objective and clinically measured index of body fat composition rather than self-reported or less accurate measures of obesity that are prone to error or misclassification. Importantly, at the same three appointments, we measured participants' self-control, patience, and risk tolerance using standard incentivized choice tasks used in experimental economics. To allay concerns over external validity, we furthermore investigate the relationship between impatience and yearly weight changes using data from 6,118 adults with obesity, including those who expressed an intention to lose weight, sourced from Australia's leading nationally-representative household survey (Household, Income, and Labour Dynamics in Australia (HILDA) Survey[4]).

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[1] BMI often wrongly classifies muscular (and healthy) people as being affected by overweight or obesity. It could also classify a person who is going through a health intervention trial and improving their health because they are gaining muscle and losing weight as getting more overweight, questioning the usefulness of the existing findings.

[2] Three studies estimated a statistically significant associations between preference measures and weight loss, three had mixed findings for different measures, and another three found no statistically significant association. Across studies that used a hypothetical delay discounting task that resembles economic preference elicitation in which people are asked to choose between smaller sooner and larger later rewards reported mixed findings.

[3] The medical intervention tested the effectiveness of food supplements, α-cyclodextrin and hydrolyzed ginseng, on cholesterol control and glycemic control, respectively. Bessell et al.(2020) find that α-Cyclodextrin and hydrolyzed ginseng extract are not more effective than placebo which is why we pull together data from different supplement treatments.

[4] Summerfield M, Garrard B, Hahn M, et al. HILDA user manual—release 20. Melbourne Institute of Applied Economic and Social Research, University of Melbourne. Dec 8, 2021. https://melbourneinstitute.unimelb.edu.au/hilda/for-data-users/user-manuals (accessed Dec 19, 2021).

Among participants who completed the trial, we found no evidence that self-control, patience, or risk tolerance measured at the start of the health intervention trial predict success in improving body fat composition in 6 and 12 months from the start of the trial. This result replicates in the nationally representative sample of Australians using HILDA. We did, however, find that participants who have lower levels of impatience are more likely to complete the clinical trial. This is consistent with earlier studies that found that patience increases adherence to treatment (e.g., Brandt & Dickinson, 2013; Goldzahl, Hollard, & Jusot, 2018; Madsen et al., 2019). Our findings lead us to conclude that greater patience may be a useful trait for weight loss but only through treatment adherence when effective treatments are available. In our previous paper (Pastore et al., 2023), using the same data, we documented a lack of relationship between impatience or self-control and body fat percentage, BMI, and waist circumference at the start of the trial. Together with the results of this paper, this leads us to conclude that impatience and self-control is unlikely the reason why people continue to live with overweight or obesity. Our findings also suggest that simple nudging strategies that subtly direct people to exert more self-control, may not be sufficient to help people, who already have obesity, improve their health.

2. Design

2.1 Field data

We use data from a randomized controlled trial overseen by The Boden Collaboration for Obesity, Nutrition, Exercise & Eating Disorders, conducted at Royal Prince Alfred and Nepean Hospitals in Australia. The protocol is previously reported in Bessell et al. (2019) and primary outcomes in Bessell et al. (2020). The trial assessed the effectiveness of two supplements: α-cyclodextrin on cholesterol control and hydrolyzed ginseng on glycemic control. Participants were randomly assigned to one of four groups to receive active or placebo versions of each supplement[5] for 6 months, followed by a 6-month follow-up period until month 12. Figure 1 illustrates the timeline of the trial. Overall, each eligible participant attended nine visits in the hospital (excluding the screening appointment). In each of these appointments their weight was measured. Importantly, during the first six appointments, all participants met with a study dietitian and received personalized advice for weight loss, focusing on a healthy low-calorie diet and moderate-intensity exercise. We conducted financially incentivized choice experiments to elicit risk and time preferences before, in the middle, and at the end of the trial (see below and Pastore et al. 2023 for a description).

In this paper, we use data from the baseline (0 months), 6-month, and 12-month appointments during which economic preferences and precise body fat percentage measurements were taken. The trial was approved

[5] The treatment groups were: alpha-cyclodextrin + hydrolyzed ginseng, alpha-cyclodextrin + placebo, placebo + hydrolyzed ginseng, or placebo + placebo. Bessell et al.(2020) show that the these supplements are generally not effective for cholesterol and glycaemic control.

by the Human Research Ethics Committees at the Sydney Local Health District (Royal Prince Alfred Hospital zone) and the University of Sydney. It is registered with the Australian New Zealand Clinical Trials Registry (ACTRN12614001302640).[6]

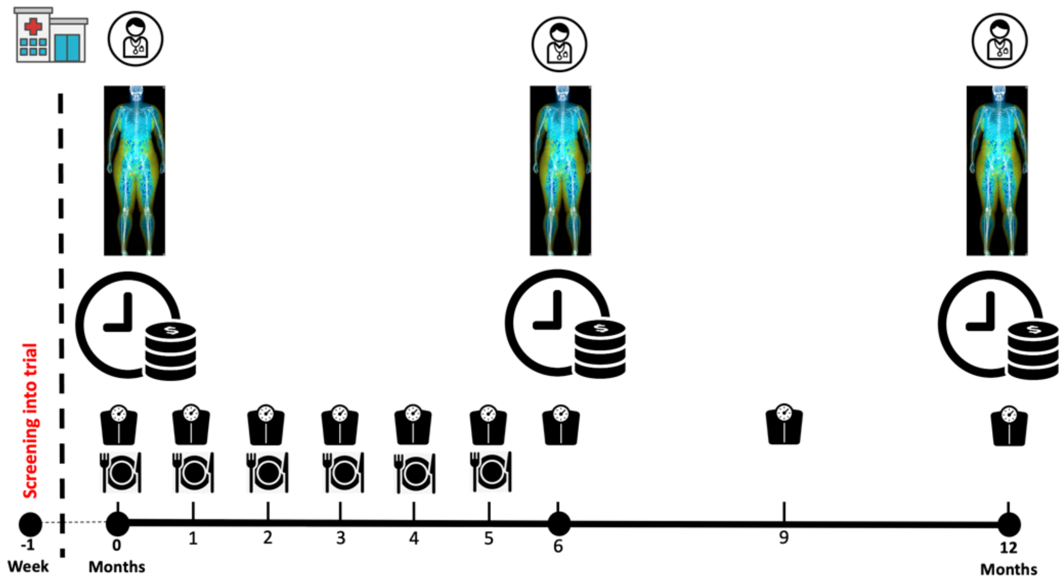


Figure 1. Timeline of the study.

2.2 Participants

Potential participants were considered eligible if they were ≥18 years old, had a BMI ≥25 kg/m^2, and blood sugar levels placing them at high risk of diabetes (referred to as pre-diabetes per the American Diabetes Association guidelines). Participants were recruited from the Boden Collaboration's clinical trials database and through a range of advertising efforts between July 2015 and October 2018. Full details regarding inclusion and exclusion criteria can be found in the study protocol (Bessell et al., 2019). Out of 293 individuals who completed the economic preferences component of the trial at the baseline, 226 remained in the trial after 6 months, and 205 finished the whole trial. For those who finished the trial, BMI and bodyfat (both measured at baseline) averaged 34 and 41, respectively. Not every individual reported their demographic and socioeconomic characteristics. Table A2 shows the number of observations for each variable of interest. Table A3 shows the demographic and socioeconomic characteristics of the participants who completed the whole trial. Of the trial completers, 61% are female, with an average age of 56. One in two have a university degree, and the average weekly work hours for the 186 participants who reported work hours, is 31 hours per week. This average includes two participants who reported 0 hours.

[6] See Bessell et al.(2019) for additional details on the study.

2.3 Economic preferences measurement

To measure participants' risk preferences, we constructed 30 lotteries, each with two possible outcomes: $0 or one of ten positive amounts ($10, $16, $22, $28, $34, $41, $47, $53, $61, $69). Each amount was paired with one of three probability levels (25%, 50%, or 75%), resulting in a total of 30 different lotteries. In each decision scenario, participants were offered a choice between one of the lotteries and a sure amount equal to $10. We quantify an individual's *risk tolerance* as the percentage of decision scenarios on which they selected the lottery over the sure payoff.

