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Role of Time preferences in Explaining the Burden of Malnutrition: Evidence from Urban India

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Abstract

This study uses a simple theory model to examine how time preferences influence food choices made by individuals, which in turn have implications for their future health. The theory results demonstrate that individuals with higher bias for the present or lower patience will have poorer health outcomes: that is, they will either be underweight (low BMI) or overweight (high BMI). The pathway from time preferences to BMI is through food. To empirically validate these predictions, we use both the nationally-representative India Human Development Survey (IHDS) to estimate a reduced form equation relating savings (a proxy for time preferences) to BMI; and a primary survey of 885 adults conducted in West Delhi. Using quantile regression and SEM estimation, we provide empirical validation for the theory results; namely that time preferences have significant effect on food choices which in turn has a significant impact on BMI. Thus, such psychometric measures are useful in identifying early on those at potential risk of being overweight or obese later as adults.

Keywords: BMI, overweight or obese, underweight, time preferences, time-inconsistency, time consistency, present bias, risk and time discounting
JEL: I12, I15, I18, D91, C93

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1 Introduction

Economic research in India has traditionally focused on undernutrition, because India is home to the largest number of undernourished people in the world (SOFI, 2017). The prevalence of undernutrition, especially among children and women, is still very high. The prevalence of overweight and obesity, also an aspect of malnutrition (overnutrition), is also amplifying in India, and currently affects almost 1 in 5 adults (National Family Health Survey (NFHS)-4, National Fact Sheet, 2016).[1] This is concerning because there is compelling evidence that obesity contributes to the chronic diseases such as cancer, diabetes and cardio-vascular ailments (Must et al., 1999). This dual burden of malnutrition is a major public health problem in India, as is the case with other developing countries that are rapidly going through the nutrition transition.

Much of the literature in developing and developed countries has focused on changing economic incentives as one of the key drivers for rising overnutrition. Factors such as falling relative prices of energy dense foods, and the rising cost of physical activity at work and home have received strong theoretical and empirical support as major determinants of increased overweight/obesity over time (see for example Philipson and Posner 1999; Lakdawalla et al. 2005; and Lakdawalla and Phillipson 2002; Dang et al. 2019; Sarma et al. 2014 and Popkin et al. 2012).[2] These factors can explain rising

[1] Overnutrition among adults in NFHS is measured by percentage of individuals with a Body Mass Index (BMI) greater than or equal to 25. The body mass index (BMI) is defined as the ratio of weight in kilograms to the square of height in meters (kg/m^2). These national figures hide the regional heterogeneity in these numbers: the prevalence of overweight and obese is most prevalent in the North-Western states of Delhi, Punjab, Jammu and Kashmir, Himachal Pradesh and the Southern states such as Andhra Pradesh, Kerala, Tamil Nadu, and is more evident among women than men. Proportion of overweight among women in these states are over 30%.

[2] Philipson and Posner (1999) (using static framework), Lakdawalla et al. (2005) and Lakdawalla and Phillipson (2002) (used dynamic framework) argue that technological change explains increased obesity in the United States, as it has lowered the cost of calories by making agricultural production more efficient and raised the cost of physical activities by making household and market work more sedentary. In economies where home and market production involve manual labour, work is strenuous and food is expensive; meaning that the worker is paid to exercise. In societies such as the United States, most work entails little exercise and not working may not cause a reduction in weight, because food welfare benefits are available to the unemployed. As a result, people have to pay for undertaking, rather than be paid to undertake, physical activity mainly in terms of forgone leisure, because leisure-based exercise, such as jogging or gym activities, must be substituted for work-based exercise. Additionally, they predict that a rise in earned income resulting from more skilled, sedentary work raises weight, and growth in unearned income raises the demand for thinness. Unearned income may come, for example, from asset markets or

average BMI over time, but, they cannot explain why some individuals experience higher increase in BMI than others; that is why some people react more to the changing economic incentives than others. One reason for this heterogeneity in change in BMI across individuals could be due to variation in time preferences. People who are more impatient or present biased (care more about today) might care less about future health relative to individuals who are patient or less present biased due to changing environment. These psychological factors than just economic factors might also be important in explaining overnutrition/undernutrition.

While there is a sizeable empirical literature on time preferences and body weight outcomes, there is limited empirical evidence on developing countries, and one for India. This paper attempts to contribute to bridge this gap by examining the role of time preferences in explaining both underweight and overweight aspects of malnutrition which are relevant for developing countries. This study has two objectives: firstly, using a simple model, we show how individuals make food choices involving intertemporal trade-offs between the utility that individuals get in the present, and health benefits in the future (also known as time preferences). These food choices help in explaining the dual burden of malnutrition. Secondly, we take theory to data, elicit time preferences of individuals (by conducting field experiment) and find that food is the channel through which time preferences affect health status (BMI) of individuals.

This paper builds on the literature and contributes to it in significant ways. Firstly, unlike much of the literature, our model can help explain both *underweight* and *overweight* aspects of dual burden of malnutrition. A second contribution of this paper is that we employ quasi-hyperbolic discounting model that accounts for inconsistent or changed preferences.[3] Thirdly, we provide empirical evidence that food is one possible mechanism that explains connection between time preferences and body weight.

