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DISCUSSION PAPER SERIES

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Chiara Pastore
University of York

Stefanie Schurer
University of Sydney and IZA

Agnieszka Tymula
University of Sydney

Nicholas Fuller
University of Sydney

Ian Caterson
University of Sydney

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Economic Preferences and Obesity: Evidence from a Clinical Lab-in-Field Experiment*

We study economic decision-making of 284 people with obesity and pre-diabetes who participated in a 6-months randomised controlled trial to control weight and prevent diabetes. To elicit preferences, we use incentive-compatible experimental tasks that participants completed during their medical screening examination. We find that, on average, participants are risk averse, show no evidence of present bias, and have impatience levels comparable to healthy samples described in the international literature. Variations in present bias and impatience are not significantly associated with variations in markers of obesity. But we find a significant negative association between risk tolerance and BMI and other markers of obesity for women. A 1 standard deviation increase in risk tolerance is associated with a 0.2 standard deviation drop in BMI and waist circumference. Impatience moderates the link between risk tolerance and obesity. We replicate the key finding of interaction effects between risk and time preferences using survey data from a nationally representative sample of 6,281 Australians with similar characteristics. Deviating markedly from the literature, we conclude that risk tolerance brings benefits for health outcomes if combined with patience in this understudied but highly policy-relevant population.

JEL Classification: C9, D9, D81, I12

Keywords: impatience, risk tolerance, obesity, incentive-compatible economic experiment, lab-in-field experiment

Corresponding author:
Stefanie Schurer
School of Economics
University of Sydney
Sydney, NSW, 2006
Australia

E-mail: stefanie.schurer@sydney.edu.au

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1 Introduction

Obesity, defined as excessive fat accumulation that increases risk in health (Purnell, 2020), is considered to be one of the greatest public health challenges in the 21st century. Considering current trends, obesity will affect 20% of the global population by 2026 (NCD Risk Factor Collaboration, 2016). It is considered to be one of the main drivers in the risk of non-communicable disease, such as type 2 diabetes, hypertension, cardiovascular disease, and several cancers (Haslam and James, 2005). Obesity is also associated with loss in productivity (Cawley, 2015). As resources need to be diverted within the health care system towards treating its medical consequences (Cawley and Meyerhoefer, 2012), obesity produces significant social costs.

Unlike other health conditions, obesity is in principle preventable. While heritability plays a significant role in determining an individual's adiposity, genetics alone cannot account for the rapid increase in obesity rates of the last forty years (Albuquerque et al., 2017). Weight accumulates if there is an imbalance between calorie intake and expenditure. Such imbalance can be reversed through behavioral changes, such as dietary improvements and an increase in physical activity (Hill et al., 2012). Yet, behavioral sciences have demonstrated that it is exceptionally difficult to change lifestyle behaviors and therefore to break unsustainable weight trajectories (Cawley and Ruhm, 2011; Teixeira et al., 2015). It is thus imperative to gain a more solid understanding of the determinants of decision-making among individuals at risk of obesity.

In this paper, we focus on the behavioural foundations of obesity. We ask whether the core elements of economic decision theory are risk factors of obesity or its severity. A common intuition based on economic theory is that willingness to take risk, impatience, and self-control problems – which is referred to in the literature as present bias (Thaler and Sunstein, 2008) – increase the likelihood of engaging in risky health behaviors, including over-eating and under-exercising (e.g. Hunter et al., 2018). Empirical tests of this hypothesis are ample. The literature, which we will review in Section 2 generally supports the notion of some link between preferences and obesity. With a small number of exceptions however, most of the previous work relies on a research design based on attitudinal surveys, where people are asked to self-report their economic preferences and their Body Mass Index (BMI), a widely used marker of obesity. This is problematic as systematic reporting errors are likely to lead to estimation biases.

To improve upon the previous literature, we conducted a lab-in-field experiment measuring economic preferences and obesity in a large, clinical population. The experiment was conducted as a sub-study of a six-months randomised controlled trial, which tested for the efficacy of alpha-cyclodextrin and hydrolysed ginseng aid in cholesterol and glycemic control in people with obesity and pre-diabetes. Post treatment, the participants were followed for another six months. The trial was conducted between July 2015 and October 2018 at the Royal Prince Alfred and Nepean Hospitals, both located in Sydney, Australia. To be eligible, participants had to be ≥ 18 years, provide evidence of pre-diabetes within six months of study entry and have a body mass index (BMI) ≥ 25 kg/m^2. The trial protocol and first results are published in Bessell et al. (2019) and Bessell et al. (2020).

At the baseline visit, participants made a set of incentive-compatible decisions designed to elicit their risk and time (patience and present bias) preferences based on standard experimental economics methodology (e.g. Hey and Orme, 1994; Holt and Laury, 2002; Andersen et al., 2008). Completing the decision task in about 20 minutes, subjects received incentive payments of $30 on average. This pay out is equivalent to 4.5 times the minimum hourly wage,[1] and twice the 2017 average national hourly wage for full-time workers ($40) (Australian Bureau of Statistics, 2017), making the financial incentives in this experiment strong. We linked these data with information on human capital obtained through a survey, and with data on body fat clinically recorded by trained health care professionals. For the analysis, we use measures of BMI, waist circumference and dual-energy x-ray absorptiometry (DEXA). Variety in measurement is important because BMI often misclassifies lean but muscular participants as overweight although they are quite healthy individuals (Purnell, 2020).

Our findings are multifold. The sample is characterized by older (mean age 55) but

[1]The Australian minimum wage was $19.48 per hour in 2017. The average payout in the experiment is equivalent to $90 per hour. See Fair Works Commission on minimum wages, `https://www.fairwork.gov.au/pay/minimum-wages`.

highly educated (51 percent with tertiary education) participants with an average BMI of 34.5 (range 25.24 to 55.5). Three quarters (74%) of the sample are having obesity (BMI ≥ 30) and one in six have BMI ≥ 40.[2] With mean waist circumference of 110 cm (range 86-150 cm) and mean body fat of 42 percent (range 24-58 percent), every individual in our sample has obesity. The participants in the sample exhibit economic preferences that can be characterized on average as risk averse and patient. There is no evidence that the participants exhibit self-control issues (present bias).

Importantly, variation in impatience and present bias is not significantly associated with variation in BMI or other markers of obesity. Yet, we find a statistically significant negative association between risk tolerance and markers of obesity for women. For instance, a 1 standard deviation increase in risk tolerance is associated with a 0.2 standard deviation reduction in BMI or waist circumference. The association between risk tolerance and BMI is positively moderated by impatience. The moderating effect of impatience is not specific to our trial population or driven by sample size. Analysing data on a comparable sample of 6,821 individuals which we sourced from a nationally-representative survey[3], we find similar risk tolerance-impatience gradients in BMI.

Our findings are novel. Comparable studies using lab-in-field experiments to test the link between preferences and obesity usually find a positive association between risk tolerance and BMI (de Oliveira et al., 2016; Sutter et al., 2013; Anderson and Mellor, 2008) and some find a positive association between impatience and BMI (Sutter et al., 2013). de Oliveira et al. (2016) find that risk tolerance increases BMI for patient individuals, while we find the opposite.

One explanation for the deviation of our findings from other studies is that we collect economic preferences from an at-risk clinical population that cares about the future. Our participants are not recruited for the purpose of studying economic decision making per se, but to control weight and prevent type 2 diabetes. This assures that our partici-

[2]People with BMI of 40 or above is referred to in the literature as having extreme obesity, which is a serious health condition that results from an abnormally high body mass index. A person having extreme obesity may have difficulty performing daily functions, such as walking and breathing, and is at increased risk for many serious health problems (Purnell, 2020).

[3]We used data from the Household, Income and Labour Dynamics in Australia (HILDA) survey (Summerfield et al., 2017).

pants are not self-selected in terms of interest in making money but to address future health problems. Furthermore, unlike the study participants in de Oliveira et al. (2016), our sample comprises a highly educated population. This is further evidence that the participants in our study have had the ability in the past to make investments in their human capital that pay off in the future. We conclude that these relatively high levels of patience bring health benefits when combined with an ability to tolerate risk, a truly novel finding.

The remainder of the manuscript is as follows. We present a theoretical framework and review the existing literature in Section 2. We present details about data collection in our study in Section 3. A detailed description of our sample is presented in Section 4. The main results are presented in Section 5. We discuss our findings and their economic implications in Section 6. An appendix provides supplementary material.

2 Literature review

2.1 Theoretical framework

Economic theory presumes that people make decisions by considering trade-offs between the existing options and then pick whatever maximizes their utility. In the context of weight management, the trade-offs crucially involve an intertemporal aspect in which immediate costs (e.g. exercising, foregoing a high-calorie cake) are traded off against future gains (healthy body). Given that maintaining a healthy weight requires sacrifices in the present and brings benefits in the future, economic theory trivially predicts that more impatient people, usually modelled as "exponential discounters" (Samuelson, 1937), will achieve a less healthy body mass index (BMI) in the long-run (Philipson and Posner, 2003; Komlos et al., 2004).

The major challenge in economics models for years has been to capture a different type of behaviour – why people have every intention to make healthy choices but fail to do so. In this aspect, the major contributions of behavioural economics are the cornerstone models of inconsistent time preferences that can capture why people fail to fulfil their intentions. By relaxing the assumption of stationary preferences (Frederick et al., 2002; Kable, 2013), these models are better equipped to predict socially-costly behaviours including obesity, insufficient savings, and school dropouts. In the "quasi-hyperbolic discounting model", people are modelled to have a "present bias" towards current consumption by devaluing all outcomes in the future in addition to standard exponential discounting of future rewards (Laibson, 1997). This present bias is sometimes referred to in the literature as lack of self-control (Thaler and Sunstein, 2008).

In the so-called "hyperbolic discounting model", the rate at which people discount is assumed to decrease as time progresses (Strotz, 1955; Ainslie, 1975; Mazur, 1987; Loewenstein and Prelec, 1992). These models offer additional insights into human behaviour because they can capture the phenomenon of people making plans which they will never fulfil. In the context of obesity, this model would explain postponement of the adoption of healthy lifestyles into the future, e.g. "next week". When the next week arrives, a hyperbolic discounter would succumb to temptation (e.g. eating unhealthy food, skipping the gym) while still planning to start a healthy lifestyle the "next week".

Empirical literature still needs to establish if and to what degree time-inconsistent preferences are responsible for unhealthy weight. Early literature that aimed at estimating time inconsistency often suffered from inadequate designs that could lead to behaviours that look like present bias but are not a true present bias (for example by having unequal forms of payments at different dates). More recent studies that take care of such issues surprisingly do not find present bias for monetary rewards in student samples (Andersen et al., 2014; Andreoni et al., 2015; Andreoni and Sprenger, 2012a), challenging the usefulness of the present bias concept. However, Augenblick et al. (2015) suggest that the null results of these studies can be due to the nature of monetary rewards, as they find substantial present bias for effort but not for money. Finding present bias for monetary rewards in a sample of disadvantaged Chinese adolescents, Cheung (2020) suggest that the lack of the present bias in some of the existing studies may be due to a WEIRD (White, Educated, Industrialized, Rich, and Democratic) subject pools. Our study adds to the literature by quantifying present bias in obesity, an outcome used in behavioural economic theory as a flagship example for illustrating the time-inconsistent preference models.

Although impatience is the key preference parameter discussed in the literature to shape health behaviours, some discuss also willingness to take risks as another important preference parameter that shapes decision-making. Risk-taking is associated with a preference for uncertain outcomes, for instance, when playing the lottery. While it is often assumed in the health literature that willingness to take more risks leads to poorer health outcomes, theoretically, this association in the context of obesity is less clear. More risk-tolerant individuals should indeed be more willing to engage in activities that may result in an increase in weight and therefore in the risk of obesity. Overeating, unhealthy eating and sedentary lifestyles could be understood as risk-taking behaviour as they increase the likelihood of chronic illness in the future. Examples of playing with your own health as if it was a lottery are binge consumption of alcohol or other sugar-dense products. However, it is also possible that higher levels of risk tolerance promote participation in inherently risky physical activities that help maintain a healthy weight. Examples are competitive sports, mountaineering or sailing.