To measure participants' time preferences, we constructed 30 decision scenarios in which participants chose between a smaller sooner reward of $34 in t weeks, and a larger later reward of \$$x$ in $t + 8$ weeks with $x \in \{35, 37, 39, 41, 43, 45, 47, 49, 51, 53\}$. We used three front-end delays (delays until the receipt of the sooner reward) $t \in \{0, 4, 21\}$ but the delay between the receipt of the sooner and later reward was always 8 weeks. We quantify participant's time preferences using three measures. *Impatience* is the percentage of decision scenarios in which the participant selected the sooner option when the front-end delay was either 4 or 21 weeks ($t \in \{4,21\}$). We exclude the data from decision scenarios in which the sooner option was available with no delay to make sure we do not confound impatience with present-bias. We define *present-bias* as the difference between the percentage of the decision scenarios when the sooner option was selected when the front-end delay was zero and when the front-end delay was four weeks. Thus, present bias allows us to measure if participants become more impatient when the sooner option is available without delay, compared to decision scenarios when sooner rewards are received in the future. Finally, we measure *stationarity,* a distinct trait from present bias, as the difference between the percentage of the decision scenarios when the sooner option was selected when the front-end delay was equal to 4 and 21 weeks. Stationarity captures whether participants become more patient as the payment dates for the sooner and later options, both delayed and with equal delay between them, are pushed more into the future.

2.4 Incentives and other details

To preserve incentive compatibility, we paid each participant according to their decision on one randomly selected decision scenario. The task took about 20 minutes to complete, and participants received $30 on average. This implies an hourly wage of $90 per hour, an equivalent of 4.5 times the national minimum hourly wage in 2017 and twice the 2017 average national hourly wage for full-time workers ($40) (Australia Bureau of Statistics, 2017), meaning that the financial incentives in this experiment are strong. Payments were made via bank transfers into participants' bank accounts on the day when payment was promised.

Participants completed the same set of 60 decision scenarios using tablet devices provided at the hospitals at three-time points during the trial: during their first appointment, midway through the trial (at 6 months from the initial appointment), and at the end of the trial (at 12 months from the initial appointment). Each decision scenario was presented on a separate screen and participants could not skip questions. Before completing the task, participants received written instructions and completed comprehension questions with feedback (Appendix B).

2.5 Health outcomes

Trained healthcare professionals measured participants' weight, height, and body fat percentage, ensuring accuracy and consistency across individuals. Body fat was measured as a percentage of total body composition by a dual-energy X-ray absorptiometry (DXA) scan. DXA is considered the gold standard for assessing body fatness. It provides detailed and precise information about body composition (bone density, lean mass, and fat mass), and the distribution of fat. Overall DXA gives a very accurate representation of the unhealthiness of body composition that is superior to the Body Mass Index (BMI) which has been the most used measure of obesity in the behavioral economics literature. While convenient and easily accessible, BMI is an imperfect measure. The main problem with BMI is that it does not distinguish between fat and muscle. Consequently, individuals with a high muscle mass, such as athletes or bodybuilders, may have a high BMI despite having low body fat. Additionally, individuals with low muscle mass may be classified as normal weight despite their high fat percentage. Thus, using BMI alone has a much higher chance of misclassifying an individual's health status than when using body fat percentage. For this reason, in the main body of the paper, we focus on body fat percentage as our main variable of interest. For comparison with our representative sample analysis (see below) and other datasets, we replicate all the analyses using BMI which can be readily calculated from recorded weight and height (kg/m^2).

2.6 Representative population data

To verify whether our results replicate, we draw a sample of 6,118 individuals with inclusion criteria that match our clinical sample from a representative of Australian population. We draw our sample from the Household, Income and Labour Dynamics in Australia (HILDA) survey which is Australia's first and now long-running nationally representative household-based longitudinal survey. To maintain consistency with our clinical sample, we include adults between 18 and 74 years old who have a BMI $\geq$25 kg/m^2. The average BMI in this sample is 32, which indicates that the average sample member has obesity, similar to our clinical trial sample with an average BMI at baseline of 34. We use participants' impatience and risk attitudes measured in the 2014 wave of HILDA and analyze whether they explain the change in their BMI in the next year thus mimicking the duration of our clinical trial (12 months) as well as the point in time when it took place.

HILDA measures respondents' risk attitudes by asking them "Are you generally a person who is willing to take risks or are you unwilling to take risks?" with answers on a scale from 0 (unwilling to take risks) to 10 (very willing to take risks). Impatience is measured by asking: "In planning your saving and spending, which of the following time periods is most important to you?" with possible responses: "(1) The next week; (2) The next few months; (3) The next year; (4) The next 2–4 years; (5) The next 5–10 years; (6) More than 10 years ahead".[7] Respondents' BMI is calculated from self-reported height and weight at two time points – 2014 and 2015 HILDA waves. Body fat percentage is not available in HILDA.

3. Results

3.1 Preliminaries

We begin by characterizing economic preferences and health of 205 participants who completed the 12-month trial.

3.1.1 Behavior

Participants understood the task well. They responded to incentives by choosing the risky lottery more often when the lottery's reward and probability of receiving it was higher and choosing the sooner option more often the less they could gain by waiting (Table A4). Consistent with many previous papers (Eckel & Grossman, 2008; Holt & Laury, 2002), we found that women were less likely to choose the risky option (Table A4). In three decision scenarios, participants decided between $10 and a dominated lottery that paid $10 with a 25%, 50%, or 75% chance. Participants selected the dominated lottery (and thus violated the first-order stochastic dominance) in 10.57% of these scenarios which is less or comparable to previous literature (Charness, Karni, & Levin, 2007; Tymula et al., 2013). Overall, we conclude that participants understood the task and responded to incentives as expected.

[7] This is the best and only proxy available for time preferences in the HILDA survey. It has been adopted from the Survey of Consumer Finances, a triennial cross-sectional survey of U.S. families. It has been widely used as a proxy for time preferences in the economics literature (e.g. Fisher & Montalto, 2010; James, 2009) and in the context of healthy habit formation (Cobb-Clark, Kassenboehmer, & Schurer, 2014). This variable has been used to study the association between time preferences and smoking (e.g. Adams, 2009; Adams & Nettle, 2009; Khwaja et al., 2007) as well as physical exercise (e.g. Adams & Nettle, 2009). Adams & Nettle (2009) tested the validity of this time preference measure to proxy impatience. The correlation of this time preference measure and other measures of time preferences is up to 0.33.

Figure 2 shows the distribution of impatience, present bias, stationarity, and risk tolerance in our sample at the beginning, middle (6 months from start), and end of the trial (12 months from start). While participants did not make identical decisions in each session, none of the preferences systematically changed throughout the trial. We determined this, for the whole sample and each gender separately, by a series of paired t-tests in which we compared each preference at baseline and six months, six months and twelve months, and baseline and twelve months ($p > 0.1$ for all tests). Participants were on average risk-averse throughout the trial. A risk-neutral chooser would select the lottery 73.33% of the time in our task. Instead, our participants chose the lottery less frequently. Perhaps unexpectedly, our participants, both male and female, showed a future-bias (negative value of present-bias) at the beginning of the trial. This means that they made more patient decisions when the sooner payment is available immediately. As participants progressed in the trial, the average future-bias went away for men (present-bias = -0.75, 2.38, 1.38 at the baseline, 6 months, and 12 months, respectively) and was reduced for women (present-bias = -7.04, -4.24, -0.24 at the baseline, 6 months, and 12 months, respectively). These changes in averages are not statistically significant though. Participants made non-stationary choices, in line with what a behavioral economist would expect. As outcomes are less delayed to the future, there is an observed tendency for increased impatience among individuals.

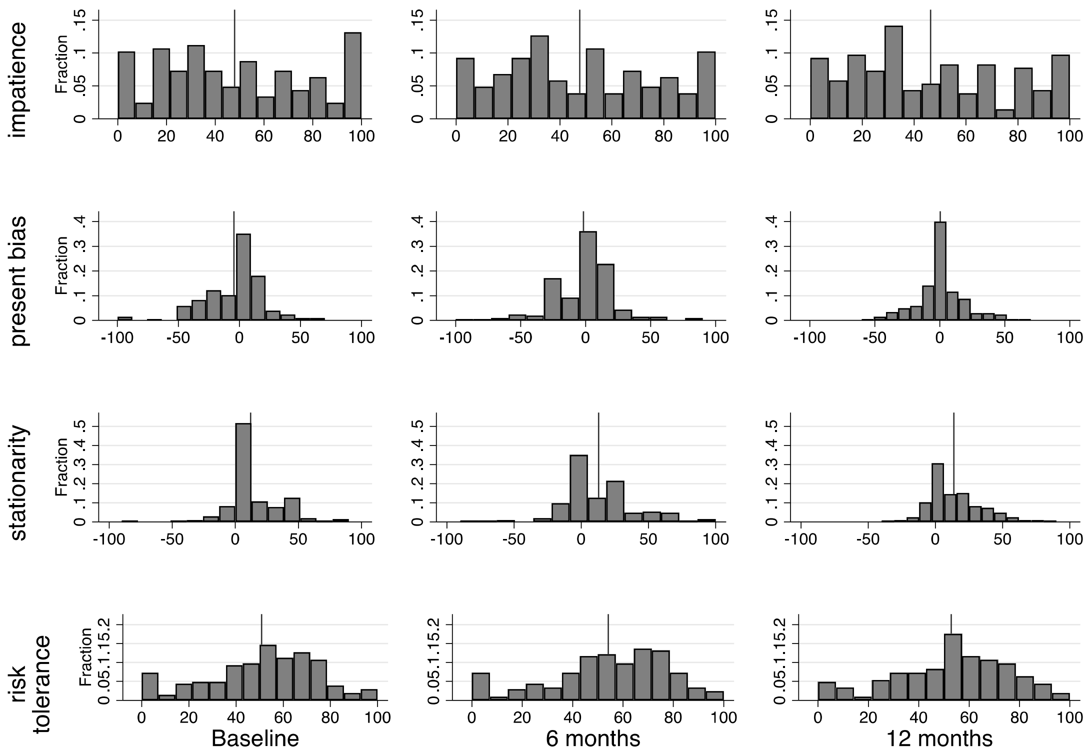


Figure 2. The distribution of economic preferences at the baseline, 6 months and 12 months.