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from the income of a spouse. This may explain why people who are wealthier are thinner than poorer people within countries where workplace technologies are more uniform.

[3] A standard assumption of time-consistent preferences in intertemporal choice models means decisions taken in advance for future remain valid as time progresses i.e. preferences do not change with time. However, evidence suggests that preferences do change as time passes- individuals appear more patient

The literature focusing on time preferences as a predictor of health/weight is not new: for example, Grossman (1972) first used time preferences to analyse health choices, which he modeled as investment decisions. Becker and Murphy (1988) and Fuchs (1986, 1991), use time preferences to model various health choices such as smoking and alcohol consumption.[4] A common metric for overnutrition is the body mass Index (BMI) with values exceeding 25 indicating overweight and those exceeding 30, indicates obesity. Much of the literature that quantifies the relationship between time preferences and BMI is focused on developed countries. The earlier work relies on proxies for time preferences. Komlos et al. (2004) utilizing national-level time-series data, use the national savings rate and consumer debt as a proxy for time preferences finding that rising obesity rates in the United States coincide with low savings rate and high debt.[5] Smith et al. (2005) using National Longitudinal Survey of Youth, utilize savings and dissavings information to capture time preferences among American youth (aged 24-32), and Borghans and Golsteyen (2006) use both financial indicators (assets and

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for decisions that are farther in the future, but they turn impatient when the future becomes the present, exhibiting self-control problems. Such preferences are termed as "time-inconsistent" and are captured by quasi-hyperbolic discounting, the very model used in this paper. Quasi-hyperbolic discounting nests exponential discounting, which assumes time-consistent preferences.

[4] More relevant to this paper are the studies by Komlos et al. (2004) (maximising lifetime utility function), Borghans and Golsteyn (2006) and Courtemanche et al. (2014) (using two-period model) show that differences in food intake/BMI across individuals can be explained by the rate of time preferences. An implication is that food intakes and weight are increasing (decreasing) in the discount rate (discount factor). Courtemanche et al. (2014) build a two-period model where food intake provides utility in the first period, and consumer pays price of eating the food in the current period. In the second period, utility is decreasing in food because weight is a function of food and utility decreases with increase in weight. They show that optimum food consumption is a function of the discount factor and price of food and the consumers who are more patient have lower weight. Furthermore, Courtemanche et al. (2014) consider a three-period extension of the model allowing for a consumer with time-inconsistent preferences using quasi hyperbolic discounting which incorporates present bias. As in the two-period model, as consumers discount the future more or as consumers become more present-biased, food consumption and weight increase. Additionally, they evaluate the cross partial derivative to see how consumers with different discount factors react to change in prices. They predict that impatient people are relatively more concerned with present costs and therefore, are more responsive to the monetary price and will thus have higher weights. However, the cross partial derivative of weight with respect to price and discount factor (or present bias) is ambiguous and it is left to their empirical analysis to determine the sign. They find that the sign of cross-partial derivate coincides with their intuition i.e. individuals focusing more on present, either because of a lower discount factor or because of a lower present bias, respond more strongly to price.

[5] Low saving rate or high debt is suggestive of a high discount rate. Further, considering the cross-sectional relationship between savings rates and obesity for a number of developed countries, Kolmos et al. (2004) show that countries such as Finland, Spain and the United States with highest obesity rates have some of the lowest savings rates. Countries like Switzerland and Belgium that have the highest savings rates, had obesity rates about half those in the United States.

liabilities) and attitude, as well as indirect measures (based on will-power) of the discount rate among the Dutch. They find some evidence of association between time preferences and BMI.[6] Zhang and Rashad (2008) find that conditional on covariates, there is a positive association between BMI and time preferences (using will power as a proxy) for men in the U.S.[7]

Proxy measures of time preferences may have some disadvantages. For example, dissaving/savings may depend on age, income, or it may also represent shocks due to say expenditure on health care. Many recent studies have therefore employed more direct measures using questions on intertemporal tradeoffs. For instance, Chabris et al. (2008) using a sample of adults in Boston area, show that inter-individual variation in discount rate predicts BMI, as well as other behaviour such as exercise and smoking.[8] Sutter et al. (2013) elicit time preferences among school children and adolescents (aged 10-18) in Austria and find that impatient children are more likely to (a) have higher BMI, (b) smoke, (c) consume alcohol, (d) misbehave in school and (e) are less likely to save.[9]

None of the studies mentioned above distinguish between time-consistency and inconsistency. A few recent studies incorporate time inconsistency in teasing out the

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[6] Questions related to financial attitude included questions on management of income such as whether the respondent spent more money than he received in the past 12 months. The reason for including such question is that respondents with higher discount rates are more tempted to spend money immediately and will have more problems managing their money. Therefore, the expected correlation of these three variables with the discount rate and BMI is negative. The other group of questions were about savings behavior. The next round of questions had statements about the attitude referring to the trade-off between the present and the future. For example, whether people agree to a large extent with the statement ‘‘I am only concerned about the present, because I trust that things will work out in the future’’ will generally have a higher discount rate.