2.2 Empirical evidence

Searching the empirical literature with a focus on "economic preferences" and "obesity" yielded 36 published articles since 2004.[4] A summary is presented in Table S.5 (Supplement). Only eight out of the 36 articles analyzed both risk and time preferences, while 26 out of 36 studies investigated the role of time preferences only,[5] and two explored the role of risk aversion alone. More than half of the studies used US data, and only one study used Australian survey data. Most studies used self-reported BMI as a marker of obesity and elicited time and/or risk preferences through hypothetical choices in the financial domain. While it has been shown that people tolerate different levels of risk in hypothetical and consequential decisions (Holt and Laury, 2002), only eight out of 21

[4] Search last updated in December 2018 on Web of Science [v.5.31].

[5] Studying the influence of time preferences on health outcomes without controlling for risk preference will lead to an upward bias. It is therefor important to correct for the curvature of the utility function (Andersen et al., 2008), which is described by an individual's ability to tolerate risk.

experimental studies used actual, as opposed to hypothetical, rewards.

Findings from this literature are mixed. Seven out of the 34 studies surveying time preferences find no significant association with obesity, while three out of ten studies found no association between risk tolerance and obesity. Studies finding a significant association of preferences and obesity indicate that more impatient individuals have higher BMI or propensity for behaviors that lead to obesity, while more risk-averse individuals are less obese on average. Several studies focus on one gender only (Davis et al., 2010; Epstein et al., 2014; Jiang and Hong, 2016; Thamotharan et al., 2016), while others find that the associations are gender-specific (Koritzky et al., 2012; Galizzi and Miraldo, 2017).

Among the 36 studies surveyed, the most relevant ones to the present analysis in terms of methodology and hypotheses are Anderson and Mellor (2008), Chabris et al. (2008), de Oliveira et al. (2016), Richards and Hamilton (2012), and Sutter et al. (2013). Of these, only de Oliveira et al. (2016) and a subsample of Chabris et al. (2008) measured BMI in the laboratory, as opposed to self-reports. Anderson and Mellor (2008) collected preference and BMI data on 1,047 adults and students from the state of Virginia, US. They find that risk-averse individuals are less likely to be obese. Such findings were replicated in other lab-in-field experiments of Sutter et al. (2013); de Oliveira et al. (2016). Sutter et al. (2013) collected preference and BMI data on children and adolescents aged 10-18 in Austrian schools (N=661) and linked these to field behaviour. de Oliveira et al. (2016) collected preference and BMI data on very heavy and poor African Americans (N=169). Both studies find that more risk-averse individuals have lower BMI. Sutter et al. (2013) furthermore show that highly impatient children display higher BMI. This finding is similar to studies on adults (Chabris et al., 2008; Richards and Hamilton, 2012). The magnitude of the effect varies, although authors argued it is at least as large as that of other important demographics (Chabris et al., 2008; Sutter et al., 2013). For instance, a one standard deviation increase in risk aversion is associated with an 8.9% decline in the probability of being overweight or obese for American adults (Anderson and Mellor, 2008), but only to a decline of 0.014 BMI points in Austrian children (Sutter et al., 2013).

de Oliveira et al. (2016) is the only study to test for interaction effects between impatience and risk tolerance. Arguably, the most important finding of this study is that the negative association between risk aversion and obesity is stronger for very patient participants than for impatient ones. In plain words, this means that BMI is more sensitive to changes in risk attitudes for patient individuals. The rationale for exploring interaction effects is that the individual's assessment of future costs and benefits is influenced by the common perception that the future is more uncertain than the present, so both time and risk preferences are at play. A recent review of the literature on time preferences based on multi-country data confirms that individuals with higher 'uncertainty avoidance' discount the future more heavily (Wang et al., 2016). Interaction effects between preferences thus receive special attention in our analysis.

We contribute to the extant literature in three important ways. First, we study economic decision-making of a high-risk adult clinical population. Such a population has never been studied before. Second, our findings produce insights about the heterogeneity in economic decision-making and its link to health outcomes from a more advantaged population than for example in de Oliveira et al. (2016) but a population that is nevertheless at immediate risk of developing chronic disease. This is important because these are the individuals targeted by public policies aimed at reducing obesity before it triggers complications that are more damaging for the individual and costlier to treat. Furthermore, our participants are highly-educated individuals, for whom preferences, rather than financial or availability constraints, are likely to determine dietary choices and physical activity. Finally, high quality experimental and clinical data and a relatively large sample allow us to explore both gender differences in the link between obesity and preferences and the potential interaction effects between risk and impatience.

3 Data description

3.1 Population

The data was collected as a part of a randomized controlled trial carried out by The Boden Collaboration for Obesity, Nutrition, Exercise & Eating Disorders at Royal Prince

Alfred and Nepean Hospitals, Australia. The primary purpose of the trial was to examine the efficacy of α-cyclodextrin on cholesterol control, and the efficacy of hydrolized ginseng on glycemic control. Participants are eligible for inclusion in the trial if they are aged $\geq$ 18 years, have a body mass index $\geq$ 25 kg/m^2 and have pre-diabetes (determined by blood test results at the screening visit or within 6 months prior to the screening visit), as defined by the American Diabetes Association (ADA) guidelines.

Participants were recruited from existing clinical trials database at the Boden Institute and from advertising on the Sydney Local Health District intranet, the University of Sydney website, the SFI Research Study website, the Australian Clinical Trials website, and in the media. In total, 295 individuals participated in our sub-study on economic preferences. Further information on inclusion and exclusion criteria is provided in the Supplement (see S4) and in the study protocol (Bessell et al., 2019).[6] The Human Research Ethics Committees at Sydney Local Health District and the University of Sydney approved this trial and it is registered with the Australian New Zealand Clinical Trials Registry (ACTRN12614001302640). Additionally, all participants provided written consent.

Participants are followed over twelve months. They are randomly assigned to one of four weight-loss interventions during the first six months, and then followed up for the next six months. The present paper is exclusively concerned with baseline data collected prior to the interventions.

3.2 Health outcomes

Weight, height, waist circumference, and body fat were measured and recorded by trained health care professionals. Clinical measurement guarantees accuracy and consistency across individuals. BMI can be readily calculated from recorded weight and height (kg/m^2). Although this has been the most commonly used measure of obesity in behavioural economics literature, BMI is an imperfect measure. It can classify very muscular individuals as overweight when they are healthy, and individuals with low muscle mass

[6] The randomised controlled trial started in July 2015 and was completed in October 2018.

as normal weight, when their fat percentage exceeds the healthy range (Purnell, 2020). Body fat was measured as a percentage of total body composition by a dual-energy X-ray absorptiometry (DXA) scan. DXA body fat gives an accurate representation of the unhealthiness of body composition. Waist circumference (in cm) is a good indicator of visceral fat, an accurate predictor of obesity-related diseases (National Heart Lung and Blood Institute, 1998). Healthy ranges of body fat and waist circumference differ for men and women (see Appendix Table S.1), and this is accounted for in the analysis.

3.3 Economic preferences

Participants made 60 decisions designed to measure individual risk and time (impatience and present bias) preferences as well as violations of first-order stochastic dominance (FOSD) using tablet devices provided to participants at the hospitals. Before starting the task, participants read the instructions and completed comprehension questions with feedback (see Section S5, Supplement). Each decision scenario was presented on a separate choice screen and participants were not allowed to skip questions.

To elicit their risk preferences, participants were asked to make 30 binary choices between a sure amount of \$10 and a risky lottery. The lottery paid either \$0 or a positive amount $\$x \in \{10, 16, 22, 28, 34, 41, 47, 53, 61, 69\}$ that would be received with varying probability $p \in \{0.25, 0.5, 0.75\}$. Each of the ten amounts was matched with each of the three probability levels for a total of 30 decision scenarios. Table 1 captures the order in which risky decision scenarios were presented. Questions 1, 11, and 21 served as a rationality check since the safe option first-order stochastically dominates the risky one.

After participants finished the risky-choice task, they moved to a task that measured their time preferences. Participants were asked to choose between a smaller, sooner (SS) reward of \$34 in t weeks, and a larger, later (LL) reward of $\$x$ in $t + 8$ weeks, with $t \in \{0, 4, 21\}$ and $x \in \{35, 37, 39, 41, 43, 45, 47, 49, 51, 53\}$. The values of t represent three different front-end delays, while the interval between the sooner and later choice is constant (8 weeks). Table 2 lists the decision scenarios in the order of their presentation. For all values of t, we expect individuals to choose LL rewards as the reward increases.

Table 1: Risk preference task

	p=0.25				**p=0.5**				**p=0.75**		
No.	Safe	Risky		No.	Safe	Risky		No.	Safe	Risky	
		p	$x			p	$x			p	$x
1	$10 for sure	0.25	$10	11	$10 for sure	0.5	$10	21	$10 for sure	0.75	$10
2	$10 for sure	0.25	$16	12	$10 for sure	0.5	$16	22	$10 for sure	0.75	$16
3	$10 for sure	0.25	$22	13	$10 for sure	0.5	$22	23	$10 for sure	0.75	$22
4	$10 for sure	0.25	$28	14	$10 for sure	0.5	$28	24	$10 for sure	0.75	$28
5	$10 for sure	0.25	$34	15	$10 for sure	0.5	$34	25	$10 for sure	0.75	$34
6	$10 for sure	0.25	$41	16	$10 for sure	0.5	$41	26	$10 for sure	0.75	$41
7	$10 for sure	0.25	$47	17	$10 for sure	0.5	$47	27	$10 for sure	0.75	$47
8	$10 for sure	0.25	$53	18	$10 for sure	0.5	$53	28	$10 for sure	0.75	$53
9	$10 for sure	0.25	$61	19	$10 for sure	0.5	$61	29	$10 for sure	0.75	$61
10	$10 for sure	0.25	$69	20	$10 for sure	0.5	$69	30	$10 for sure	0.75	$69

More impatient individuals will require a larger LL reward to wait an additional eight weeks to receive a payment. We can, therefore, quantify how impatient each individual is by calculating the number of SS choices.

The use of three front-end delays with a fixed delay between sooner and later options allows us to test for the inconsistency of time preferences as the front-end delay increases. Under the exponential discounting model, we would predict individuals to switch from SS to LL rewards for the same monetary equivalent of the LL reward, independent of the front-end delay. Under the quasi-hyperbolic discounting model, we would predict a spike in the number of impatient choices when the SS option is available right now, and a smaller number of impatient choices when the SS payment is in the future. Such a feature of behaviour is called present bias. Under the hyperbolic discounting model, we would expect individuals to become more impatient the more the front-end delay is pushed into the future. Both quasi-hyperbolic and hyperbolic discounting models can capture behaviours leading to obesity, such as postponing exercise and healthy diets into the future. Our data allows us to classify participants into each of the three discount model categories and quantify the degree of present bias and time inconsistency in their choices.

Table 2: Time preference task

	t=0			**t=4**			**t=21**	
No	Smaller, sooner	Larger, later	No	Smaller, sooner	Larger, later	No	Smaller, sooner	Larger, later
31	$34 now	$35 in 8 weeks	41	$34 in 4 weeks	$35 in 12 weeks	51	$34 in 21 weeks	$35 in 29 weeks
32	$34 now	$37 in 8 weeks	42	$34 in 4 weeks	$37 in 12 weeks	52	$34 in 21 weeks	$37 in 29 weeks
33	$34 now	$39 in 8 weeks	43	$34 in 4 weeks	$39 in 12 weeks	53	$34 in 21 weeks	$39 in 29 weeks
34	$34 now	$41 in 8 weeks	44	$34 in 4 weeks	$41 in 12 weeks	54	$34 in 21 weeks	$41 in 29 weeks
35	$34 now	$43 in 8 weeks	45	$34 in 4 weeks	$43 in 12 weeks	55	$34 in 21 weeks	$43 in 29 weeks
36	$34 now	$45 in 8 weeks	46	$34 in 4 weeks	$45 in 12 weeks	56	$34 in 21 weeks	$45 in 29 weeks
37	$34 now	$47 in 8 weeks	47	$34 in 4 weeks	$47 in 12 weeks	57	$34 in 21 weeks	$47 in 29 weeks
38	$34 now	$49 in 8 weeks	48	$34 in 4 weeks	$49 in 12 weeks	58	$34 in 21 weeks	$49 in 29 weeks
39	$34 now	$51 in 8 weeks	49	$34 in 4 weeks	$51 in 12 weeks	59	$34 in 21 weeks	$51 in 29 weeks
40	$34 now	$53 in 8 weeks	50	$34 in 4 weeks	$53 in 12 weeks	60	$34 in 21 weeks	$53 in 29 weeks

To preserve incentive compatibility, we paid participants the reward of one decision scenario picked at random. The participant received the reward corresponding to their choice in that scenario. The average payment in the experiment was \$30. As the economic choice task took about 20 minutes to complete, this implies an hourly wage of \$90/*hour*. This pay out is equivalent to 4.5 times the national minimum hourly wage in 2017[7] and twice the 2017 average national hourly wage for full-time workers (\$40) (Australian Bureau of Statistics, 2017), making the financial incentives in this experiment strong. Payments were made via bank transfers into participants' bank accounts on the day when payment was promised.