3.1.2 Body fat

Figure 3 shows the distribution of body fat in our sample at the start, middle, and end of the trial.[8] We present this separately for male and female participants because the guidelines for healthy fat percentage are higher for women than for men. The American Council on Exercise considers the cutoff for obesity to be ≥25% of body fat for men and ≥32% of body fat for women. According to this definition, all participants in our sample are classified as having obesity. Importantly, both male and female participants improve their body fat percentage in the first six months of the trial. On average, women reduce their fat percentage from 46.34% to 45.65% (1.49% reduction relative to baseline, $p < 0.001$) and men from 34.24% to 32.89% (3.94% reduction relative to baseline, $p < 0.001$). For the next six months of the trial, on average women maintain exactly the new reduced body fat percentage and men regain 0.23% of fat but it is not a statistically significant gain.[9]

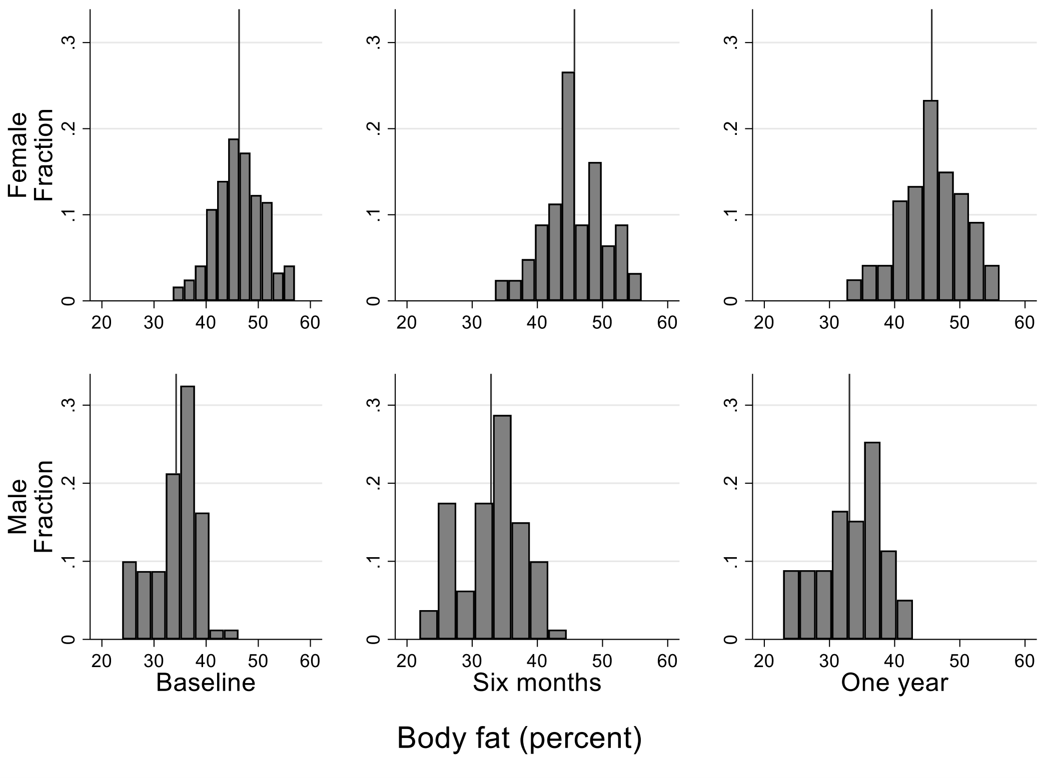


Figure 3. Distribution of body fat at the baseline, 6 months and 12 months separately for female and male. Solid lines indicate the average body fat for each cohort.

[8] The distributions of BMI are in the appendix in Figure A1. The correlation between BMI and body fat at baseline is 0.51, see Figure A2.

[9] We observe the same pattern for BMI. There is a significant ($p < 0.001$) reduction in the first six months. On average, women reduce their BMI from 34.44 to 33.02 and men from 33.07 to 31.83. There is no significant BMI change in the last six months of the trial. Women end trial with an average BMI of 31.83 and men with 31.78.

3.2 Economic preferences and reduction in body fat

From a behavioral economics perspective, we would expect that individual preferences, in particular time preferences, will predict who is successful at improving their body fat percentage. According to theory (Berns, Laibson, & Loewenstein, 2007; Delaney & Lades, 2017; Laibson, 1997), people who are more impatient, more present-biased, and have higher stationarity index should lose less. There is no evidence that this is the case in our data. In Table 1 columns (1) – (4) we regressed a person's body fat percentage at the end of the trial on their economic preferences measured at baseline (standardized to mean of zero and standard deviation of one) and some demographic variables while controlling for their body fat at the start of the trial. The only significant predictors of body fat at the end of the trial are the initial body fat and gender with women losing less. A common caveat when measuring impatience is that assumption of linear utility leads to upward-biased discount rate estimates if utility is concave. To eliminate this potential bias due to functional form misspecification and omitted variables, in column (5) we added risk tolerance as a control variable. The insignificant relationship between impatience and weight loss holds when controlling for heterogeneity in risk attitude.[10]

In our earlier analysis, we saw that the biggest drop in fat percentage occurred in the first six months, we therefore rerun our analysis using body fat percentage at 6 months (instead of at 12 months) as the dependent variable using the same sets of independent variables (Table A5). As one would expect, the coefficients on the initial body fat are slightly smaller capturing the general trend of body fat reduction in the first six months and the coefficient on female is positive indicating that women lost less body fat percentage than men on average. However, also in the first six months, economic preferences do not explain who loses more body fat. For easier comparison with economic papers that usually focus on BMI, in the Appendix, we replicate this analysis for BMI (Table A6).[11]

[10] Another way to control for the utility curvature while estimating time preferences is through structural estimation. In Appendix C, we imposed a quasi-hyperbolic discounted utility model (Laibson, 1997) and used maximum likelihood method to jointly estimate three parameters: the discount factor δ, present bias β, and utility curvature α. We obtain qualitatively the same result – no relationship between preferences and weight loss.

[11] We regressed a person's BMI at 12 months on their economic preferences measured at baseline. We replicate the lack of relationship between weight loss and impatience, present bias and risk. We found that participants with higher measure of stationarity tended to lose more weight. This relationship is not in line with the behavioral economics intuition and only significant at margin.

Table 1. Relationship between baseline economic preferences and body fat at trial completion (OLS regression). The dependent variable is percent body fat at 12 months. impatience(std) /present bias(std) /stationarity (std) /risk(std) are preference measures at baseline standardized to mean of zero and standard deviation of one. age is in years. university is an indicator variable for participants with bachelor's degree or above. working hours is the number of working hours per fortnight (missing value is treated as 0). working hours (missing) is an indicator variable for individuals with missing value for working hours.