[7] Zhang and Rashad (2008) use two datasets - small Roper Center Obesity survey and Behavioral Risk Factor Surveillance System (BRFSS) for their study. Will-power a measure was based on the question asking the respondent whether or not lack of will-power is the greatest barrier to weight control. But it is only asked to those individuals who indicate that they would want to lose weight. While no comparable variable exists in the BRFSS data set, the variable ‘trying to lose weight’ was used. A dummy variable ‘desire but no effort’ was created that equals 1 if the respondent desires to weigh at least five pounds less than his or her current weight and yet did not report trying to lose weight.

[8] They observed that the correlation between discount rate and field behaviour is small as none of them exceed 0.28. Nonetheless, discount rate variable has at least as much predictive power as any other variable in their data such as age, sex, education. In fact, they observed that other variables have even less predictive power than time-discounting variable.

[9] Children were asked whether they save money in the questionnaire presented to them.

connection between BMI and time preferences. Ikeda et al. (2010) (among Japanese adults), for the full and female samples, find that BMI is positively associated with impatience and observe a significant positive relationship between hyperbolic discounting and BMI only for some measures.[10] Courtemanche et al. (2014) also account for time-inconsistent preferences in their study of American adults and find evidence that both present bias and the long run discount factor are negatively correlated with BMI.[11] Bradford et al. (2017) study whether survey-elicited estimates of time-consistency and/or present bias are related to diverse set of outcomes including health, energy and finance among US citizens.[12] Their results are particularly strong for health. They observe that time preferences coefficients (that is time-consistent discount factor and long run discount factor under quasi-hyperbolic discounting) are associated with higher rates of obesity, though neither is statistically significant. Their findings suggest that low discount factors reduce exercise and contribute to unhealthy eating. Further, self-control problems may be relevant for exercise decisions, as present biased individuals exercise significantly less than their counterparts, though there is no significant relationship between present bias and snacking. These studies underline the importance of these behavioral measures to understand the determinants of BMI.

Our simple theory model suggests that present biased individuals or individuals with lower patience will have poorer health outcomes: that is, they will either be underweight (low BMI) or overweight (high BMI). Food is the channel through which time

[10] They used a dummy variable for whether the respondent discounted the future more heavily for a shorter delay than for a longer delay as a more direct measure for hyperbolic discounting. Note that Ikeda et al. (2010) also test if BMI was non-monotonically related to time-discounting because it is possible that underweight people, as well as obese individuals might be less patient than those with normal weight. However, they find that associations between body mass and each of the time discounting variables are monotonic.

[11] However, if the sample is stratified by sex, the present bias term is significant for women and long run discount factor is insignificant while opposite holds true for men. Similarly, stratification by race shows that both present bias and long-term discount factor is associated with BMI for whites only.

[12] The first set of health variables were related to self-assessed health. Respondents were asked if they would say that their health in general is excellent, very good, good, fair, or poor. The next set of health questions were related to health behaviors such as BMI, non-work-related exercise in the past 30 days, number of times snacks (sweet or salty) consumed on a typical day. In addition, questions on current smoking status and number of cigarettes smoked per day among smokers and about alcohol use were asked. Finally, information on the use of sunscreen and seat belts, two behaviors that protect health were also asked.

preferences affect BMI. To empirically corroborate these predictions and to accurately capture the behavioral parameters, we conducted a primary survey of 885 adults (25-60 years) in West Delhi, in which we elicited time preferences and risk parameters through an experiment. Information on the consumption of healthy/unhealthy foods, exercise as well as on BMI was also collected. Our sample had virtually no underweight adults. Using a simultaneous equation model (SEM), we then estimated the relationship between time preferences, food and BMI. We find that time preferences have significant effect on food choices which in turn has a significant impact on BMI, reinforcing our theory results. Our findings (using primary survey) suggest that time preferences are not correlated with age, implying that psychometric tests based on eliciting these behavioral parameters could be used a screening device to identify individuals early on who might be at the risk of becoming overweight in the future. Further, we also utilized the India Human Development Survey (IHDS) data to estimate a reduced form equation with BMI as a function of savings (a proxy for time preferences). We use quantile regressions and find support for our theory predictions pertaining to underweight and overweight empirically.

The remainder of the paper is organized as follows. The next section details the theory model. Section 3 describes the dataset used for the empirical analysis of the study, sets out the outcome variables, and describes the estimation of time and risk preferences. Sections 4 and 5 present descriptive statistics and empirical findings, and section 6 concludes.

2 Simple Model

In order to accommodate time inconsistent preference, we set up a simple three period model.

2.1 The Setting

An agent chooses food consumption (f) which affects his weight and in turn his health in the future. The per period utility function U of the agent is: $U(f_t, h_t) = u(f_t, c_t) + h_t$. Per period utility is a function of food consumed (f_t), other non-food consumption (c_t) and health status (h_t). The utility function is assumed to be continuous, and is assumed to be separable and linear in its health argument.