For the main analysis, we construct proxies for risk preferences, time preferences, and irrationality from counting the number of risky, smaller and sooner (SS), and what could be considered irrational choices that participants make, respectively. Time preferences will be captured in two indices. The measure of *impatience* is defined as the number of SS choices at the 4-week and 21-week front end delay. The measure of *present bias* is defined as the difference between the number of SS choices when there is no front-end delay (0-week) and the number of SS with the 4-week front-end delay. Individuals who are more risk-tolerant, impatient, and irrational will score higher numbers. Individuals who have present bias will have a large value on the present bias index.

3.4 Control variables

Age, gender, and human capital are included as control variables since they have all been demonstrated to predict economic preferences (Falk et al., 2018) and the health outcomes considered. Human capital measures, education and personality traits, are collected through a survey administered to participants after they completed the economic decision task. We distinguish between three levels of highest education achieved (Tertiary education, some post-secondary education, and completing high school or less). Educational attainment has been associated with higher risk tolerance and lower levels

[7]The Australian minimum wage is currently set at \$19.48. The average payout is therefore \$90 per hour (see Fair Works Commission on minimum wages, `https://www.fairwork.gov.au/pay/minimum-wages`.

of impatience (Golsteyn et al., 2014), and often with lower risk of having obesity (Cohen, 2013). We also control for personality traits, as these have been shown to be complementary to economic preferences in predicting behaviour (Becker et al., 2012) and are linked to health behaviours (Cobb-Clark et al., 2014). Participants completed 13 self-report items designed to elicit measures of two Five-Factor Model (FFM) personality traits: conscientiousness and openness to experience. Conscientiousness, defined as the degree to which a person is willing to comply with conventional rules, norms, and standards (Borghans et al., 2009), has been linked to higher patience (Daly et al., 2009). Openness is highly correlated with crystallised intelligence and cognition, which have been shown to affect decision behaviour in experimental tasks (Almlund et al., 2011; Goff and Ackerman, 1992; Duckworth and Quinn, 2009). Grit, a measure of perseverance and passion for long-term goals, measured using the self-reported Short Grit Scale (Grit-S), has been associated with higher levels of physical activity.

4 Sample characteristics

A total of 295 individuals participated in our sub-study. Accounting for missings in baseline health outcomes (N=6) and demographic variables (N=5), we have a sample of 284 study participants for the analysis.[8] Summary statistics are reported in Table S.2 (Supplement). Our participants are adults with an average age of 55 years (range 24-74 years) and two-thirds are female. Notably, the sample is highly educated, with over half of the participants (52%) having completed a University degree (49% women, 57% men). The high level of human capital in our clinical population distinguishes our study from the high-weight samples of the previous literature (de Oliveira et al., 2016; Best et al., 2012; Takada et al., 2011).

[8] For 14 more participants we have no information on body fat, leaving a sample of 270 for the analysis with body fat as outcome variable.

4.1 Obesity

The average BMI in the sample is 34.54. Three in four participants are having obesity (BMI ≥ 30), while the remaining quarter are overweight ($30 > BMI \geq 25$). Almost one in six has extreme obesity (Purnell, 2020).[9] The full distribution of BMI is illustrated in Figure 1a, separately for men (blue) and women (pink). The dashed lines depict the gender-specific means, and the solid line the obesity cutoff. The distribution of female BMI is wider than for men, and the heaviest participants in our sample are female.

Figure 1b shows the distribution of body fat (in percent) for both men and women. For both groups, average body fat percentages also sit above the cutoffs for obesity (Purnell, 2020).[10] For men, the average body fat is 34.32% (obesity cutoff: 25%) and for women, it is 46.66% (obesity cutoff: 32%). Figure 1c plots the distribution of waist circumference (in cm). While the obesity cutoffs are 80 cm (women) and 92 cm (men), the averages for women and men are 107 cm and 114 cm, respectively. Almost no one in the sample scores below the obesity cutoffs.

In Figure 2, we overlay the BMI distributions of our experimental sample and of a nationally-representative sample sourced from the Household, Income, and Labour Dynamics in Australia (HILDA) survey.[11] The BMI distribution of our experimental sample lies in the right-hand tail of the HILDA sample, which has a mean BMI of 27.

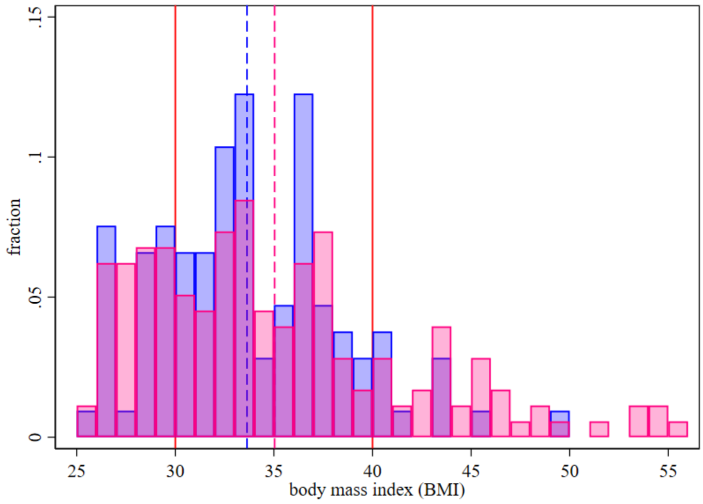
[9] See also WHO guidelines in Akram et al. (2000) and Table S.1 for cut-off values that indicate obesity for BMI, waist circumference, and body fat.

[10] American Council on Exercise guidelines `https://www.acefitness.org/education-and-resources/lifestyle/tools-calculators/percent-body-fat-calculator`.

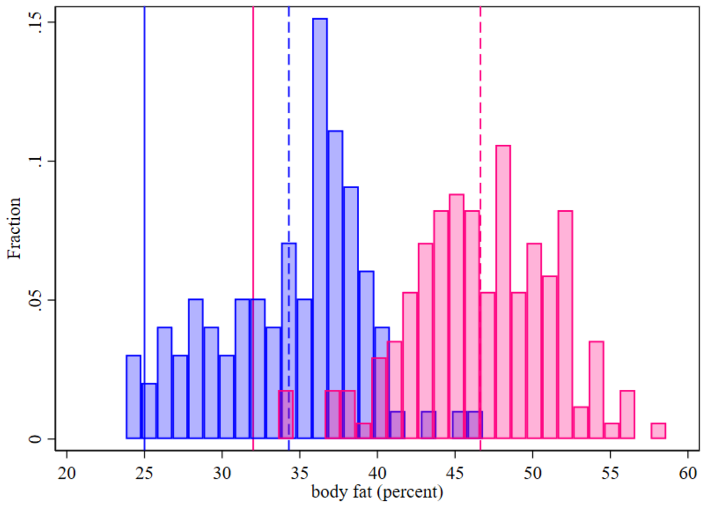
[11] HILDA data is derived from waves 2014 and 2018, when self-assessed weight and height information, and self-assessed risk and impatience information was recorded.

Figure 1: Histogram of obesity measures for men in blue and for women in pink

(a) Body mass index



(b) Body fat percentage



(c) Waist circumference

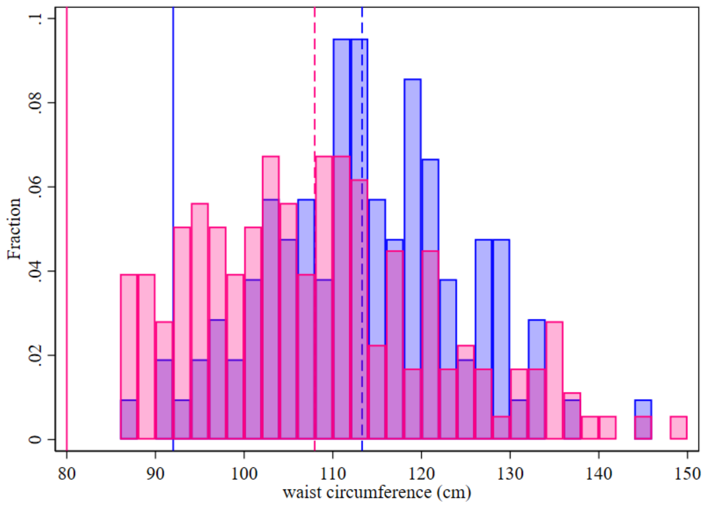
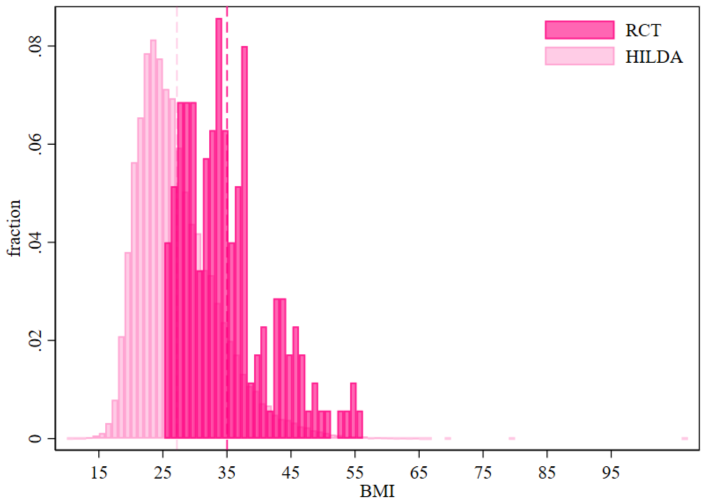
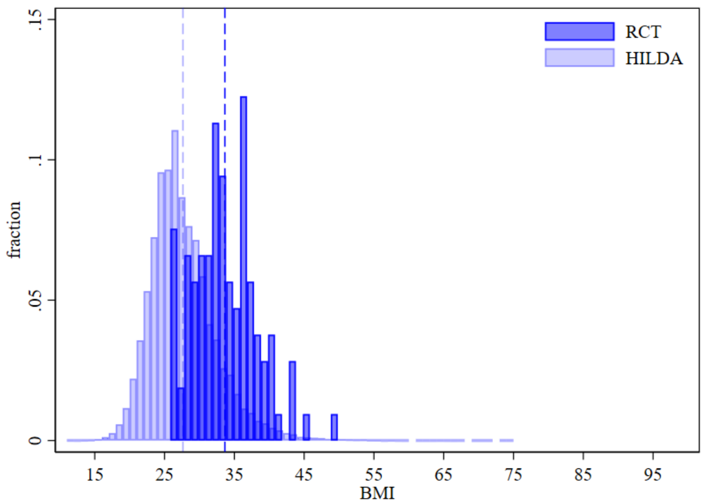


Figure 2: Distribution of BMI in HILDA sample (years 2014 and 2108) versus experimental (RCT) sample (years 2015-2017)

(a) Women



(b) Men



4.2 Economic decision-making

We now describe the distribution of economic preferences in our study sample. Summary statistics are presented in Table 3.

4.2.1 Decision errors

We first explore to what degree our sample members made mistakes according to expected utility theory. Approximately 21% of the sample made a decision error at least once by violating the so-called first-order stochastic dominance (FOSD) condition. This violation occurred when the subject chose the lottery even though its expected payout was lower than the safe payout. This is not an unusual finding. Previous studies with a comparable experimental task and study population found similar proportions of sample members who forgo the opportunity for a better payout at lower risk (Besedeš et al., 2012; Anderson and Mellor, 2008; Tymula et al., 2013). However, the majority of the participants violated FOSD only once (16% of the total sample). There was only a small fraction of participants who violated FOSD twice (4%) or three times (1%). We thus conclude that most participants in the study behaved as predicted by expected utility theory.