	(1)	(2)	(3)	(4)	(5)
impatience (std)	-0.0414				-0.0390
	(0.1661)				(0.1743)
present bias (std)		-0.1493			
		(0.1599)			
stationarity (std)			0.0225		
			(0.1578)		
risk tolerance (std)				0.0227	0.0173
				(0.1573)	(0.1652)
bodyfat at baseline	0.9412***	0.9394***	0.9399***	0.9402***	0.9410***
	(0.0259)	(0.0256)	(0.0264)	(0.0260)	(0.0264)
age	0.1824	0.1984	0.1831	0.1875	0.1844
	(0.1773)	(0.1737)	(0.1774)	(0.1773)	(0.1779)
age^2	-0.0013	-0.0015	-0.0013	-0.0014	-0.0014
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
female	0.9505*	0.9357*	0.9625**	0.9681**	0.9551*
	(0.4865)	(0.4859)	(0.4848)	(0.4884)	(0.4942)
university	-0.2150	-0.2222	-0.2129	-0.2132	-0.2160
	(0.3337)	(0.3313)	(0.3342)	(0.3332)	(0.3334)
working hours	-0.0093	-0.0096	-0.0097	-0.0097	-0.0094
	(0.0108)	(0.0111)	(0.0113)	(0.0111)	(0.0108)
working hours	-0.2570	-0.2758	-0.2781	-0.2697	-0.2606
(missing)	(0.4594)	(0.4690)	(0.4692)	(0.4670)	(0.4590)
constant	-4.4869	-4.7585	-4.4396	-4.5805	-4.5314
	(5.0739)	(4.9230)	(5.0989)	(5.0738)	(5.0857)
N	196	196	196	196	196

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

3.3 Replication in a representative sample

Even though our clinical sample is well powered for the analysis of within-subject changes in health outcomes, we consider it important to verify whether it replicates in a larger sample. To test for the external validity of our findings, we replicate our clinical trial results in nationally representative survey data. For this analysis, we rely on self-reported weight and height measurements which we convert to a BMI index.

Consistent with the results from the clinical trial, in the representative sample of 6,118 overweight Australians, we find that neither impatience nor risk tolerance predict change in BMI over a period of 12 months (Table 3 models (1) and (4)). It is possible that this lack of relationship is due to HILDA respondents being perfectly comfortable with their weight and thus not interested in weight loss. As another robustness check, we further restrict our sample to participants who in 2013 indicated that they were trying to lose weight over the past year. While this is not an indication of whether they were hoping to lose weight in 2014/15 (in HILDA there are no questions about the intent to lose weight in the future), it is at least an indication that they wanted to lose weight recently. This condition reduces our HILDA sample to 1,431 respondents. Among these participants, again, we do not find a significant relationship (statistically and economically) between respondents' preferences and weight change over the subsequent 12 months (Table 2 models (2) and (5)). For completeness, we also show that in our clinical sample impatience and risk tolerance also do not predict BMI change in the same table (Table 2 models (3) and (6)).

Table 2. **Economic preferences and BMI change in HILDA.** HILDA data is sourced from Waves 13, 14, and 15. BMI outcome data is from wave 15. BMI at baseline, risk tolerance, and time preferences are from wave 14. Data includes respondents aged between 25 and 74 with a baseline BMI > 25. In models (2) and (5), the sample is restricted to individuals who in wave 13 indicated that they dieted in the past 12 months. In models (1), (2), (4) and (5) we use the HILDA sample. In models (3) and (6) we use the clinical trial sample.

	HILDA (1)	HILDA (2)	Clinical (3)	HILDA (4)	HILDA (5)	Clinical (6)
impatience (std)	0.0341	0.1029	0.1645	0.0343	0.1032	0.1704
	(0.0307)	(0.0657)	(0.1340)	(0.0307)	(0.0658)	(0.1354)
risk tolerance (std)				0.0041	0.0048	0.0541
				(0.0314)	(0.0669)	(0.1301)
BMI at baseline	0.9476***	0.9515***	0.9591***	0.9476***	0.9515***	0.9590***
	(0.0062)	(0.0112)	(0.0277)	(0.0062)	(0.0113)	(0.0278)
age	0.0076	-0.0152	0.0618	0.0077	-0.0151	0.0691
	(0.0173)	(0.0377)	(0.1346)	(0.0173)	(0.0378)	(0.1328)
age^2	-0.0001	0.0000	-0.0005	-0.0001	0.0000	-0.0006
	(0.0002)	(0.0004)	(0.0012)	(0.0002)	(0.0004)	(0.0012)
female	0.1099*	-0.0062	-0.2727	0.1112*	-0.0046	-0.2667
	(0.0633)	(0.1409)	(0.2819)	(0.0641)	(0.1426)	(0.2822)
university	-0.0541	-0.3368**	-0.1524	-0.0550	-0.3373**	-0.1526
	(0.0690)	(0.1449)	(0.2665)	(0.0694)	(0.1451)	(0.2670)
working hours	-0.0012	-0.0003	-0.0105	-0.0012	-0.0003	-0.0109
	(0.0017)	(0.0037)	(0.0098)	(0.0017)	(0.0037)	(0.0099)
working hours			-0.4314			-0.4425
(missing)			(0.3981)			(0.4014)
constant	1.4430***	2.3774***	-1.3185	1.4388***	2.3718***	-1.5037
	(0.4251)	(0.9072)	(3.9600)	(0.4263)	(0.9109)	(3.8971)
N	6118	1431	205	6118	1431	205

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

3.4 Trial completion and economic preferences

Our results so far indicate that individual economic preferences do not explain success in reducing body fat percentage (and BMI). Economic preferences may nevertheless matter if they determine who stays in the trial until completion. From a theoretical perspective, we would expect less impatient and less present-biased participants to be more likely to carry through with their plans and be more likely to stay in the trial for the full twelve months. We find some evidence in our data in support for this hypothesis.[12] Impatient participants are significantly more likely to complete the trial (Table 3). Specifically, a one percent increase in our measure of impatience reduces the probability of finishing the trial by 0.18% ($p < 0.05$, column (1)). No other economic preferences explain who completes the trial. The estimate is insensitive to including also risk preferences (0.0017, $p < 0.05$, column (4)).

Table 3. Economic preferences and trial completion. Dependent variable equals to one if an individual completed the 12-month trial. impatience/present bias/stationarity/risk are measured at baseline. age is in years. university is an indicator for participants who have bachelor's degree or above. working hours is the number of working hours per fortnight (missing value is treated as 0). working hours (missing) is an indicator variable for individuals who have missing values for working hours.

	(1)	(2)	(3)	(4)	(5)
impatience	-0.0018**				-0.0017**
	(0.0008)				(0.0008)
present bias		-0.0001			
		(0.0012)			
stationarity			-0.0011		
			(0.0012)		
risk tolerance				0.0010	0.0007
				(0.0011)	(0.0011)
age	0.0180	0.0223	0.0243	0.0243	0.0197
	(0.0207)	(0.0210)	(0.0207)	(0.0208)	(0.0210)
age^2	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
female	-0.0964*	-0.0964*	-0.0869	-0.0915*	-0.0933*
	(0.0537)	(0.0546)	(0.0543)	(0.0539)	(0.0538)
university	0.0609	0.0646	0.0668	0.0614	0.0589
	(0.0529)	(0.0533)	(0.0531)	(0.0529)	(0.0528)
working hours	-0.0012	-0.0013	-0.0013	-0.0014	-0.0012
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
working hours	0.0102	0.0036	0.0101	0.0019	0.0086
(missing)	(0.0748)	(0.0752)	(0.0768)	(0.0754)	(0.0753)
constant	0.0670	-0.1382	-0.1851	-0.2447	-0.0194
	(0.5434)	(0.5466)	(0.5424)	(0.5553)	(0.5637)
N	293	293	293	293	293

Standard errors in parentheses
* p<0.1 ** p<0.05 *** p<0.01

[12] To test these hypotheses, we estimated a regression model in which the dependent variable is a binary indicator that takes the value 1 if a participant completed the full 12-month trial, and 0 otherwise. Unlike our previous analyses, here we include all participants who started the trial (88 more than those who finished the trial). Participants who are more impatient are less likely to complete the trial.

4. Discussion

We find that impatience and present bias, key components of behavioral economics models of choice, are not statistically significant predictors of body fat or weight change for individuals with obesity. Contrary to the common assumption that obesity is a behavioral condition and that treatments should focus on correcting individuals' impatience or self-control, the results indicate that these traits do not predict whether people, who have the intention to improve their health, reduce or increase body fat or weight over a one-year period. Instead, the study suggests that patience may be beneficial through treatment adherence when effective treatments for improving body composition are used.

Previous literature in behavioral economics focused only on the cross-sectional relationship between time preferences and body weight at a particular point in time (see literature review and Table SB.1 in Pastore et al.(2023)). Using the dataset from this study as a cross-section, Pastore et al.(2023) found perhaps surprising evidence that most participants with obesity are future-biased and that patience, self-control, and risk tolerance alone do not correlate with BMI at baseline. Many, but not all, other studies in economics find the intuitive positive association between patience or self-control and lower BMI. However, as most of these studies focus on self-reported survey responses about participants' assessment of their own self-control or patience, we cannot rule out the possibility that people who were successful in achieving their goals (such as weight loss) attribute their success to their own virtues, and thus we cannot be sure that better self-control or patience led to these better health outcomes. We overcome this problem with the panel structure of our data. We first measure participants' preferences and then, over a period of one year, we observe how their body fat percentage and weight change. For neither participants with obesity drawn from a nationally representative survey nor participants with obesity in a clinical health-improvement trial, their time preferences predict the change in body fat percentage or weight.