Food consumption is chosen by the agent but health is not entirely at agent's discretion and is determined by the equation of motion: $h_{t+1} = h_t(1-\lambda) + \varphi(f_t)$. His health depreciates if he doesn't eat at all, where λ is the rate of depreciation (0< $\lambda \leq 1$) and φ captures how the agent can build his health stock by eating food; it is the health returns from eating food. We assume that φ is inverted U-shaped, that is there exists f^{id} level of food consumption, where f^{id} is the ideal food consumption level. Here f^{id} refers to both quality and the quantity of food. The ideal f^{id} corresponds to ideal weight (and therefore, ideal health). There are two kinds of individuals in our model, individuals who are to the left of f^{id} and individuals who are to the right of f^{id}. Individuals who are to the left of f^{id}, have sufficiently low food intake and/or are not consuming enough nutritious food, such that they are *underweight*. In this case, increase in food intake that provides sufficient nutrition (in terms of quality and quantity of food) has a positive return on health which means $\varphi_f > 0$. Individuals who are to the right f^{id}, are individuals who are eating low quality food in excess (food high in empty calories and low in nutrient content, for example, highly processed foods or foods/drinks high in sugar, fat etc.) such that they are *overweight*. In this case, eating less of poor quality of food has a positive return on health which means $\varphi_f < 0$.

The agent faces a budget constraint in every period, which is represented by: $Y_t = pf_t + c_t$. Y_t is income in time period t, p is the price of food which is assumed to be same in every period and c_t is the non-food consumption in time period t. We assume that in every period, the agent spends all his income on food and/or non-food consumption that is agent doesn't save.

When we take theory to data, we utilize BMI as an indicator of health. If somebody starts with very low BMI (is undernourished), an increase in BMI will improve his health, but after a threshold, increase in BMI depletes health because it might lead to a condition of excessive weight (overweight) and could result in obesity related health problems.

2.2 Intertemporal preferences

Considering a three-period model, the lifetime utility of the agent at time t = 1 can be written as:

$V_1 = u(f_1, c_1) + h_1 + \beta\delta[\, u(f_2, c_2) + h_2] + \beta\delta^2[\, u(f_3, c_3) + h_3]$, where $0 < \beta < 1$ & $0 < \delta < 1$

When $\beta = 1$, it reduces to standard exponential discounting, where the agent is time-consistent. If $\beta < 1,$ it represents quasi-hyperbolic discounting where the agent has different discounting for present and future periods. The discount factor between the present period and the next period is $\beta\delta$, while the discount factor between two adjacent periods in the future is simply δ. The difference between the short-run and the long-run discount factors creates *time-inconsistency.* When agent has time-consistent preferences, the discount factor between present and the next period, and the discount factor between two future adjacent periods remains δ. Therefore, the β parameter brings in time-inconsistent preferences for immediate gratification and the agent discounts the immediate future more sharply than in case of exponential discounting.[13] Lower β represents higher bias for the present and therefore, lower weight to the future utility. Similarly, agents with lower δ represent higher impatience and therefore, care less about future.

A (partially) naive agent expects to have $1, \hat{\beta}\delta, \hat{\beta}\delta^2$ discounting stream where $\beta < \hat{\beta} < 1$. The agent correctly anticipates that he will have time-inconsistent preferences but overestimates his future present bias parameter that is he thinks his present bias will be $\hat{\beta},$ but actually it turns out be β. While a *sophisticated* agent is aware that he has time-inconsistent preferences and correctly predicts his future present biasedness i.e. $\beta = \hat{\beta}$. We assume the agent is sophisticated that is he knows his future self is not going to stick to decisions made by earlier selves and can correctly anticipate his present biasedness and therefore, his future choices. Solving the model assuming a (partially)

[13] β reflects special status of the current period or the bias towards present and devalues all future utilities (except present), over and above the down-weighting associated with time-consistent discounting factor (δ^t) which exponentially discounts all future period utilities.

naive agent does not change our (comparative statistics) results. Therefore, this case is explained in the appendix A3 below.

2.3 Optimal Food Choice

Agent at time period t = 1 will maximize:

$$V_1 = u(f_1, c_1) + h_1 + \beta\delta[\, u(f_2, c_2) + h_2] + \beta\delta^2[\, u(f_3, c_3) + h_3] \;\; w.r.t \;\; to \; f_1$$

$$s.t. \;\; to \;\; h_2 = h_1(1-\lambda) + \varphi(f_1); \;\; h_3 = h_2(1-\lambda) + \varphi(f_2)$$

$$and \;\; Y_t = pf_t + c_t \; for \; t = 1, 2 \; \& \; 3 \qquad (1)$$

The agent maximizes (1) taking into consideration the optimal choices of future periods (i.e. f_2 and f_3) made by her future selves.