Table 3: Descriptive statistics for economic decision making

	Pooled				Women				Men			
	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
Number of risky choices	14.95	7.29	0	30	14.30	7.73	0	30	16.05	6.34	0	27
Nr. risky choices when p=0.25	3.14	2.90	0	10	3.04	3.00	0	10	3.29	2.72	0	10
Nr. risky choices when p=0.5	5.19	2.85	0	10	4.90	2.97	0	10	5.67	2.57	0	9
Nr. risky choices when p=0.75	6.63	2.72	0	10	6.35	2.90	0	10	7.08	2.33	0	10
Number of smaller, sooner choices	15.48	8.80	0	30	15.48	8.73	0	30	15.46	8.91	0	30
Nr. smaller, sooner choices at t=0	5.34	3.27	0	10	5.28	3.27	0	10	5.43	3.28	0	10
Nr. smaller, sooner choices at t=4	5.73	3.31	0	10	5.91	3.26	0	10	5.42	3.38	0	10
Nr. smaller, sooner choices at t=21	4.41	3.25	0	10	4.29	3.21	0	10	4.61	3.31	0	10
FOSD[a] violated	0.21	0.41	0	1	0.25	0.43	0	1	0.14	0.35	0	1
FOSD violated once	0.16	0.37	0	1	0.19	0.39	0	1	0.10	0.30	0	1
FOSD violated twice	0.04	0.20	0	1	0.04	0.21	0	1	0.04	0.19	0	1
FOSD violated 3 times	0.01	0.10	0	1	0.02	0.13	0	1	0.00	0.00	0	0
Number of switches in risk task	2.56	1.46	0	16	2.52	1.72	0	16	2.63	0.87	0	5
Number of switches in time task	2.21	1.22	0	9	2.25	1.27	0	9	2.14	1.12	0	4
>3 switches in risk task	0.10	0.30	0	1	0.12	0.32	0	1	0.07	0.25	0	1
>3 switches in time task	0.05	0.22	0	1	0.06	0.24	0	1	0.03	0.17	0	1
>3 switches in either task	0.13	0.34	0	1	0.15	0.36	0	1	0.09	0.29	0	1
Picked one side only	0.16	0.36	0	1	0.17	0.38	0	1	0.13	0.34	0	1
Observations	284				178				106			

[a] FOSD: First-order stochastic dominance.

Another way to illustrate whether participants made decision errors is to count the number of times participants switched from left to right in each task. Regardless of their impatience or risk tolerance, we would expect participants to switch at most once from left to right for each value of the upfront delay t or lottery probability p. According to expected utility theory, we would expect at most three switches for each task. The switching point in the time (risk) task represents the minimum monetary amount at which the respondent gives up the smaller and sooner (safe) reward for the larger and later (risky) reward. A rational agent would never return to the smaller and sooner (safer) option when presented with the larger and later (riskier) amounts.[12] In our sample, about one in eight participants (13%) switched more often than predicted between the left and the right sides. This implies that the rest of our sample (87%) is rational in this sense.

We also verified that participants choose risky options more often as their expected value increases and choose later and larger rewards more often, the larger the amount associated with the later payment.[13] Overall, our three rationality checks indicate that most of the participants in our study did not make grave decision errors. They behaved rational and similarly to study participants of comparable previous studies, further validating our method to measure economic preferences in this clinical sample.

4.2.2 Risk tolerance

Overall, our sample can be described as risk-averse. The mean number of risky choices (15, or 50%) was lower than the risk-neutral prediction (22). Women were significantly more risk-averse than men ($p < 0.001$), with mean risky choices of 14.3 (48%) and 16.1 (54%) respectively. As expected, the proportion of risky choices increases with the probability of winning in the lottery. Willingness to takes risks, with associated increasing winning probabilities, is higher for men.

[12]Based on this reasoning, switching points have often been used in the literature to infer bounds for preference parameters (Harrison and Rutström, 2008).

[13]These results are available upon request.

4.2.3 Time preferences

On average, participants chose more than half of the time the smaller, but sooner payout (15.5 out of 30 times, or 52%). Men (52%) and women (53%) did not differ in their impatience ($p = 0.283$).

As explained in Section 3, using participants' choices in the time preference task, we can classify them into exponential, quasi-hyperbolic, and hyperbolic discounters. In our task, for exponential discounters, the number of times a smaller and sooner payout is chosen should be independent of the front-end delay, as the time interval between payouts is always eight weeks. Quasi-hyperbolic discounters should make more impatient choices with no front end delay ($t = 0$) than when both payouts are postponed into the future ($t = 4$ and $t = 21$). They should also make the same number of impatient choices when front-end delay is equal to 4 and 21 weeks. Hyperbolic discounters should decrease the number of impatient choices as the front-end delay increases.

Our data suggests that, on average, our sample members are discounting neither exponentially nor quasi-hyperbolically. To some degree, we find evidence for hyperbolic discounting. First, the average number of impatient choices is 5.34 for $t = 0$, 5.73 for $t = 4$, and 4.41 for $t = 21$. A test of equality of these three means is rejected for both the pooled sample ($p < 0.001$), and for men and women separately (both $p < 0.001$). This implies that our participants are not exponential discounters.

Quasi-hyperbolic discounting (and hence present bias) is rejected because the mean number of impatient choices at $t = 0$ (5.34) is significantly smaller than at $t = 4$ (5.73) ($p = 0.010$) and the mean number of impatient choices is significantly smaller with $t = 4$ than with $t = 21$ ($p < 0.001$). While for men the number of impatient choices between front-end delays of $t = 0$ and $t = 4$ did not differ significantly ($p = 0.771$), female participants made most often impatient choices at $t = 4$ which is significantly more often than at $t = 0$ ($p < 0.001$). Both men and women are least impatient at the longest front-end delay of 21 weeks, with an average number of impatient choices of 4.6 and 4.3, respectively. The number of impatient choices at different front-end delays reveals that our data is most is consistent with the predictions of the hyperbolic discounting model.

To further investigate individual heterogeneity in time consistency in our sample, we classified every participant into one of nine possible choice patterns based on the proportion of impatient choices for each of the front-end delays. Table 4 captures the results of this classification exercise. Slightly more than one in four of our participants were most impatient at $t = 4$ (Panel F: 76 out of 284, 26.8%). This behaviour cannot be explained by any of the theories on discounting behaviour. Also slightly more than one in four of the participants made choices consistent with the hyperbolic discounting model (Panel H: 40 out of 284, 14.1% and Panel E: 34 out of 284, 12%). One in five made time-consistent choices as predicted by the exponential discounting model (Panel A: 55 out of 284, 19.4%). Only 6.7% of our participants were quasi-hyperbolic discounters (Panel C: 19 out of 284).

Table 4: Most common patterns of discounting behaviours

Panel	$t = 0$ & $t = 4$	$t = 4$ & $t = 21$	Total	Women	Men	Prop.
A	$SSchoice^{t=0} = SSchoice^{t=4}$	$SSchoice^{t=4} = SSchoice^{t=21}$	55	29	26	0.194
B	$SSchoice^{t=0} < SSchoice^{t=4}$	$SSchoice^{t=4} = SSchoice^{t=21}$	18	11	7	0.063
C	$SSchoice^{t=0} > SSchoice^{t=4}$	$SSchoice^{t=4} = SSchoice^{t=21}$	19	11	8	0.067
D	$SSchoice^{t=0} = SSchoice^{t=4}$	$SSchoice^{t=4} < SSchoice^{t=21}$	8	3	5	0.028
E	$SSchoice^{t=0} = SSchoice^{t=4}$	$SSchoice^{t=4} > SSchoice^{t=21}$	34	23	11	0.120
F	$SSchoice^{t=0} < SSchoice^{t=4}$	$SSchoice^{t=4} > SSchoice^{t=21}$	76	58	18	0.268
G	$SSchoice^{t=0} < SSchoice^{t=4}$	$SSchoice^{t=4} < SSchoice^{t=21}$	13	8	5	0.046
H	$SSchoice^{t=0} > SSchoice^{t=4}$	$SSchoice^{t=4} > SSchoice^{t=21}$	40	23	17	0.141
I	$SSchoice^{t=0} > SSchoice^{t=4}$	$SSchoice^{t=4} < SSchoice^{t=21}$	21	12	9	0.074

Notes: This table reports the proportion of participants in each possible choice pattern with respect to their number of impatient choices for each front-end delays.

4.2.4 Structural estimates of preferences

The count measures used are practical for analysis, but they cannot be easily compared to other studies. We therefore also provide structural estimates of the discounted utility model to be able to compare our sample to samples in the broader literature. Using a joint elicitation procedure (Andersen et al., 2008), we fit participants' choices with a constant relative risk attitude (CRRA) utility function and a hyperbolic discounting function. We chose a CRRA utility function because of its popularity in the literature and hyperbolic rather than quasi-hyperbolic discounting because it is more consistent with the patterns in our data (Table 4). Let's assume that individual utility of receiving reward x at time

t is given by:

$$U(x_t) = \frac{1}{1+kt} x_t^{\alpha} \tag{1}$$

where α is the risk tolerance parameter and k is the impatience parameter. Parameter values $\alpha < 1$, $\alpha = 1$, and $\alpha > 1$ indicate risk-averse, risk-neutral and risk-loving attitudes, respectively. Larger values of k indicate higher levels of impatience. We assign choice probabilities according to Luce (1959) and estimate separate error terms for the risk-preference (μ) and time-preference task (ν). Table 5 presents the estimation results.

Table 5: Non-parametric estimates of risk tolerance and impatience

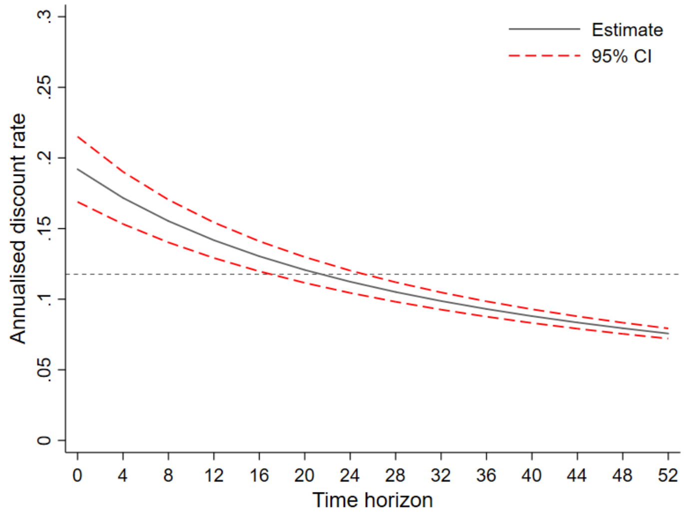
Parameter	**Coef.**	**Adj. S.E.**	**95% C.I.**
α	0.706	0.027	0.652-0.760
k	0.030	0.002	0.026-0.033
μ	0.434	0.021	0.393-0.474
ν	0.086	0.005	0.076-0.096

Notes: Estimates are obtained from a structural equation model of the discounted utility model using a joint elicitation procedure as proposed by Andersen et al. (2008). To fit participants' choices, we use constant relative risk attitude (CRRA) utility function and hyperbolic discounting function. The estimation sample is based on 284 individuals.

With an estimate of $\alpha = 0.706$, our sample is described as risk averse. This is consistent with the findings derived from the count measure analysis. However, the degree of risk aversion is lower than found in previous studies. Using similar elicitation and estimation techniques, Andersen et al. (2008) find $(1-r)\alpha = 0.26$ in a nationally representative sample of Danes. In a different study also based on a nationally representative Danish sample, Andersen et al. (2014) estimate $(1-r) = \alpha = 0.466$. Andreoni et al. (2015) find $(1-r) = \alpha = 0.528$ in a sample of undergraduate students.

The estimated time preference parameter $k = 0.030$ falls largely within the ranges found in the previous literature (Andersen et al., 2008). Chabris et al. (2008) estimate a common hyperbolic discounting parameter of $k = 0.015$ in a sample of individuals whose BMI is (29 ± 7.1). Andersen et al. (2008) estimate a hyperbolic discounting parameter of $k = 0.103$, which is three times as high as in our sample. Our estimated k implies annualised discount rates of 14% for a 3-month horizon (12 weeks), 11% for a 6-month horizon (24 weeks) and 7.5% for a 1-year horizon (52 weeks) (Figure 3). These estimates are largely comparable to the annualised discount rates found in similar experimental literature, although they are somewhat lower than average (Frederick et al., 2002; Andersen et al., 2013).