Our study is unique for several other reasons. First, only a few studies have investigated the relationship between economic preferences and weight loss, and none in the economics literature (see Table A1 for a review). Among these studies, we are the first to estimate the relationship between changes in body fat percentage (and BMI) and economic preferences measured using an incentive-compatible task. Previous studies have quantified time preferences either using self-reported measures or hypothetical choices. We are also the first to distinguish between different aspects of preferences (patience, present bias, stationarity, and risk attitudes), allowing for a more nuanced investigation of the relationship between economic preferences and weight loss. In many previous studies, researchers used tasks such as the stop signal task or balloon analogue risk task or psychological scales, which do not make this distinction. Our health measurement, body fat percentage, is the gold standard for measuring the healthiness of body composition. Our evaluation period is also very long, with only three other studies lasting a full year. Finally, our trial is relatively light-touch, as it is outpatient and does not involve a mandatory calorie restriction or exercise program, allowing economic preferences, rather than constraints, to be stronger drivers of behavior. Lastly, unlike any other paper, we replicate our results using a large, representative data set of Australians with obesity.

One potential objection to our study is that our outcome health variables and preferences are measured in different domains. While preferences have been shown to be largely domain-specific when measured using questionnaires (e.g., Blais & Weber, 2006), when they are measured using incentivized tasks, the correlation across domains is very strong. Cheung, Tymula, & Wang (2022) find the correlation between preferences measured using money and food to be significant and in the 0.6-0.8 range for impatience, present bias, and utility curvature. Levy & Glimcher (2011) find similar correlations for utility curvature for money and food, and Reuben, Sapienza, & Zingales (2010) also confirm a significant moderate correlation between time preferences estimated for food and money. One previous study that evaluated the relationship between preferences and weight loss and measured delay discounting using monetary and food rewards found qualitatively the same results for both (Best et al., 2012). There is also a large literature showing that economic preferences measured using monetary rewards predict non-monetary outcomes (Castillo et al., 2011; Cheung, Tymula & Wang, 2022; Khwaja, Silverman, & Sloan, 2007; Sutter et al., 2013). All this evidence suggests that even though we measure economic preferences in the monetary domain, they should be relevant for decisions related to health.

We caution against generalizing our findings to populations without obesity. It is possible that while economic preferences are not relevant for people with obesity (who may have underlying medical conditions that cause overweight), economic preferences do explain weight gain and loss for those of healthy weight. We did not focus on groups with healthy weight because there is little health or economic benefit to it. Likewise, all previous studies that related weight loss to preferences focused on samples with overweight or obesity.

The reasons for excessive body fat and weight are multifold. Genetics, medical conditions, cultural background, medication, sleep, work/home environment, disability, and unhealthy behaviors have all been indicated as factors. The important question, given the increasing rates and costs of obesity, is how to prevent or cure it, and our study's conclusions have important implications for the design of successful treatment strategies for obesity. Our findings also highlight the need to move beyond the popular interpretation in the behavioral economics literature that obesity is a behavioral condition and that treatments should focus on correcting individuals' impatience or self-control. The typical logic in behavioral economics research is that self-control and patience enable people to stick with healthy diets and exercise routine which leads to weight loss. Interestingly, the only existing study (Will Crescioni et al., 2011) that investigated this mechanism in participants with obesity, could not conclude that weight loss was due to people with higher self-control exercising more or having healthier diet even though those with higher self-control lost more weight. Overall, at its current state, the literature emphasizes the complexity of obesity and the need for a more nuanced understanding of its causes and solutions. We suggest that policymakers and healthcare professionals should look beyond individual-level factors such as impatience and present bias, and consider the broader social, economic, and environmental factors that contribute to obesity. A combination of interventions that promote patience (and thus adherence) and offer an effective treatment seem to be the most promising solution.

Reference

Adams, J. (2009). The mediating role of time perspective in socio-economic inequalities in smoking and physical activity in older english adults. *Journal of Health Psychology*, *14*(6), 794–799.

Adams, J., & Nettle, D. (2009). Time perspective, personality and smoking, body mass, and physical activity: An empirical study. *British Journal of Health Psychology*, *14*(1), 83–105.

Australia Bureau of Statistics. (2017). *Average Weekly Earnings, Australia, May 2017- 6302.0*. Retrieved from https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/6302.0Main+Features1May 2017?OpenDocument=

Australian Institute of Health and Welfare. (2023). *Overweight and obesity*. *Australian Institute of Health and Welfare*. Retrieved from https://www.aihw.gov.au/reports/overweight-obesity/overweight-and-obesity/contents/overweight-and-obesity

Berns, G. S., Laibson, D., & Loewenstein, G. (2007, November 1). Intertemporal choice - toward an integrative framework. *Trends in Cognitive Sciences*. Elsevier Current Trends.

Bessell, E., Fuller, N. R., Markovic, T. P., Burk, J., Picone, T., Hendy, C., … Caterson, I. D. (2019). Effects of alpha-cyclodextrin on cholesterol control and Compound K on glycaemic control in people with pre-diabetes: Protocol for a Phase III randomized controlled trial. *Clinical Obesity*, *9*(4).

Bessell, E., Fuller, N. R., Markovic, T. P., Lau, N. S., Burk, J., Hendy, C., … Caterson, I. D. (2020). Effects of α-Cyclodextrin on Cholesterol Control and Hydrolyzed Ginseng Extract on Glycemic Control in People With Prediabetes: A Randomized Clinical Trial. *JAMA Network Open*, *3*(11), E2023491.

Best, J. R., Theim, K. R., Gredysa, D. M., Stein, R. I., Welch, R. R., Saelens, B. E., … Wilfley, D. E. (2012). Behavioral economic predictors of overweight children's weight loss. *Journal of Consulting and Clinical Psychology*, *80*(6), 1086–1096.

Blais, A.-R., & Weber, E. U. (2006). A Domain-Specific Risk-Taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, *1*(1), 33–47.

Castillo, M., Ferraro, P. J., Jordan, J. L., & Petrie, R. (2011). The today and tomorrow of kids: Time preferences and educational outcomes of children. *Journal of Public Economics*, *95*(11–12), 1377–1385.

Charness, G., Karni, E., & Levin, D. (2007). Individual and group decision making under risk: An experimental study of Bayesian updating and violations of first-order stochastic dominance. *Journal of Risk and Uncertainty*, *35*(2), 129–148.

Cheung, S. L., Tymula, A., & Wang, X. (2022). Present bias for monetary and dietary rewards. *Experimental Economics*, *25*(4), 1202–1233.

Cobb-Clark, D. A., Kassenboehmer, S. C., & Schurer, S. (2014). Healthy habits: The connection between diet, exercise, and locus of control. *Journal of Economic Behavior and Organization*, *98*, 1–28.

Delaney, L., & Lades, L. K. (2017). Present Bias and Everyday Self-Control Failures: A Day Reconstruction Study. *Journal of Behavioral Decision Making*, *30*(5), 1157–1167.

Eckel, C. C., & Grossman, P. J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior and Organization*, *68*(1), 1–17.

Fisher, P. J., & Montalto, C. P. (2010). Effect of saving motives and horizon on saving behaviors. *Journal of Economic Psychology*, *31*(1), 92–105.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, *92*(5), 1644–1655.

James, R. N. (2009). Tenant time preference as a barrier to homeownership. *Applied Economics Letters*, *16*(10), 1073–1077.

Khwaja, A., Silverman, D., & Sloan, F. (2007). Time preference, time discounting, and smoking decisions. *Journal of Health Economics*, *26*(5), 927–949.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, *112*(2), 442–477.

Levy, D. J., & Glimcher, P. W. (2011). Comparing apples and oranges: Using reward-specific and reward-general subjective value representation in the brain. *Journal of Neuroscience*, *31*(41), 14693–14707.

Lung, T., Jan, S., Tan, E. J., Killedar, A., & Hayes, A. (2019). Impact of overweight, obesity and severe obesity on life expectancy of Australian adults. *International Journal of Obesity*, *43*(4), 782–789.

National Institute of Diabetes and Digestive and Kidney Diseases. (2017). Overweight & Obesity Statistics. Retrieved May 28, 2024, from https://www.niddk.nih.gov/health-information/health-statistics/overweight-obesity

OECD. (2023). *Health at a Glance 2023: OECD Indicators* (Health at a Glance). *OECD*. OECD.

Pastore, C., Schurer, S., Tymula, A., Fuller, N., & Caterson, I. (2023). Economic preferences and obesity: Evidence from a clinical lab-in-field study. *Health Economics (United Kingdom)*, *32*(9), 2147–2167.