We use backward induction and therefore, first solve for f_2. A sophisticated agent, in time period t = 1, for t = 2 will maximize the following problem:[14]

$$V_2 = u(f_2, c_2) + h_2 + \beta\delta[\, u(f_3, c_3) + h_3] \, w.r.t \;\; to \; f_2$$

$$s.t. \;\; to \;\; h_3 = h_2(1-\lambda) + \varphi(f_2) \;\; and \; Y_2 = pf_2 + c_2 \qquad (2)$$

The first order condition is:

$$u_f(f_2, \; Y_2 - pf_2) - pu_c(f_2, Y_2 - pf_2) + \beta\delta \; \varphi_f(f_2) \; = 0 \rightarrow \; f_2^*(\beta, \delta, Y_2, p) \qquad (3)$$

We assume that V_2 is strictly concave in f_2 which ensures unique solution for maximization problem above, that is, for equation (2). The above first order condition (equation (3)) indicates that marginal utility of non-food consumption must be equal to the overall marginal utility of food which equals to the marginal utility of eating (u_f) plus discounted marginal utility of change in health induced by eating ($\beta\delta \; \varphi_f$).

[14] Obtaining optimum food consumption f_3 is not of interest because the agent is anyway going to die in third period.

The optimal food consumption $f_2^*(\beta, \delta, Y_2, p)$ can lie above or below f^{id}. Therefore, there are two scenarios to consider here. The first scenario is of undernutrition where food intake is so low that is it is insufficient to maintain healthy weight status that is $f_2^*(\beta, \delta, Y_2, p) < f^{id}$.While the second scenario is of overnutrition, where food intake is higher than the ideal food consumption that is $f_2^*(\beta, \delta, Y_2, p) > f^{id}$.[15]

The change in food consumption (which ultimately affects health of the agent) with change in $\beta \; and \; \delta$, is given by:

$$\frac{\partial f_2^*}{\partial \beta} = \frac{-\delta \, \varphi_f(f)}{u_{ff}(f, Y-pf) - 2pu_{cf}(f, Y-pf) + p^2 u_{cc}(f, Y-pf) + \beta\delta\varphi_{ff}(f)} \tag{4}$$

$\frac{\partial f_2^*}{\partial \beta}$ can also be written in terms of period 2's lifetime utility, that is,

$$\frac{\partial f_2^*}{\partial \beta} = -\frac{\partial^2 V_2 / \partial f \partial \beta}{\partial^2 V_2 / \partial f^2} \tag{5}$$

Similarly,

$$\frac{\partial f_2^*}{\partial \delta} = \frac{-\beta \, \varphi_f(f)}{u_{ff}(f, Y-pf) - 2pu_{cf}(f, Y-pf) + p^2 u_{cc}(f, Y-pf) + \beta\delta\varphi_{ff}(f)} \tag{6}$$

$$\frac{\partial f_2^*}{\partial \delta} = -\frac{\partial^2 V_2 / \partial f \partial \delta}{\partial^2 V_2 / \partial f^2} \tag{7}$$

We are also interested in knowing how change in $\beta \; and \; \delta$ affects health, this effect can be seen by evaluating the derivative $\partial h_3^* / \partial \delta \; and \; \partial h_3^* / \partial \beta$.[16]

$$\frac{\partial h_3^*}{\partial \delta} = \varphi_f(f) * \frac{\partial f_2^*}{\partial \delta} \tag{8}$$

and

[15] See appendix A1 for calculations.
[16] Refer to appendix A1 for calculations.

$$\frac{\partial h_3^*}{\partial \beta} = \varphi_f(f) * \frac{\partial f_2^*}{\partial \beta} \tag{9}$$

The denominator in (4), (5), (6) and (7) is always negative, while the numerator could either be negative or positive depending on which side of f^{id} the optimal food consumption (f_2^*) is.[17]

There are two scenarios:

Scenario 1: When $f_2^*(\beta, \delta, Y_2, p) < f^{id}$ an increase in nutritious food has a positive return on health which means $\varphi_f > 0$. The sign of $\frac{\partial f_2^*}{\partial \beta}$ can also be seen in terms of lifetime utility, the denominator of equation (5) (and (4)) is negative, so the sign of $\frac{\partial f_2^*}{\partial \beta}$ is same as that of $\frac{\partial^2 V_2}{\partial f \partial \beta}$ and $\frac{\partial^2 V_2}{\partial f \partial \beta} > 0$ because $\varphi_f > 0$. Hence the numerator of equation (4), (5) is negative which implies that $\frac{\partial f_2^*}{\partial \beta} > 0$. The cross partial derivative $\frac{\partial^2 V_2}{\partial f \partial \beta}$ tells that how change in β affects the marginal lifetime utility of food consumed in the present through its effect on health tomorrow. If $f_2^*(\beta, \delta, Y_2, p) < f^{id}$, keeping all other things constant, a higher β increases the positive incremental effect (because $\varphi_f > 0$), it is optimal for the agent to increase its food consumption. So, if an agent has a higher present bias, his optimal food consumption (f_2^*) is closer to f^{id}. Therefore, agents with lower β (have higher present bias) care more about present at the expense of health in the future and therefore, consume less food today, consume more of non-food items and have worse health outcomes (in this case, lower BMI). Similarly, $\frac{\partial f_2^*}{\partial \beta} > 0$, that is, higher δ will increase the positive effect of eating food and therefore, agent will increase its optimal food consumption food consumption and ultimately have higher health status in the future (higher BMI).