Figure 3: Annualised discount rates

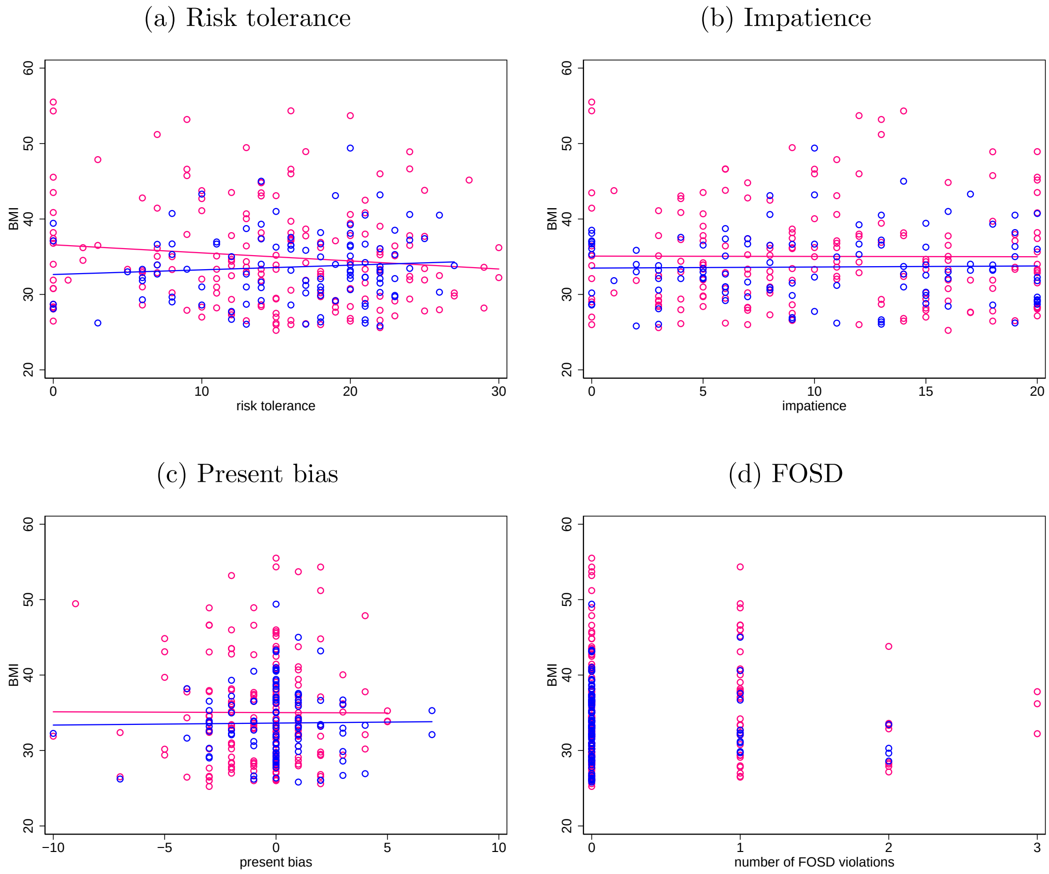


Note: This figure plots the estimates of the annualised discount rate for time horizon t from 0 to 1 year.

5 Economic preferences and obesity

We now turn to the relationship between the degree of obesity and economic preferences. Simple plots of BMI against risk tolerance, impatience, and present bias suggest that, overall, there is no relationship between obesity and economic preferences (Figures 4a, 4b, 4c). However, more risk-tolerant women seem to have a lower BMI. There is no indication that BMI is related to the number of times participants violate first-order stochastic dominance (FOSD) (Figure 4d).

Figure 4: Relationship between BMI and economic preferences



One reason why we do not find broad evidence for a link between economic preferences and obesity severity is that other characteristics, such as age and human capital, drive variation in both obesity and economic preferences, but in opposite directions. We estimate therefore separate regression models using ordinary least squares (OLS) in which we control for these characteristics in addition to whether the participants made decision errors.

The model of risk preferences is:

$$Y_i = \beta_0 + \beta_1 RT_i + FOSD_i' \delta + X_i' \gamma + \epsilon_i, \tag{2}$$

where Y_i is BMI of participant i (or % body fat, waist circumference in cm, or the probability of having extreme obesity), RT_i is the number of risky choices, and $FOSD_i$ is a vector of indicator variables that capture the number of times that an individual violated

FOSD. X_i is a vector of control variables including age, age squared and indicators for the participant's highest level of education (some postsecondary education (e.g. vocational training) or completing high-school or less relative to the base category of university education). We also control for three personality traits – conscientiousness, openness to experience, and grit. Economic preferences and personality traits are standardised to mean 0 and SD 1 for ease of comparison across estimation models.

The model for impatience is:

$$Y_i = \beta_0 + \beta_1 RT_i + \beta_2 I_i + FOSD_i'\delta + X_i'\gamma + \epsilon_i, \tag{3}$$

where I_i is the number of smaller and sooner choices, while controlling for risk tolerance and all other covariates outlined in Eq. 2. In an alternative specification of this model, we replace I_i with a proxy of present bias (PB_i), which measures the difference between the number of impatient choices made with front-end delay $t = 0$ and the number of impatient choices made with front-end delay $t = 4$.

Finally, we allow for interaction effects between risk tolerance and impatience as suggested in de Oliveira et al. (2016):

$$Y_i = \beta_0 + \beta_1 RT_i + \beta_2 I_i + \beta_3 RT_i \times I_i + FOSD_i'\delta + X_i'\gamma + \epsilon_i, \tag{4}$$

where $RT_i \times I_i$ is the interaction term, and β_3 measures whether impatience moderates the effect of risk tolerance on obesity.

Our estimation results for BMI are reported in Table 6. Column (1) reports the estimates without controls, column (2) reports the estimates with controls, and columns (3) and (4) report the estimates with controls for women and men separately. Panel A shows the estimates for risk tolerance, Panel B for impatience, and Panel C for present bias. Full estimation results are reported in Table S.3 (Supplement).

Panel A shows a negative association between risk tolerance and BMI. Although not statistically significant, the association is large in magnitude. A 1 standard deviation (SD) increase in risk tolerance is associated with a reduction in BMI by 0.50-0.56 points.

Interestingly, in the female sample, the association between risk tolerance and BMI is stronger and significant (p<0.05). A 1 SD increase in risk tolerance is associated with a 1.25 drop in BMI. For the male sample, the coefficient has a positive sign, implying an increase in BMI of 0.49 points for 1 SD increase in risk tolerance. Yet the estimate is not statistically significant.

Panel B shows that there is no statistically significant relationship between impatience and BMI, while the relationship between BMI and risk tolerance remains the same as in Panel A. Finally, the association between present bias and BMI (Panel C) is not statistically significant.

Table 6: Relationship between BMI and preferences

	(1) Raw	(2) Controls	(3) Women	(4) Men
Panel A				
Risk tolerance (Std)	-0.496	-0.563	-1.252**	0.487
	(0.390)	(0.399)	(0.567)	(0.441)
Panel B				
Impatience (Std)	-0.022	-0.085	-0.289	0.130
	(0.373)	(0.409)	(0.637)	(0.424)
Risk tolerance (Std)	-0.499	-0.577	-1.310**	0.503
	(0.400)	(0.416)	(0.603)	(0.449)
Panel C				
Present bias (Std)	-0.069	0.012	0.052	-0.115
	(0.381)	(0.364)	(0.530)	(0.415)
Observations	284	280	175	105

Notes: Clustered standard errors are reported in parentheses. Controls (Column 2): Age, education, number of first-order stochastic dominance violations, and personality traits.
Significance level: * $p < .10$, ** $p < 0.05$, *** $p < 0.01$

We repeated the same analysis using waist circumference and body fat as markers of obesity. Table 7 reports estimation results for all three obesity measures, each standardised to mean 0 and standard deviation of 1 to make results comparable across columns. Columns (7) and (8) report the estimation results for the probability of extreme obesity (BMI$\geq$ 40).

We find that for women the results are qualitatively the same independent of the marker of obesity (BMI, waist circumference, and the risk of extreme obesity). The only exception is that there is no significant association for body fat (column (5)). Again, the estimated associations are substantial. A 1 SD increase in risk tolerance is significantly associated with a 0.19 SD reduction in BMI, a 0.19 standard deviation reduction in waist circumference, and reduction in the risk of extreme obesity by 18.4 percentage points (all $p < 0.05$). Relative to the baseline mean of 20.5% extreme obesity in our sample, this implies an 87% reduction.

For men, the estimation results depend on the marker of obesity. For instance, we now find significant positive associations between risk tolerance and waist circumference ($p < 0.10$). A 1 SD increase in risk tolerance is associated with a 0.16 SD increase in waist circumference ($p < 0.10$). The regression results also reveal a statistically significant association between impatience and the risk of extreme obesity ($p < 0.05$). A 1 SD increase in impatience for men is associated with an increase in the risk of extreme obesity by 21.8 percentage points, or 231% relative to the baseline mean (9.4 percent).

Thus, once we consider a broader range of obesity markers (body fat), we find a statistically significant relationship between economic preferences and obesity severity for men that are consistent with economic theory predictions. For instance, more risk tolerant and more impatient men have more excessive body fat.

Table 7: Relationship between obesity and risk tolerance, various outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BMI (Std)		Waist circum. (Std)		Body fat (Std)		Morbid obesity (p.p.)	
	Women	Men	Women	Men	Women	Men	Women	Men
Panel A								
Risk tolerance (Std)	-0.185**	0.105	-0.197**	0.162*	0.027	0.079	-0.184**	0.098
	(0.084)	(0.096)	(0.081)	(0.087)	(0.083)	(0.101)	(0.073)	(0.089)
Panel B								
Impatience (Std)	-0.043	0.028	-0.117	0.028	0.022	0.133	-0.108	0.218**
	(0.094)	(0.092)	(0.091)	(0.093)	(0.101)	(0.104)	(0.086)	(0.091)
Risk tolerance (Std)	-0.193**	0.109	-0.221***	0.165*	0.032	0.093	-0.205***	0.124
	(0.089)	(0.097)	(0.084)	(0.089)	(0.091)	(0.105)	(0.076)	(0.087)
Panel C								
Present bias (Std)	0.008	-0.025	0.022	-0.053	-0.010	-0.084	-0.004	0.007
	(0.078)	(0.090)	(0.077)	(0.101)	(0.078)	(0.078)	(0.075)	(0.053)
Observations	175	105	176	104	167	98	175	105

Notes: All outcome measures are standardised to mean 0 and SD 1 to facilitate comparisons across columns (1)-(6). Morbid obesity is defined as BMI > 40. The base probability for women and men is 0.21 and 0.09 respectively. All models control for age, education, Age, education, number of first-order stochastic dominance violations, and personality traits. Clustered standard errors are reported in parentheses.
Significance level: * $p < .10$, ** $p < 0.05$, *** $p < 0.01$

Finally, in Figure 5a we present our estimation results of interaction effects between risk tolerance and impatience graphically. The vertical axis reports the change in BMI points for a 1 SD increase in risk tolerance. The horizontal axis reports values of impatience, where low numbers indicate low levels of impatience and high numbers high levels of impatience. We demonstrate a strong interaction effect for women, and no interaction effect for men. Less impatient and more risk tolerant women had lower BMI. For instance, a very patient woman (who never chooses the sooner and smaller option) is estimated to be three BMI points lighter for an increase in risk tolerance by 1 SD. In contrast, a relatively impatient woman who chooses the smaller and sooner option at least three out of four times, does not have a BMI premium in risk tolerance. In other words, for highly impatient women risk tolerance is not associated with BMI. Results are similar when using waist circumference (Figure 5b), body fat (Figure 5c), and the risk of extreme obesity (Figure S.1, Supplement) as outcome measures.

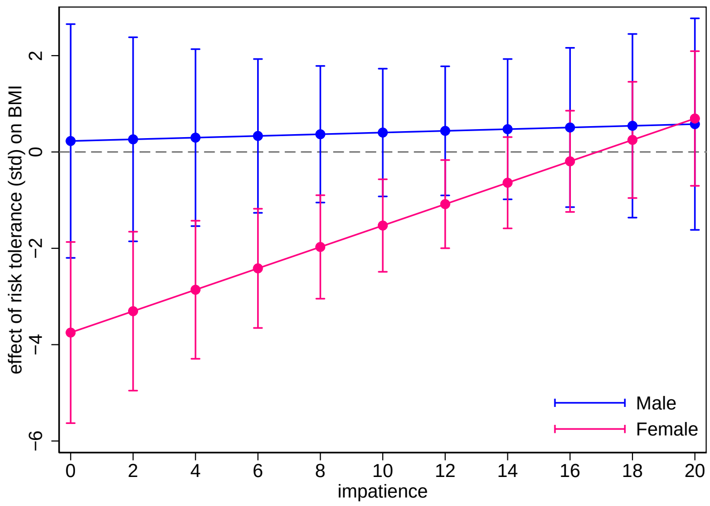
Our finding of an upward-sloping risk-impatience gradient in obesity (for women) is in contrast to the findings in de Oliveira et al. (2016) who estimated a downward-sloping gradient. One explanation for this contradiction in results is the difference in our sample characteristics. Our sample consists of predominantly tertiary-educated participants (52%) while de Oliveira et al. (2016) work with a sample of participants from highly disadvantaged backgrounds, where the majority of participants is poor (50%) and unemployed (60%). Hence, it could be the case that our risk-impatience gradients in obesity are driven by tertiary-educated participants.