Puhl, R. M., & Heuer, C. A. (2010). Obesity stigma: Important considerations for public health. *American Journal of Public Health*, *100*(6), 1019–1028.

Reuben, E., Sapienza, P., & Zingales, L. (2010). Time discounting for primary and monetary rewards. *Economics Letters*, *106*(2), 125–127.

Sutter, M., Kocher, M. G., Daniela, G. R., & Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review*, *103*(1), 510–531.

Tymula, A., Belmaker, L. A. R., Ruderman, L., Glimcher, P. W., & Levy, I. (2013). Like cognitive function, decision making across the life span shows profound age-related changes. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(42), 17143–17148.

Will Crescioni, A., Ehrlinger, J., Alquist, J. L., Conlon, K. E., Baumeister, R. F., Schatschneider, C., &

Dutton, G. R. (2011). High trait self-control predicts positive health behaviors and success in weight loss. *Journal of Health Psychology*, *16*(5), 750–759.

World Health Organization. (2024). *Obesity and overweight*. *World Health Organization*.

World Obesity Federation. (2023). *Economic impact of overweight and obesity to surpass $4 trillion by 2035 | World Obesity Federation*. *World Obesity Federation*. Retrieved from https://www.worldobesity.org/news/economic-impact-of-overweight-and-obesity-to-surpass-4-trillion-by-2035

Appendix A. Additional tables and figures

Table A.1 Summary of literature review

Authors	Sample	Trial Description	Trial Duration	Health Measure	Preference Measurement	Relationship
Nederkoorn et al. (2007), *Behav. Res. Ther.*	n=26, BMI = 120% overweight, children	weekly group behavioral sessions for children for 8-10 weeks; 3 parent group sessions	2 months	% BMI	stop signal task	positive
Crescioni et al. (2011) *J. Health Psychol.*	n=86, BMI range: 25.01 - 53.92, adults	weekly group meetings with expert advice; goal setting: weighing	12 weeks	BMI	Brief Self-Control Scale^	positive
Best et al. (2012) *J. Consult. Clin. Psychol.*	n=241, BMI ≥ 85th percentile, children, one parent with BMI ≥ 25	weekly group advice	4 months	BMI fat %	delay discounting task ($) delay discounting task (food)	positive positive
Kulendran et al. (2014) *Int. J. Obes. (Lond)*	n=53, BMI range: 22.7 - 76.3, children	camp with structured daily routine; compulsory physical activity; monitoring; advice	2 months	BMI	stop signal task delay discounting task ($)	positive no association

Halberstadt et al. (2017) *BMC Obes.*	n=120, BMI > 99th percentile, 8-19 y. o.	inpatient and outpatient expert-run intervention focusing on exercise, diet, socioemotional skills, eating and mood disorders	6 months or 12 months	BMI	stop signal task balloon analogue task	no association no association
Manasse et al. (2017) *Apetite*	n=190, BMI range: 27.21 - 51.99, adults	25 group meetings with expert advice	12 months	BMI	stop signal task delay discounting task ($)	positive no association
Galioto et al. (2018) Obes. Med.	n=24, BMI range: 33.7 - 51.9, adults	weekly group expert advice; calorie restriction via dietary plan	2 months	BMI	BRIEF-A Scale"	no association
Dassen et al (2018) *J. Behav. Med.*	n=82, BMI range: 30.9 - 65.38, adults	weekly group expert advice; weekly group sport	6 months or 12 months	BMI	stop signal task delay discounting task ($) BRIEF-A Scale"	no association no association positive
Schurer et al.	n=205, ≥ 25 BMI, adults	6 months of monthly 1:1 expert advice; weighing; ginseng & α-cyclodextrin supplement	12 months	BMI fat %	delay discounting task ($)* lottery task*	no association no association

^Tangney et al., 2004
"Roth et al., 2005
*incentivized task

Table A2. The number of observations for each variable of interest in each wave. There are 6 participants who have missing values for body fat at baseline and 3 participants who have missing values for body fat at 12 months resulting in 196 participants for our main analysis.

	Preferences	Body fat	BMI	Gender	Age	University	Working hours
Baseline	293	289	243	293	293	293	221
Six months	226	224	226	226	226	226	163
One year	205	199	205	205	205	205	143

Table A3. Health at baseline, demographics and socio-economic characteristics for participants who completed the whole trial. Female is an indicator variable for female participants; age is age in years; university is an indicator variable for participants who have bachelor's degree or above; working hours is the number of working hours per fortnightly.

	n	mean	s.d.	min	max
BMI at baseline	205	34.08	6.01	25.6	54.3
Bodyfat at baseline	205	41.48	7.63	23.9	57
female	205	0.61	0.49	0	1
age	205	56.26	9.22	31	77
university	205	0.52	0.50	0	1
working hours	152	30.76	19.88	0	90

Table A4. Preliminary results – participants respond to incentives as expected. In (1), the dependent variable equals to one if an individual selected a lottery and zero otherwise. lottery amount is the reward stake of a lottery option; lottery probability is the probability of winning a lottery; female is an indicator variable for female participants. In (2), the dependent variable equals to one if an individual selected the sooner option and zero otherwise. later option amount is the reward stake of the later reward; back-end delay is delays until the receipt of the later reward.

	Baseline	Six month	One year
(1)			
lottery amount	0.0131***	0.0135***	0.0141***
	(0.0003)	(0.0003)	(0.0002)
lottery probability	0.6956***	0.7093***	0.7288***
	(0.0257)	(0.0254)	(0.0248)
female	-0.0359***	-0.0449***	-0.0675***
	(0.0107)	(0.0106)	(0.0103)
constant	-0.3156***	-0.2990***	-0.3318***
	(0.0164)	(0.0160)	(0.0153)
(2)			
later option amount	-0.0408***	-0.0414***	-0.0420***
	(0.0009)	(0.0009)	(0.0009)
back-end delay	-0.0049***	-0.0064***	-0.0075***
	(0.0006)	(0.0006)	(0.0006)
female	-0.0471***	-0.0229**	0.0005
	(0.0116)	(0.0114)	(0.0114)

constant	2.3842***	2.4321***	2.4531***
	(0.0398)	(0.0392)	(0.0388)
N	6150	6150	6150

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table A5. Relationship between body fat and economic preferences (OLS regression). Dependent variable is the body fat measured at 6 months. impatience(std) /present bias(std) /time inconsistency(std) /risk(std) is the measure of impatience/present bias/time inconsistency/risk at baseline standardized to mean of zero and standard deviation of one. bodyfat at baseline is the body fat measured at baseline. age is age in years. female is an indicator variable for female participants. university is an indicator variable for participants who have bachelor's degree or above. working hours is the number of working hours per fortnight (missing value is treated as 0). working hours (missing) is an indicator variable for individuals who have missing value for working hour.

	(1)	(2)	(3)	(4)	(5)
impatience (std)	0.1399				0.1414
	(0.1426)				(0.1465)
present bias (std)		-0.0861			
		(0.1326)			
stationarity (std)			0.1316		
			(0.1095)		
risk tolerance (std)				-0.0086	0.0108
				(0.1205)	(0.1237)
bodyfat at baseline	0.9338***	0.9360***	0.9335***	0.9367***	0.9336***
	(0.0264)	(0.0259)	(0.0262)	(0.0259)	(0.0266)
age	-0.0809	-0.0822	-0.1016	-0.0908	-0.0796
	(0.1479)	(0.1443)	(0.1457)	(0.1480)	(0.1499)
age^2	0.0009	0.0009	0.0011	0.0010	0.0009
	(0.0014)	(0.0013)	(0.0013)	(0.0014)	(0.0014)
female	1.3470***	1.2891***	1.3020***	1.3029***	1.3499***
	(0.4484)	(0.4429)	(0.4391)	(0.4418)	(0.4512)
university	-0.3379	-0.3556	-0.3570	-0.3489	-0.3385
	(0.2871)	(0.2884)	(0.2883)	(0.2888)	(0.2872)
working hours	-0.0053	-0.0043	-0.0049	-0.0042	-0.0054
	(0.0094)	(0.0095)	(0.0096)	(0.0094)	(0.0094)
working hours (missing)	-0.2272	-0.2035	-0.2700	-0.1962	-0.2294
	(0.3941)	(0.4040)	(0.4001)	(0.4019)	(0.3914)
constant	2.8778	2.8717	3.5071	3.0274	2.8498
	(4.1992)	(4.0693)	(4.1486)	(4.1890)	(4.2450)
N	196	196	196	196	196

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table A6. **Relationship between economic preferences and BMI (OLS regression)**. Dependent variable is the BMI measured at 12 months. impatience(std) /present bias(std) /time inconsistency(std) /risk(std) is the measure of impatience/present bias/time inconsistency/risk at baseline standardized to mean of zero and standard deviation of one. age is age in years. female is an indicator variable for female participants. university is an indicator variable for participants who have bachelor's degree or above. working hours is the number of working hours per fortnightly (missing value is treated as 0). working hours (missing) is an indicator variable for individuals who have missing value for working hour. bodyfat at baseline is the body fat measured at baseline.