Scenario 2: When $f_2^*(\beta, \delta, Y_2, p) > f^{id}$ the agent's consumption of food is excessive as it contributes to obesity. In this case, increased consumption of poor quality (high in

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[17] Denominator is negative because we assume V_2 to be strictly concave. Refer to appendix A1 for details.

fats and sugar) food has a negative return on health which means $\varphi_f < 0$. Sign of $\frac{\partial f_2^*}{\partial \beta}$

$\frac{\partial f_2^*}{\partial \beta}$ is same as that of $\frac{\partial^2 V_2}{\partial f \partial \beta}$ and $\frac{\partial^2 V_2}{\partial f \partial \beta} < 0$ because $\varphi_f < 0$. Hence the numerator of equation (4) and (5) is positive (and denominator is negative), so which implies that $\frac{\partial f_2^*}{\partial \beta} < 0$. Agent with higher β indicates lower present bias, implying that it increases the negative incremental impact, so it is optimal for the agent to reduce the food consumption.[18] Therefore, lower β leads to higher (junk) food consumption (that is further away from f^{id}) and hence lower health outcome (that is higher BMI). Similarly, $\frac{\partial f_2^*}{\partial \delta} < 0$, lower δ results in higher food consumption today and ultimately lower health status (in this case, higher BMI).

After solving for period 2 food consumption, agent will now maximize V_1.

Agent at time period t = 1 will maximize:

$$V_1 = u(f_1, c_1) + h_1 + \beta\delta\left[\, u\big(f_2(\beta, \delta, Y_2, p), Y_2 - pf_2(\beta, \delta, Y_2, p)\big) + h_2\right] \\ + \ \beta\delta^2[\, u(f_3, c_3) + h_3] \ \ w.r.t\ to\ f_1$$

$$s.t.\ to\ \ h_2 = h_1(1-\lambda) + \varphi(f_1); \ \ h_3 = h_2(1-\lambda) + \varphi(f_2)$$

$$\&\ Y_t = \ pf_t + c_t\ for\ t = 1{,}2\ \&\ 3 \tag{10}$$

The first order condition is:

$$u_f(f_1,\ Y_1 - pf_1) - pu_c(f_1, Y_1 - pf_1) + \beta\delta\ \varphi_f(f_1)[1 + \delta(1-\lambda)]{=}0 \rightarrow f_1^*(\beta, \delta, Y_1, \lambda, p) \tag{11}$$

How food consumption changes with change in $\beta\ and\ \delta$ is given by:

$$\frac{\partial f_1^*}{\partial \beta} = \frac{-\ \delta\ \varphi_f(f)[1+\delta(1-\lambda)]}{u_{ff}(f, Y-pf)\ -2pu_{cf}(f, Y-pf) + p^2 u_{cc}(f, Y-pf) + \beta\delta\varphi_{ff}(f)[1+\delta(1-\lambda)]} = \frac{\partial^2 V_1 / \partial f \partial \beta}{\partial^2 V_1 / \partial f^2} \tag{12}$$

[18] Agents with higher β will worry less about health (that comes in the future) and will eat more today.

$$\frac{\partial f_1^*}{\partial \delta} = \frac{-\beta\, \varphi_f(f)[1+2\delta(1-\lambda)]}{u_{ff}(f,Y-pf)\; -2pu_{cf}(f,Y-pf)+p^2u_{cc}(f,Y-pf)+\beta\delta\varphi_{ff}(f)[1+\delta(1-\lambda)]} \tag{13}$$

We are ultimately interested in knowing how change in $\beta\ and\ \delta$ affects health, and this effect can be seen by calculating ${\partial h_2^*}/{\partial \delta}\ and\ {\partial h_2^*}/{\partial \beta}$. [19]

$$\frac{\partial h_2^*}{\partial \delta} = \varphi_f(f) * \frac{\partial f_1^*}{\partial \delta} \tag{14}$$

and

$$\frac{\partial h_2^*}{\partial \beta} = \varphi_f(f) * \frac{\partial f_1^*}{\partial \beta} \tag{15}$$

The numerator could be either be negative or positive depending on whether the optimum food consumption (f_1^*) is to the left or right of which side of f^{id}, while the denominator in (12) and (13) is always negative. [20]

Again, the predictions of the model differ depending on which scenario we are considering. The predictions are similar to what we have explained above. In scenario 1, $\frac{\partial f_1^*}{\partial \beta}\ and\ \frac{\partial f_1^*}{\partial \delta} > 0$; $\frac{\partial h_2^*}{\partial \delta}\ and\ \frac{\partial h_2^*}{\partial \beta} > 0$. It indicates that agents with lower $\beta\ or\ \delta$ will eat less in the present time period, and therefore, will have poorer health outcome (lower BMI). While in scenario 2, $\frac{\partial f_1^*}{\partial \beta}\ and\ \frac{\partial f_1^*}{\partial \beta} < 0$; $\frac{\partial h_2^*}{\partial \delta}\ and\ \frac{\partial h_2^*}{\partial \beta} > 0$, this implies that among individuals who are to the right hand side of f^{id} (overnourished), those who care more about the present(have lower β) or individuals with lower patience (lower δ), will eat more bad quality of food in the present time period and hence, will have higher BMI.