By repeating our analysis separately for three education groups – tertiary education, some post-secondary training, high school completion or less – we are able to test this hypothesis directly. We find no conclusive evidence that this is the case (see Figures 6a and 6c, full estimation results are reported in Table S.4, Supplement). Figure 6a shows that for women we find the same upward-sloping risk-impatience gradient in BMI across all three education groups. The interaction effects are statistically significant for women with tertiary education (1.335, $p<0.10$) and high school education (1.780, $p<0.10$). In terms of magnitude, the effect sizes are large. For instance, at very low levels of impatience, a 1 SD increase in risk tolerance is associated with a BMI decrease of 4 BMI points for women with tertiary education. At high levels of impatience, we find no statistically significant relationship.

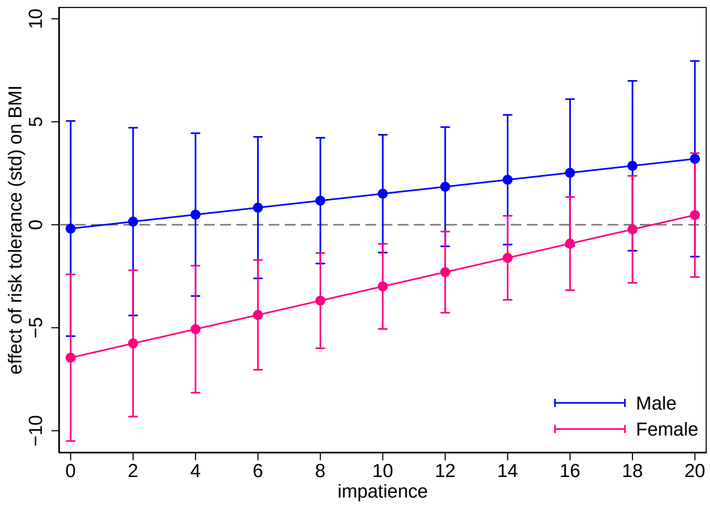
For men (Figure 6c), findings are similar, although none of the interaction effects are statistically significant. The only exception is that the risk-impatience gradient for men with some post-secondary training is negative (-0.25), while for both other groups it is positive (> 0.50).

Figure 5: Effect of risk tolerance on obesity by levels of impatience

(a) Body mass index



(b) Waist circumference



(c) Body fat

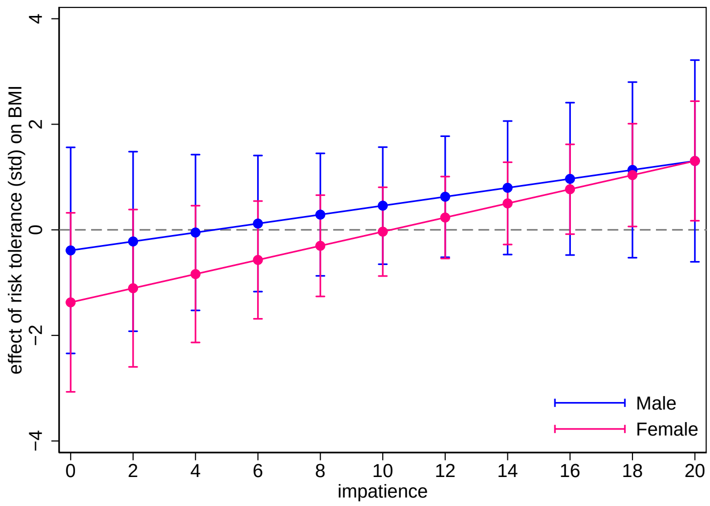
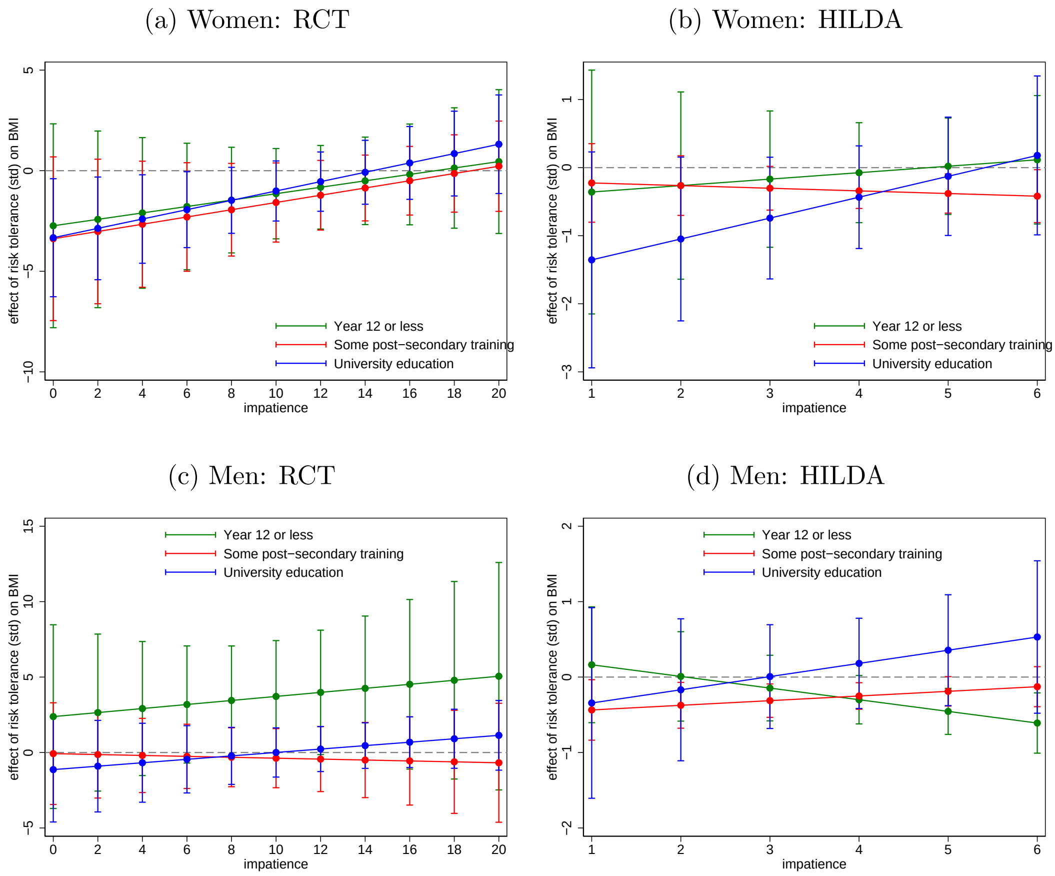


Figure 6: Effect of risk tolerance on BMI by levels of impatience, across education groups



One concern with this sub-group analysis is that the sample size for participants with less than tertiary education is too small. For instance, we only have 18 men with high school education, and 26 with some postsecondary training. As a second test, we therefore conduct the same analysis using nationally-representative survey data. Using a large sample sourced from waves 14 (2014) and 18 (2018) of the Household, Income, and Labour Dynamics in Australia (HILDA) survey allows us to estimate the risk-impatience gradient in BMI with more precision.[14] In total, we have a sample of 2,576 women and 3,705 men with similar characteristics as in our experimental data in terms of age and

[14]This test is only possible with self-assessed data. HILDA provides information on risk tolerance, impatience and BMI through self-assessments. The exact questions are: Risk tolerance "Are you generally a person who is willing to take risks or are you unwilling to take risks? Please indicate by crossing one box below. The more willing you are to take risks the higher the number of the box you should cross. The less willing you are to take risks, the lower the number of the box you should cross." with response categories: Unwilling to take risks 0 1 2 3 4 5 6 7 8 9 10 Very willing to take risks; Impatience: "In planning your saving and spending, which of the following time periods is most important to you?" with response categories (Cross one box): (1) The next week; (2) The next few months; (3) The next year; (4) The next 2 to 4 years; (5) The next 5 to 10 years; (6) More than 10 years ahead. HILDA also provides information on self-assessed weight and height, which can be used to construct BMI.

BMI. Main results are reported in Figures 6b and 6d. Full estimation results are reported in Table S.4 (Supplement).

We replicate the positive interaction effects between risk tolerance and impatience for women. However, now with a larger sample of individuals with lower levels of education, we find that tertiary education is driving the upward-sloping risk-impatience gradient in BMI for both women (Figure 6b) and men (Figure 6d). The interaction effect between risk tolerance and impatience for tertiary-educated women is 0.472 ($p<0.10$). At very low levels of impatience, a 1 SD increase in risk tolerance is associated with a BMI decrease of 1.3 BMI points for women. At high levels of impatience, we find no statistically significant relationship. There is no statistically significant interaction effect for women with lower levels of education.

For tertiary-educated men, we find a positive risk-impatience gradient in BMI of roughly half the size as for tertiary-educated women (0.251 versus 0.472). However, this interaction effect is not statistically significant. The only notable difference between the experimental and HILDA data analysis is the risk-impatience gradient in BMI for men with low levels of education. While in the experimental data it is upward sloping (0.591), in the nationally-representative data it is downward sloping (-0.245), although not statistically significant. This latter finding is consistent with de Oliveira et al. (2016), who estimate a negative interaction effect on BMI in the magnitude of -0.204 ($p< 0.05$).

We conclude that human capital may play an important role in how economic preferences shape field behaviours.

6 Discussion and conclusion

Our lab-in-field study is the first to collect data on economic preferences of medically at-risk people in a hospital setting. Our data collection is a sub-study of a randomised controlled trial that tested the efficacy of food supplements in weight control and prevention of diabetes. Our study sample is at great risk of developing non-communicable disease relative to the general population. While the Australian population average in

BMI are around 27, which indicates overweight, our participants have an average BMI of 35, which indicates obesity. We elicited risk and time preferences through high-stakes financial choices and collected survey data on the participants' education and personality, which allows us to control for human capital in the broadest sense. These measurements were linked to clinical data including BMI, adiposity, and waist circumference, all measured with high precision by trained health care professionals. Our data thus allow us to characterise the relationship between economic preferences and obesity in an understudied, but policy-relevant, population.

At first sight, it seems surprising that our sample shows no evidence of self-control problems (present bias). Behavioural theory associates poor outcomes such as obesity, low education levels, and insufficient savings with present-biased preferences (Laibson, 1997). People who are present-biased discount all outcomes in the future relative to those received now, which makes immediate consumption pleasurable and delayed costs more acceptable. With such preferences, present-biased individuals may forever postpone the start of a healthy diet or physical exercise, while in the present choosing to indulge in unhealthy foods and sedentary lifestyles. However, our participants are on average neither present-biased nor does variation in present bias correlate with variation in obesity.

One explanation for this finding is that self-control problems are not the cause of obesity. In line with our findings, several recent studies using similar methods to ours (but different populations) find no or little present bias, putting the theory into question (Andersen et al., 2014; Andreoni et al., 2015; Andreoni and Sprenger, 2012b; Augenblick et al., 2015). Another explanation is that present bias is domain-specific, and estimates obtained from monetary decisions have little explanatory power over one's decisions for food or exercise. In line with this argument, Augenblick et al. (2015) find considerable present bias for effort decisions but almost none for monetary outcomes. However, Cheung (2020), who investigated the correlation in present bias for dietary and monetary rewards, found the correlations to be positive and moderate, implying that choices over money should be moderately predictive of choices for food.

Finally, it is possible that people in our sample have high levels of self-control. Our study participants are self-selected individuals who decided to commit to a six-months intervention with the aim to control weight and prevent diabetes. It is possible that specifically for these individuals excessive weight is not a result of present-biased decision-making. Another factor that could explain why our participants are not present-biased is their high levels of education, which cannot be obtained without substantial self-control.