	(1)	(2)	(3)	(4)	(5)
impatience (std)	0.1645				0.1704
	(0.1340)				(0.1354)
present bias (std)		-0.1011			
		(0.1323)			
stationarity (std)			-0.2360*		
			(0.1229)		
risk tolerance (std)				0.0354	0.0541
				(0.1289)	(0.1301)
bodyfat at baseline	0.9591***	0.9598***	0.9679***	0.9603***	0.9590***
	(0.0277)	(0.0278)	(0.0275)	(0.0276)	(0.0278)
age	0.0618	0.0598	0.0708	0.0558	0.0691
	(0.1346)	(0.1321)	(0.1350)	(0.1312)	(0.1328)
age^2	-0.0005	-0.0005	-0.0006	-0.0004	-0.0006
	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0012)
female	-0.2727	-0.3137	-0.2335	-0.2855	-0.2667
	(0.2819)	(0.2870)	(0.2834)	(0.2822)	(0.2822)
university	-0.1524	-0.1740	-0.1541	-0.1689	-0.1526
	(0.2665)	(0.2654)	(0.2643)	(0.2672)	(0.2670)
working hours	-0.0105	-0.0094	-0.0084	-0.0096	-0.0109
	(0.0098)	(0.0101)	(0.0102)	(0.0102)	(0.0099)
working hours (missing)	-0.4314	-0.4054	-0.2758	-0.4051	-0.4425
	(0.3981)	(0.4107)	(0.4081)	(0.4123)	(0.4014)
constant	-1.3185	-1.2372	-1.9862	-1.2035	-1.5037
	(3.9600)	(3.8732)	(3.9907)	(3.8558)	(3.8971)
N	205	205	205	205	205

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Figure A1. The distribution of BMI at the baseline, 6 months and 12 months by gender. The solid lines are the average BMI.

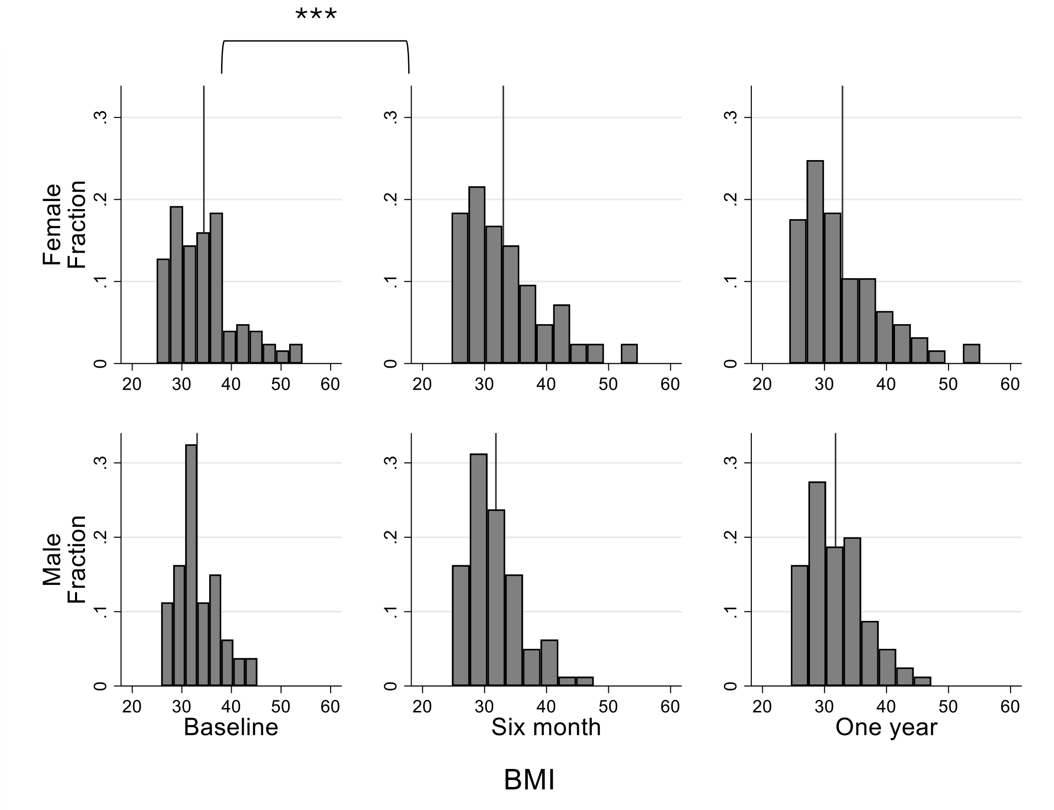
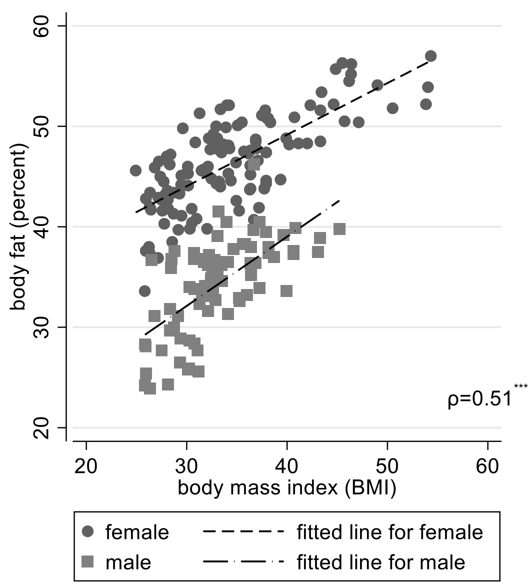


Figure A2. The correlation between body fat and BMI at the baseline by gender. The correlation coefficient is 0.51 and it is statistically significant ($p < 0.001$).



Appendix B. Instructions for economic decision-making experiments

General Instructions

This task involves choosing between two monetary options repeatedly. All together you will make 60 choices in 60 different decision scenarios. You cannot omit any scenarios. You will be making your choices on your own and we will not show them to anybody else. There are no wrong answers and people differ in what they choose. By choosing honestly the option that you prefer in every case, you can make sure that you get the payment that reflects your preferences.

Payment: Once you finish answering all 60 questions, the computer will randomly pick one of the 60 decision scenarios and the choice you made in this scenario will be implemented. So your decisions really matter. Since each one of your choices has a chance to be realized for payment, you should treat every decision that you are making as if it was for real.
The money will be paid to you via bank transfer into the bank account you have nominated at the introduction meeting. Your bank account details will be stored on a secure server and will be deleted after the end of this trial.

Task 1

You will be choosing between two monetary options that differ in the size of the reward and the probability of receiving it.
Example 1: Imagine, you were presented with the following scenario:
$15 for sure   or   50% chance of $25
Some people will prefer $15 for sure and some will prefer 50% chance of $25.
Suppose that this decision scenario was selected for payment:

- *If you chose the option on the left, you would get $15 for sure (transferred to your account today).*
- *If you chose the option on the right, you would have an equal chance of getting $25 or getting nothing. To determine whether you get the money or not, the computer would randomly generate a number between 1 and 100. If the number was between 1 and 50, we would make a transfer of $25 to your account today. If the number was between 51 and 100, you would not receive any money.*

The probability of receiving the reward in the options that involve chance will vary. You will have either a 75%, 50% or 25% chance to receive the reward. If you are to be paid based on the option that involves chance, we will use a random number generator to determine whether you get the reward or not. If that number is smaller or equal to the chance, you get the reward. If it is larger, you get nothing.

- If the chance is equal to 75%, you get the reward if the random number is between 1 and 75, and nothing if it is between 76 and 100. You are therefore three times more likely to get the reward than not.
- If the chance is equal to 50%, you get the reward if the random number is between 1 and 50, and nothing if it is between 51 and 100. You therefore have equal chances of receiving the reward or nothing.
- If the chance is equal to 25%, you get the reward if the random number is between 1 and 25 and nothing if it is between 26 and 100. Therefore you are three times more likely to get nothing than to get the reward.

Let's practice the concept of chance for one moment. Imagine two options that involve chance:

A) 50% chance of $30
B) 25% chance of $30

Which option presents higher chances of receiving $30?
Answer: [] A [] B

[INSTRUCTIONS: If wrong [participant chose [] B], the participant will see the following message on the same screen. If correct, the participant moves to [NEXT SCREEN] with the other probability comprehension question]

Not quite right. Remember, to determine whether you get the reward, the computer randomly selects a number between 1 and 100. If the chance is equal to 25%, you get the reward if this number is between 1 and 25. If the chance is equal to 50%, the range of numbers for which you get the reward is between 1 and 50. It is bigger and therefore your chances of receiving the reward are bigger. Let's practice this concept again.