3 Data and Construction of Variables in the Primary Survey

The empirical analysis is based on two data sets. First, we use data collected from a primary survey in Rohini, a locality in western Delhi to elicit time preferences parameters. Furthermore, using this primary survey, we are able to focus more

[19] Refer to appendix A2 for calculations.
[20] Denominator is negative because we assume V_1 to be quasi concave. Refer to appendix A2 for details.

specifically on the quality of food consumed by individuals, and how this mediates the relationship between time preferences and BMI. It turns out that almost negligible proportion (1%) of individuals were underweight in our survey, therefore, we could only test scenario 2 of our model using primary survey.

Second, we use a nationally-representative data set, the IHDS (2011-12) to test predictions under scenarios 1 and 2 as described in section 2. The IHDS provides a wealth of data on demographics, socio-economic characteristics, and anthropometric data on height and weight of individuals. But there is no variable that explicitly captures time preferences; therefore, we use savings information derived from income and expenditure data in the survey as a proxy. We focus on urban adults aged 25-60 in the IHDS survey for this paper.

Rohini (our study area) was chosen because it consists of dwellings representing diversity in terms of living standard, ranging from people living in slums to large penthouses.[21] We employed a stratified two-stage sampling design. All apartment buildings and slums were divided into four strata according to their property values. Stratum 1 consisted of slums, the remaining strata were assigned in ascending order of property values.[22] The sample was then assigned to each stratum based on probability proportional to size, subject to a minimum sample size of 100 households in any given stratum.[23] From each stratum, apartments were randomly selected and in stage 2 households were then randomly selected (using Rohini's electoral roll of 2018).[24] It was difficult to find electoral roll addresses in stratum 1 (slums); in this case, we took a random start, and interviewed every 5th household in the east direction until the

[21] The survey was funded by Georg-August-Universität Göttingen, Center for Modern Indian Studies (CeMIS) courtesy Professor Sebastian Vollmer. In the part of Rohini we surveyed, there are no independent houses or floors, only apartments or slums.
[22] Property dealers in the area were interviewed to obtain real estate values for ranking the apartments.
[23] Our realized sample proportions were not very different from the population proportions.
[24] The president (or vice-president) of the Resident Welfare Association (RWA) of the selected apartments was contacted to seek permission to conduct the survey in their apartment complex.

desired sample size was reached.[25] The sample consisted of 885 adults in the age group of 25-60 years. The following sub sections pertain only to the primary survey.

3.1. Dependent Variable

3.1.1 Body Mass Index

The primary outcome variable is BMI. The body mass index (BMI) is defined as the ratio of weight in kilograms to the square of height in meters (kg/m^2).[26] We use the continuous measure of BMI as the dependent variable in the regressions.

3.1.2 Food Score

We collected information on food consumption for each respondent using a food frequency questionnaire (FFQ) of 102 food and beverage items eaten during the one week preceding the survey. Each item had a choice of 8 frequency categories ranging from "did not eat last week" to "six or more times a day". We then converted frequencies to equivalent daily frequencies and assume that each eating occasion represents consumption of 1 serving of food. The FFQ module also had questions on food habits to judge salt consumption and consumption of saturated fat.[27]

We follow McNaughton et al. (2008) to create a food score variable for each individual reflecting dietary guidelines for Australian adults. These guidelines are very similar to Indian dietary guidelines provided by National Institute of Nutrition (NIN), but provide for finer classification of the food score and allow for recording of daily serving. The Australian Guideline to Healthy Eating (AGHE) provides age and sex-specific recommendations for the consumption of 5 core food groups (vegetables, fruits, cereals, meat and alternatives, and dairy) and *extra foods*. AGHE defines extra foods as those

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[25] http://ceodelhi.gov.in/AccemblyConstituentyeng1.aspx is the link that provides data on electoral roll. The list created using electoral roll matched completely with the list of apartments with the real estate agents. There are about 143 societies out of which households from 45 societies were interviewed.

[26] For the descriptive statistics we use the lower Asian cut-offs defined by World Health Organization (WHO, 2004) to group individuals on the basis of BMI into underweight (BMI < 18.5), normal weight ($18.5 \leq$ BMI <23), overweight ($23 \leq$ BMI <27.5) and obese (BMI ≥ 27.5) categories.

[27] For instance, we asked the type of milk consumed (low or high fat); frequency of consumption of butter to judge respondent's saturated fat consumption.

that do not provide essential nutrients and are “high” in calories, fat, sugar, and salt. Further, *diet quality* in the score is incorporated by inclusion of items relating to consumption of whole-grain cereals, dietary variety, low fat dairy, reduced saturated fat intake, limited salt intake, reduced or limited sugar and sugar containing foods (see Table A1 in appendix).

Thirteen components are included in the food score, and are detailed in Table A1. Each component is scored from 0–10, with 10 indicating that the respondent meets the recommendation; any intake below optimal is scored proportionately. For instance, with respect to fruit intake, an individual having 2 servings per day (recommended amount) gets 10 points, 1 serving per day scores 5 points, and no fruit consumption scores 0 points. Where as in case of extra foods (unhealthy foods), a male having less than 3 servings of extra food per day is assigned 10 points, and is assigned 0 point if he has 3 or more servings of extra food per day. Therefore, the total score is the sum of thirteen components, and has a range of 0-130, with a higher food score representing a more a healthier and a more adequate diet.