Not only do our results show that participants are not present-biased, but also only 32.8% of them can be classified as having time-inconsistent (hyperbolic or quasi hyperbolic) preferences. One in four of the participants are future-biased, but otherwise they discount future outcomes more the more they are pushed into the future. Another one in four are time-inconsistent hyperbolic discounters. One in five are a time-consistent exponential discounters. Our estimate of the hyperbolic discount rate is close to those of other populations who do not have obesity and pre-diabetes (Chabris et al., 2008) and it is approximately three times lower than for a nationally-representative sample of people from Denmark (Andersen et al., 2008), which has the lowest obesity rates in the OECD countries (OECD, 2019). Overall, we have to conclude that we do not find evidence that our sample of medically at-risk people is overly time-inconsistent, questioning the role of time inconsistency as one of the primary causes of obesity.

Even if time consistent, more impatient participants would be predicted to have higher BMI by economic theory. While the literature has usually found a positive relationship between impatience and obesity (Chabris et al., 2008; Richards and Hamilton, 2012; Sutter et al., 2013), our study is not alone in finding no effect (Conell-Price and Jamison, 2015; de Oliveira et al., 2016). Impatience alone does not predict obesity in general. One exception in our data is that patience seems to be protective of most extreme adiposity outcomes for men.

In terms of their risk preferences, our participants are risk averse, but they tend to be more risk tolerant than participants in other studies (Andersen et al., 2008, 2014; Andreoni et al., 2015). While this is consistent with the general idea that risk tolerance correlates with higher BMI, we cannot find evidence in our data that risk tolerance increases obesity severity. On the contrary, we find a significant negative association between risk tolerance and obesity for women. Our findings are thus in stark contrast to the existing literature (de Oliveira et al., 2016; Sutter et al., 2013; Anderson and Mellor, 2008). However, our result does not seem spurious, as we replicate the same effect in a nationally-representative population of 6,281 Australians with similar characteristics.

Our study also highlights the importance of the interaction of risk aversion and impatience. As the future is inherently risky, some previous studies (de Oliveira et al., 2016) suggested that interaction of risk aversion and impatience is important to account for. Critically, we find a positive interaction effect between risk tolerance and impatience. Our results imply that risk tolerance is only negatively associated with BMI for very patient women. There is no significant relationship between risk tolerance and BMI for very impatient women. This is in contrast to de Oliveira et al. (2016), who find a negative interaction term. This is surprising because both studies analyse data of people with obesity and risk of developing chronic illness. A plausible explanation for this difference is that our sample is drawn from predominantly white, middle-class and high education backgrounds, while de Oliveira et al. (2016) work with a sample of low-income African-Americans. Being able to replicate the same risk-impatience gradient in BMI for tertiary-educated women with nationally-representative survey data gives us confidence that our findings are not driven by sample selection. We conclude that risk tolerance, when combined with patience, may capture different field behaviours among highly-educated women than for women of lower socioeconomic status.

A limitation of our study is external validity. We focus only on people who fall within the overweight and obese range, despite a large variance in BMI. Our sample is on average highly educated and lives in an urban area. Our study therefore cannot shed light on the relationship between economic preferences and risk of chronic illness in a general population. However, our study population is critically important for policymakers. Our study participants have both the means and desire to make lifestyle changes. Their high level of human capital implies that they are able to understand and follow treatment regimes more easily and they are less likely to be constrained financially. Combined with their commitment to control weight and prevent diabetes, they are the ideal target for behavioural interventions. This of course does not undermine the importance of understanding the determinants of obesity among different populations, but rather stresses that successful approaches to reducing the obesity epidemic may be demographic-specific.

One key demographic difference that stood out in our study is gender. Our results on gender differences in the relationship between preferences and obesity severity are new to the behavioural economics literature but well known in biology. Obesity progression differs markedly among men and women. Weight increases steadily for men over their lifetime, while for women it increases as a stepwise function, usually following life events, such as having children, experiencing grief or major job changes (Lizcano and Guzmán, 2014; Kanter and Caballero, 2012; Garawi et al., 2014). It is thus not surprising that preferences affect obesity severity differently across gender. We, therefore, conclude that the literature should focus more on gender and other demographic differences in the response to weight loss incentives and constraints.

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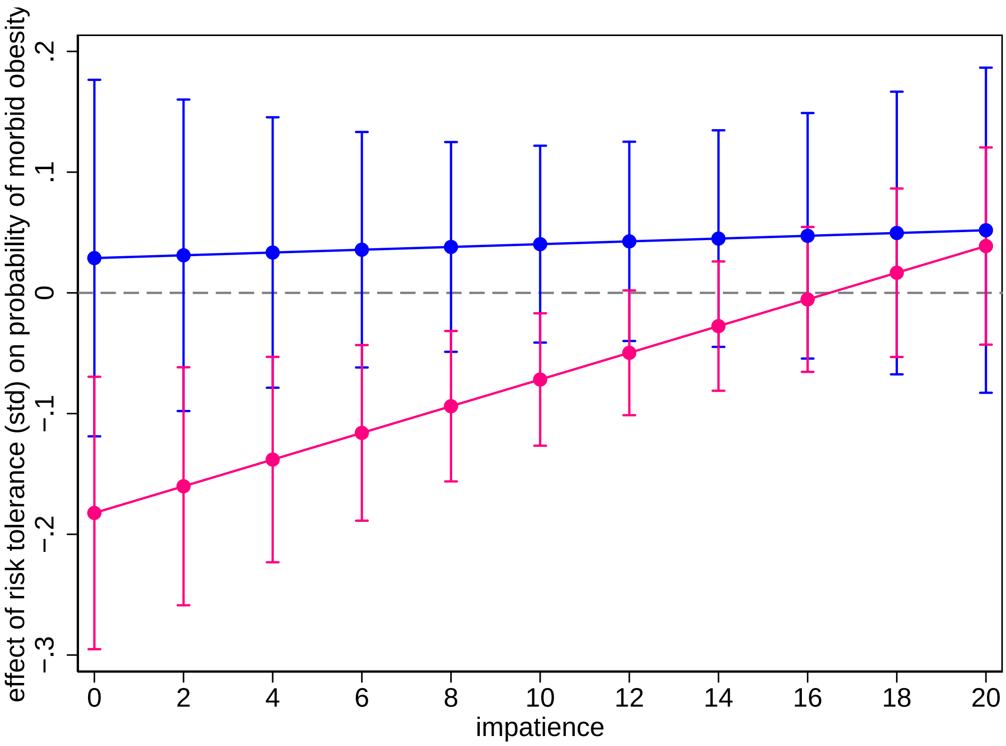
Supplement

S1 Figures

Figure S.1: Effect of risk tolerance on morbid obesity



S2 Tables

Table S.1: Guidelines for obesity cutoffs for BMI, waist circumference, and body fat percentage

	Women	**Men**
	BMI	
Normal	≥ 18.5	≥ 18.5
Overweight	≥ 25	≥ 25
Obese	≥ 30	≥ 30
	Waist circumference	
Increased risk	$\geq$80 cm	$\geq$94 cm
High risk	$\geq$88 cm	$\geq$102 cm
	Body fat	
Athletic	14-20%	6-13%
Fit	21-24%	14-17%
Acceptable	25-31%	18-24%
Obese	$\geq$32%	$\geq$25%

Notes: Sources are Akram et al. (2000) for BMI and waist circumference. American Council on Exercise (2018) for body fat percentage.

Table S.2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: Pooled					
BMI	34.491	6.089	25.24	55.5	284
Waist circumference (cm)	109.944	13.017	86	149.1	284
Body fat (percent)	42.047	7.612	23.8	58	270
Overweight	0.261	0.44	0	1	284
Obese (BMI> 30)	0.331	0.471	0	1	284
Obese (BMI> 35)	0.243	0.43	0	1	284
Morbidly obese BMI> 40	0.165	0.372	0	1	284
Age	54.484	9.928	24	74	287
Female	0.622	0.486	0	1	291
No post-secondary education	0.159	0.367	0	1	295
Some post-secondary education	0.302	0.46	0	1	295
University education	0.515	0.501	0	1	295
Conscientiousness	0	1.002	-1.735	2.941	293
Grit	0	1.002	-3.071	2.618	293
Openness to experience	0	1.002	-3.117	2.307	293
Panel B: Women					
BMI	35.037	6.78	25.24	55.5	177
Waist circumference (cm)	107.96	13.754	86	149.1	178
Bodyfat (percent)	46.636	4.634	33.6	58	170
Overweight	0.271	0.446	0	1	177
Obese (BMI> 30)	0.299	0.459	0	1	177
Obese (BMI> 35)	0.22	0.416	0	1	177
Morbidly obese BMI> 40	0.209	0.408	0	1	177
Age	55.52	9.556	24	74	179
No post-secondary education	0.149	0.357	0	1	181
Some post-secondary education	0.337	0.474	0	1	181
University education	0.486	0.501	0	1	181
Conscientiousness	-0.02	1.065	-1.735	2.759	181
Grit	0.017	0.974	-3.071	2.618	180
Openness to experience	-0.067	1.097	-3.117	2.307	181
Panel C: Men					
BMI	33.636	4.618	25.82	49.4	106
Waist circumference (cm)	113.302	10.999	86	145.5	105
Body fat (percent)	34.298	4.804	23.8	46.2	99
Overweight	0.236	0.427	0	1	106
Obese (BMI> 30)	0.387	0.489	0	1	106
Obese (BMI> 35)	0.283	0.453	0	1	106
Morbidly obese BMI> 40	0.094	0.294	0	1	106
Age	52.701	10.359	27	70	107
No post-secondary education	0.164	0.372	0	1	110
Some post-secondary education	0.245	0.432	0	1	110
University education	0.573	0.497	0	1	110
Conscientiousness	0.019	0.895	-1.735	2.941	109
Grit	-0.012	1.048	-2.414	2.15	110
Openness to experience	0.083	0.803	-2.606	1.867	109

Table S.3: Full estimation result on the relationship between BMI and risk tolerance

	(1) Raw	(2) Xvars	(3) FOSD	(4) Pers	(5) Women	(6) Men
Risk tolerance (Std)	-0.496	-0.411	-0.558	-0.563	-1.252**	0.487
	(0.390)	(0.377)	(0.388)	(0.399)	(0.567)	(0.441)
Female		1.305*	1.074	1.148*	0.000	0.000
		(0.692)	(0.684)	(0.695)	(.)	(.)
Age		-0.060*	-0.065*	-0.051	-0.054	-0.028
		(0.036)	(0.036)	(0.038)	(0.056)	(0.046)
No post-second. edu		0.716	0.623	0.692	1.160	-0.302
		(0.932)	(0.954)	(0.989)	(1.393)	(1.291)
Some post-second. edu		1.791**	1.682**	1.673*	1.890	1.628
		(0.859)	(0.848)	(0.884)	(1.209)	(1.156)
No. violations: 1			2.455**	2.115*	2.772*	0.577
			(1.116)	(1.137)	(1.496)	(1.543)
No. violations: 2			-2.336*	-2.309	-0.759	-3.419**
			(1.386)	(1.428)	(2.099)	(1.312)
No. violations: 3			1.248	1.429	2.745*	
			(1.255)	(1.249)	(1.432)	
Conscientiousness (Std)				0.246	0.050	0.490
				(0.394)	(0.568)	(0.447)
Openness (Std)				-0.080	0.017	-0.356
				(0.400)	(0.513)	(0.557)
Grit (Std)				-0.672	-1.317**	0.161
				(0.432)	(0.607)	(0.584)
Constant	34.487***	36.320***	36.468***	35.727***	36.731***	34.867***
	(0.360)	(2.038)	(2.003)	(2.068)	(3.285)	(2.401)
Observations	284	282	282	280	175	105

Notes: Clustered standard errors are reported in parentheses.
Significance level: * $p < .10$, ** $p < 0.05$, *** $p < 0.01$