PRESS CONTINUE
[NEXT SCREEN]
Imagine two options that involve chance:
A) 25% chance of $30
B) 75% chance of $30
Which option presents higher chances of receiving $30?
Answer: [] A [] B

[INSTRUCTIONS: If wrong [participant chose [] A], then the participant will see the following message on the same screen. If correct (chose B), the participant moves to [next screen] i.e. starts the task]

Not quite right. Remember, to determine whether you get the reward, the computer randomly selects a number between 1 and 100. If the chance is equal to 25%, you get the reward if this number is between 1 and 25. If the chance is equal to 75%, the range of numbers for which you get the reward is between 1 and 75. It is bigger and therefore your chances of receiving the reward are bigger.

PRESS CONTINUE

[INSTRUCTIONS: The participant continues to the task NO MATTER whether the answers were correct or not.]

[next screen]
Throughout the task, to choose the option on the left, press the "CHOOSE: LEFT" button. To select the option on the right, you will press the "CHOOSE: RIGHT" button. Once you press the "CONFIRM" button, the next decision scenario will appear. You cannot change your choice after you confirmed it.

Let's start with the actual task. Remember to pay attention to your choices. Each of the 30 choices can be selected to be paid out.

[Participants complete Task 1]
[NEXT SCREEN]

Task 2

In this task you will be choosing between two monetary rewards that differ in the reward size and the time when the reward will be transferred to your account. For all payment dates we are using the same payment method – we make a transfer into your bank account at the indicated date.

Example 1: Imagine, you were presented with the following scenario:

$35 today   or $48 in 8 weeks

Some people will prefer $35 today while others will prefer $48 in 8 weeks.

Suppose that this decision scenario was selected for payment:

- *If you chose the option on the left, we would make a transfer of $35 to your bank account today.*
- *If you chose the option on the right, we would make a transfer of $48 to your bank account in exactly 8 weeks.*

In some of the decision scenarios, both of the monetary rewards would be paid out at a future date. Let's start with the actual task. Remember to pay attention to your choices. Each of the 30 choices can be selected to be paid out.

[Participants complete task 2]

Appendix C. The relationship between economic preferences and weight loss using structural model-based analysis

In this section, we imposed a quasi-hyperbolic discounted utility model (Laibson, 1997; O'Donoghue & Rabin, 1999) with power utility function and used maximum likelihood method to jointly estimate three parameters: the discount factor δ, present bias β, and utility curvature α. The instantaneous utility from experimental payments, c, is:

$$u(c) = c^{\alpha}$$

The parameter α is utility curvature, where $\alpha = 1$ indicates linear utility, and $\alpha < 1$ $(\alpha > 1)$ indicates concave (convex) utility. With a quasi-hyperbolic discount function, the intertemporal utility from experiment payments c_t received at date t, and c_{t+k} received at date $t + k$, is:

$$U_t(c_t, c_{t+k}) = u(c_t) + \beta^{\mathbf{1}_{t=0}} \delta^k u(c_{t+k})$$

The parameter β captures present bias. When $\beta = 1$, the discount function is exponential and there is no present bias, while $\beta < 1 (\beta > 1)$ indicates present (future) bias. The variable $\mathbf{1}_{t=0}$ is an indicator of when the sooner payment date, t, is immediate. The parameter δ is the daily discount factor.

To account for stochasticity in choice, we modelled the decisions as susceptible to an error $\varepsilon \sim (0, \sigma^2)$. We assumed that participants chose the risky (or sooner) option when $EU_a - EU_b + \varepsilon > 0$, where EU_a and EU_b denote the expected utilities of the risky and safe options respectively for risk preferences questions, and denote the expected utilities of the sooner and later options respectively for time preferences questions. We related this latent index to observed choice by a logistic function. The probability of choosing the risky/soon option can then be expressed as:

$$\Pr\left(\frac{ChoseRisky}{ChoseSoon}\right) = \frac{1}{1 + \exp\left(-\left(\frac{EU_a - EU_b}{\sigma}\right)\right)}$$

In all the analysis, we clustered standard errors on the level of participant.

Table C1 shows the estimated values for the three parameters using the choices made at baseline. Similar to our findings using the simple counts, on average, our participants were slightly impatient, future biased and risk averse.

Table C1. Preliminary results. Maximum likelihood estimates of utility curvature, present bias and discount factor using the choices at baseline.

δ	0.9811***
	(0.0024)
β	1.0076***
	(0.0132)
α	0.6563***
	(0.0296)
σ	1.6388***
	(0.1725)
N	12300

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

To investigate the relationship between economic preferences and weight loss, we replaced the parameters of the utility function as follows:

$$\alpha = \alpha_0 + \alpha_1 \times weightloss + \sum_i \alpha_i \times Z_i$$
$$\beta = \beta_0 + \beta_1 \times weightloss + \sum_i \beta_i \times Z_i$$
$$\delta = \delta_0 + \delta_1 \times weightloss + \sum_i \delta_i \times Z_i$$

where Z_i is a set of control variables and $weightloss$ is an indicator variable of whether the participant has a decrease in body fat between 12 months and baseline (=1) or not (=0). To replicate our results, we also use the decrease in body fat between 6 months and baseline for $weightloss$, as well as the decrease in BMI between 12 months/6 months and baseline for $weightloss$. Tables C2 and C3 present the results which are in line with those presented in the main body of the paper.

Table C2. The relationship between economic preferences and body fat loss. Maximum likelihood estimates of discount factor, present bias and utility curvature using choices made at baseline. body fat loss equals to 1 if body fat at 12 months is smaller than that at baseline; age is age in years; female is and indicator variable for female participants.

	(1) 12 months vs. baseline	(2) 6 months vs. baseline
δ		
body fat loss	0.0014	-0.0013
	(0.0049)	(0.0047)
age	0.0023	0.0027
	(0.0020)	(0.0020)
age^2	-0.0000	-0.0000
	(0.0000)	(0.0000)
female	0.0024	0.0022
	(0.0049)	(0.0048)
constant	0.9089***	0.9036***
	(0.0540)	(0.0534)
β		
body fat loss	-0.0260	-0.0142
	(0.0293)	(0.0306)
age	-0.0224	-0.0216
	(0.0199)	(0.0198)
age^2	0.0002	0.0002
	(0.0002)	(0.0002)
female	0.0188	0.0174
	(0.0253)	(0.0255)
constant	1.5705***	1.5346***
	(0.5565)	(0.5547)
α		
body fat loss	-0.0564	-0.0380
	(0.0360)	(0.0387)
age	-0.0229	-0.0262*
	(0.0156)	(0.0152)
age^2	0.0002	0.0002
	(0.0002)	(0.0001)
female	-0.0136	-0.0235
	(0.0378)	(0.0381)
constant	1.3637***	1.4386***
	(0.3901)	(0.3822)
σ		
constant	1.5895***	1.6356***
	(0.1666)	(0.1720)
N	11760	12060

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table C3. The relationship between economic preferences and BMI loss. Maximum likelihood estimates of discount factor, present bias and utility curvature using choices made at baseline. BMI loss equals to 1 if BMI at 12 months is smaller than that at baseline; age is age in years; female is and indicator variable for female participants.

	(1) 12 months vs. baseline	(2) 6 months vs. baseline
δ		
BMI loss	0.0111*	0.0057
	(0.0064)	(0.0083)
age	0.0022	0.0018
	(0.0021)	(0.0021)
age^2	-0.0000	-0.0000
	(0.0000)	(0.0000)
female	0.0036	0.0031
	(0.0049)	(0.0049)
constant	0.9062***	0.9190***
	(0.0551)	(0.0569)
β		
BMI loss	-0.0923*	-0.1382*
	(0.0553)	(0.0723)
age	-0.0195	-0.0153
	(0.0181)	(0.0172)
age^2	0.0002	0.0002
	(0.0002)	(0.0002)
female	0.0143	0.0143
	(0.0240)	(0.0241)
constant	1.5345***	1.4692***
	(0.5077)	(0.4817)
α		
BMI loss	0.0283	0.0830
	(0.0460)	(0.0521)
age	-0.0173	-0.0154
	(0.0161)	(0.0171)
age^2	0.0001	0.0001
	(0.0002)	(0.0002)
female	-0.0307	-0.0300
	(0.0379)	(0.0376)
constant	1.1808***	1.0835**
	(0.4091)	(0.4457)
σ		
constant	1.6313***	1.6275***
	(0.1709)	(0.1714)
N	12300	12300

Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01