Table S.4: Relationship between BMI and Risk and Impatience Interactions

	(1)	(2)	(3)	(4)
	Women		Men	
	RCT	HILDA	RCT	HILDA
University education				
Risk tolerance (Std)	-0.966	-0.461	0.049	0.132
	(0.742)	(0.291)	(0.607)	(0.197)
Impatience (Std)	-0.382	0.107	-0.390	0.381*
	(0.831)	(0.285)	(0.512)	(0.231)
Risk × Impatience	1.335*	0.472*	0.501	0.251
	(0.747)	(0.278)	(0.469)	(0.184)
Age	-0.118	-0.017	-0.043	-0.006
	(0.080)	(0.028)	(0.064)	(0.020)
Constant	40.541***	40.891***	35.738***	35.653***
	(4.734)	(1.388)	(3.384)	(1.008)
Observations	85	262	62	247
Some postsecondary education				
Risk tolerance (Std)	-1.622	-0.362***	-0.497	-0.238***
	(1.119)	(0.135)	(1.156)	(0.088)
Impatience (Std)	0.195	0.604***	0.714	0.501***
	(0.837)	(0.136)	(0.896)	(0.084)
Risk × Impatience	1.167	-0.058	-0.562	0.096
	(0.852)	(0.130)	(0.984)	(0.094)
Age	0.061	-0.042***	0.094	0.002
	(0.114)	(0.013)	(0.133)	(0.008)
Constant	33.083***	33.024***	30.109***	30.250***
	(6.219)	(0.642)	(7.377)	(0.429)
Observations	60	2042	24	2624
Year 12 or less education				
Risk tolerance (Std)	-1.225	0.111	2.356*	-0.399**
	(0.875)	(0.377)	(1.138)	(0.170)
Impatience (Std)	0.257	0.350	-0.176	0.723***
	(1.099)	(0.378)	(0.900)	(0.164)
Risk × Impatience	1.780*	0.179	0.591	-0.245
	(1.015)	(0.388)	(0.960)	(0.160)
Age	-0.155	-0.003	-0.029	-0.007
	(0.099)	(0.034)	(0.073)	(0.016)
Constant	44.469***	44.504***	34.753***	34.672***
	(5.615)	(1.770)	(3.843)	(0.833)
Observations	26	272	18	834

Notes: Household Income and Labour Dynamics in Australia (HILDA) survey. Clustered standard errors are reported in parentheses. Standard errors are cluster robust on the individual level in the HILDA survey. HILDA survey waves 2014 and 2018.
Significance level: * $p < .10$, ** $p < 0.05$, *** $p < 0.01$

S3 Literature review

Table S.5: Summary of literature review

Study	Journal	Subject	Population	Cou.	Elicitation	Risk av.	Delay av.
Anderson and Mellor 2008	J Health Econ	Link RP and health behaviors	CS n=1,094 adults	US	Incentivised choice experiment, monetary	Negative eff on BMI	-
Appelhans et al. 2012	Appetite	Link TP and food consumption habits women with BMI $\geq$25	CS n=78 women	US	Hypothetical choice experiment, monetary	-	No effect on food habits
Best et al. 2012	J Consult Clin Psychol	Link between impulsivity, relative reinforcing value of food (RRV), environment and overweight children's weight loss	LG n=241 obese children	US	Hypothetical choice experiment, food and monetary domains	-	More patient more likely to lose weight
Bickel et al. 2014	Appetite	How TP differ between obese and non-obese	CS n = 1,163	US	Hypothetical choice experiment, monetary	No effect	Positive effect on pr(obese)
Borghans and Golsteyn 2006	Econ Hum Biol	Link TP and BMI	LG n=2,059 adults	Netherlar	Hypothetical choice experiment, monetary and entertainment domains	-	Sign and signficance depend on choice of proxy for TP
Brown and Biosca 2016	Soc Sci Med	Link TP and body fatness	CS n=15,591 Usoc	UK	Survey questions on people's savings habits	-	Positive effect on all measures of body fatness
Cavaliere et al. 2014	Appetite	Link TP and BMI	CS n=240 adults	Italy	Question: do you choose dietary pattern paying attention to health or taste?	-	Positive effect on BMI
Chabris et al. 2008	J Risk Uncertainty	Link TP and health behaviours	CS n=146	US	Incentivised choice experiment, monetary	-	Positive effect on BMI (but no effect on overeat)

Conell-Price and Jamison 2015	J Behav Exper Econ	Link TP, RP, LOC and health behaviours	CS n=144 univ students	US	Incentivised choice experiment, monetary domain (survey measures also included)	Negative effect on BMI	No effect on BMI, but positive effect on exercise
Courtemanche et al. 2015	Econ J	Link TP, BMI and economic incentives	LG n=12,686 adults NLSY	US	Survey questions intertemporal tradeoffs	Association found	Positive effect on BMI
Davis et al. 2010	Appetite	Link TP, BMI and education	CS n=209 adult women	Canada	Hypothetical choice experiment	-	No significant differences by obesity status
de Oliveira et al. 2016	J Econ Behav Organ	Link TP, RP and obesity	CS n=169 adults	US	Incentivised choice experiment, monetary domain	Negative effect on BMI	Patience strengthens the negative effect of RA
Dodd 2014	Econ Hum Biol	Link TP and BMI	CS data SAHOS	Australia	Survey questions intertemporal tradeoffs	-	Positive effect on BMI
Epstein et al. 2014	Obesity	Link TP, food reinforcement and BMI	CS n=199 women	US	Hypothetical choice experiment, monetary	-	Positive effect on BMI
Galizzi and Miraldo 2017	BE J Econ Analysis and Policy	Link RP and diet quality, BMI	CS n=120 univ students	UK	Incentivised choice experiment, monetary domain	No association for female, negative effect on BMI for men (disappears when diet is accounted for)	-
Garza et al. 2016	J Acad Nutr Diet	Link TP and food consumption	CS n=478 univ employees	US	Hypothetical choice experiment, monetary	-	Positive effect on pr(obese)
Golsteyn et al. 2014	Econ J	Link TP and labour market, income, health, behaviours	LG n=11,907 children	Sweden	Survey questions intertemporal tradeoffs	-	Positive effect on pr(obese)

Ikeda et al. 2010	J Health Econ	Link TP and BMI (RP controlled for)	CS n=2,987, 20+	Japan	Survey questions intertemporal tradeoffs (plus extra questions for proxies)	-	Positive effect on pr(obese)
Jarmolowicz et al. 2014	Appetite	Link TP and body mass	CS n=100, adults	US	Hypothetical choice experiment, monetary	-	Positive association with obesity
Jiang and Hong 2016	SHS Web of Conf	Link TP and eating behavior, activity level, BMI	CS n=147 female students	China	Self-assessed impulsivity task	-	Positive effect on BMI
Komlos et al. 2004	J Biosoc Sci	Link TP and obesity	LG adults NHANES	US	US personal savings rate and household debt-to-income ratio used as proxies	-	Positive effect on obesity rates
Koritzky et al. 2012	Appetite	Link RP and obesity	CS student and adults	Israel	Both hypothetical and incentivised choice tasks	Negative effect in men only	No significant differences by obesity status
Price et al. 2016	Physiol Behav	Compare models to predict obesity with TP	CS n=79 adults	UK	Hypothetical choice experiment, monetary	-	Positive effect on pr(obese)
Richards and Hamilton 2012	J Agr Resour Econ	Compare exponential and hyperbolic discounting models to predict obesity	CS n=82 students	US	Incentivised choice experiment, monetary	-	Positive effect on BMI (small)
Rieger 2015	Econ Hum Biol	Relationship between TP, RA and BMI (undernutrition).	CS n=1,025	Cambodi	Incentivised choice experiment, monetary	Negative eff on BMI	Positive effect on BMI in adults only
Robb et al. 2008	Int J Obes	Impact of smoking on BMI, isolating impact of TP on BMI.	LG n=2,970	US	Survey questions on lifestyle	-	Positive effect on BMI
Scharff 2009	J Consum Policy	Hyperbolic discounting and use of commitment devices: impact on caloric consumption	LG n=5,592 adults	US	Survey questions on lifestyle choices	-	Positive effect on pr(obese)

Smith et al. 2005	Econ Hum Biol	Link TP and obesity	LG n=12,686 adults NLSY	US	Survey questions on savings	-	Positive effect on BMI for some groups
Stoklosa et al. 2018	Econ Hum Biol	Link parents' TP, self-control and childrens' BMI	CS n=5871 parents FHHS	US	Survey questions with monetary lottery task	-	Parents' impatience and present bias positively related to their own and their children's BMI
Sutter et al. 2013	Am Econ Rev	Link RP, ambiguity, TP to BMI and health behaviours in adolescents	CS n=661 adolescents	Austria	Incentivised experiment, monetary domain	Negative eff on BMI	Effect depends on proxy used
Takada et al. 2011	J Biosoc Sci	Effectiveness of 'tele-care' intervention relative to self-help as a weight-loss method.	LG n=118 obese adults	Japan	Hypothetical choice experiment, monetary	Higher weight loss	Lower weight loss
Takagi et al. 2016	Soc Sci Med	TP as mediator between education and health behaviours	CS n=3,457 J-SHINE	Japan	Hypothetical choice experiment, monetary	-	No effect
Thamotharan et al. 2016	Eating Behaviors	Link of TP and weight concern and BMI in female adolescents	n = 60 female adolescents	US	Hypothetical choice experiment	-	Positive effect on BMI
Wang et al. 2016	J Econ Psychol	Differences in TP across countries	CS n=6,912 univ students	Intnl	Survey questions tradeoffs		Positive effect on BMI
Weller et al. 2008	Appetite	Link TP and obesity	CS n=112 students	US	Hypothetical choice experiment and impulsivity questionnaire	-	Positive effect on pr(obese)
Zhang and Rashad 2008	J Biosoc Sci	Link TP and BMI	CS n=979	US	Survey questions on personality	-	No significant effect on obesity

S4 Inclusion and exclusion criteria for clinical trial

Inclusion criteria Participants will be considered for the study if they have the following:

- Aged 18 to 70 years of age.
- BMI $\geq$ 25 kg/m^2
- Pre-diabetes (determined by bloods at the Screening visit or within six months prior to the screening visit)

Pre-diabetes criteria are based on American Diabetes Association (ADA) guidelines. To be eligible the Participants must have:

- a fasting plasma glucose $\geq$ 5.6-6.9 mmol/L AND/OR
- 2 hour post-challenge (oral glucose tolerance test) plasma glucose $\geq$ 7.8-11.0 mmol/L AND/OR
- HbA1c $\geq$ 5.7-6.4%

Participants will be excluded for any of the following reasons:

- Type 2 diabetes Type 2 diabetes criteria are based on ADA guidelines. Participants will be excluded from the study if they have:
  - a fasting plasma glucose $\geq$ 7.0 mmol/L AND/OR
  - 2 hour post-challenge (oral glucose tolerance test) plasma glucose $\geq$ 11.1 mmol/L AND/OR
  - HbA1c $\geq$ 6.5%
- Use of anti-lipidaemic medications for cholesterol control
- Use of anti-diabetic medications for pre-diabetes
- Type 1 diabetes

- Unstable angina or recent onset of cardiovascular disease (within 1 month of Screening)
- Bariatric surgery

Exclusion criteria

- A history of significant liver, kidney or gastrointestinal disease AND/OR
  - ALT or AST >2.5 times upper limit of normal
  - serum creatinine ¿ 1.5 times upper limit of normal or
  - eGFR <60ml/min/1.73m^2 or presence of microalbuminuria
- Chronic diarrhoea, bowel motility problems, or other conditions that could affect intestinal fat absorption
- Untreated thyroid disease
- Greater than 10% change in body weight over the past 3 months
- Alcohol or illicit drug abuse
- Pregnant or breastfeeding women, and women who might be planning pregnancy during the duration of the study
- Use of weight loss medications and other drugs that may affect body weight e.g. anti-psychotics, anti-depressants, or corticosteroids
- Taking the following medications which may show reduced absorption of the investigational products: antibiotics, anticoagulants, anticonvulsants, antiarrhythmics, immunosuppressants, or any other drug that is necessary to take with a meal. Short-term and prophylactic antibiotics may be taken during study participation for up to 14 days, but they should be taken at least 2 hours apart from the study drug
- Commencement of a new prescription medication within 3 months of Screening or change in dose regimen of a prescription medication within 1 month of Screening

- A history or presence of malignancy [completely resected basal or squamous cell carcinoma of the skin if treatment completed >6 months prior to enrolment and Participant is in remission for >5 years prior to Screening remain eligible]

- Inability to read and write English

- A history of frequently changed smoking habits, in addition to smoking cessation within 6 months prior to Screening. Those who wish to take on the advice of a 'Quit' smoking programme at the time of Screening will be eligible to start the trial after 6 months

- Participants may also be excluded, if in the opinion of the study Investigators, they have some other condition or disorder that may adversely affect the outcome of the study or the safety of the Participant

- Participation in a clinical trial in the last month

- Unable to commit to the appointment schedule or perform the tasks required in the study.

S5 Instructions for economic decision-making experiments

This task involves choosing between two monetary options repeatedly. Altogether 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 screening visit. 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 the higher chance of receiving $30?

(If answer B) 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.

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.

On the next screen, 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.