3.2. Estimating Time preferences and Risk Parameters

We measure both $\beta \; and \; \delta$ assuming time-inconsistent preferences. Similar to Meier and Sprenger (2010) and Bradford et al. (2017), we use four “series” of multiple price list (MPL) questions. Each series includes eight binary choices, and respondents were asked to choose between smaller sooner amount (Rs X) available in period t or larger later payment (Rs Y) at time $t + \tau$ for each of these eight binary choices. The larger later amount (Rs Y) was kept constant at Rs 900 while smaller sooner payment varied from Rs 870 to Rs 390. We use today and six months ($t = 0$ and $\tau = 6$) and six months and twelve months ($t = 6$ and $\tau = 6$) for estimating time preferences under time-inconsistency.[28]

[28] Since there is no optimum time delay to detect present bias, in our survey we asked MPL questions using 1 (i.e. $\tau = 1$) and 6-month ($\tau = 6$) delay as used in the literature as well. But for our sample, 6-month delay helped in capturing present bias better and also our results are consistent using 6-month delay.

Table 1 lists two series. It is expected that the respondents would opt for smaller sooner amounts and will switch to larger later amounts as the difference between smaller sooner and delayed amount increases (as we go down from Rs 870 to 390). This switch helps in identifying the range of values of time preferences parameter because the shift implies that the respondent was indifferent at some point along the interval between the two (smaller sooner) amounts.

In the first series, 11% respondents choose Rs 900 in six months over Rs 870 today. In both the series as expected the proportion of respondent choosing larger delayed option increases as we move down from Rs 870 and Rs 390. Given identical rate of return and same time delay, under time-consistency, one would expect respondents to choose same option for each row in both the series. Instead, we find that the percent of respondents opting for delayed amount reduces when sooner payment becomes available today, showing bias for the present or time-inconsistent preferences.[29] An example of the calculation is presented in Appendix.

In an important recent contribution, Andersen et al. (2008) highlight that there are issues using MPLs to estimate time preferences. In particular, estimated discount rates (discount factors) can be biased upwards(downwards) as linear utility is assumed. If utility is truly concave, not controlling for risk preferences in any regression can lead to misleading results (Andersen, et al., 2008; Andreoni, et al., 2013).[30] Therefore, we adopted a strategy which is similar to that of using double multiple price lists (DMPL, henceforth) and also elicit risk preferences.[31]

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[29] Comparing series today and 1-month ($t = 0$ and $\tau = 1$) and today and six months ($t = 0$ and $\tau = 6$), we find that as the delay length increases from 1 month to 6 months, respondents choosing larger later option decreases supporting the findings that individuals are less willing to wait for an option that is farther away in the future.

[30] Time preferences and risk preferences are correlated and also, risk preferences and our dependent variable (food score and BMI) might also be correlated as there are studies that highlighting individuals who are more risk loving are have higher BMI or have poor nutritional habits (Galizzi and Miraldo 2017). Not controlling for risk preference might lead to omitted variable bias.

[31] Andreoni et al. (2013) consider an alternative convex time budgets (CTB) strategy in addition to DMPL. We have used DMPL, because we tried both the methods during our pre-pilot with a few individuals and found that the computational burden on the participants of the CTB questions was way higher in CTB.

We use Gneezy and Potters (GP task, henceforth) task where respondents are asked to allocate/invest an amount between a risky and a safe option, with the expected returns from risky option being greater than the amount invested.[32] The amount invested in the risky option provides a good metric for capturing differences in attitude toward risk between individuals. While other methods such as Holt and Laury task are widely used in the laboratory contexts, we use the GP task for its ease in implementation in field contexts. [33]

Both time and risk elicitation mechanisms were made incentive compatible by offering a randomly selected respondent the amount stated in a randomly selected question. We selected 10% of our sample to give out real payments. Payments were made using cheques issued in the name of the respondent right after the survey completion. Respondents winning today payments had dates (on cheque) on which the respondent was interviewed while future payments were made by issuing a post-dated cheque from the date of survey conducted (for example 6 months from the date of survey). In case of risk question being selected, the respondent was issued cheque with the survey date. Thus, there was no difference in the transaction costs across the present and future payment.

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[32] For instance, respondents were asked to divide Rs. 500 between a safe asset and a risky investment. If the investment fails (50 percent chance of failing), respondents lose the amount invested and receive only the amount not invested. If the investment succeeds (50 percent chance of success), three times the invested amount is paid to the subject along with the amount set aside in the safe option. Given this, a risk neutral and a risk seeking individual should invest their entire Rs 500 in the risky option. One disadvantage of GP task is it cannot distinguish between a risk loving and a risk neutral individual. However, it has been observed that risk loving preferences appear to be uncommon, as very few choose to invest entire amount. Only 10% of our sample chose to invest entire Rs 500.

[33] Holt and Laury task (HL, henceforth) imposes a finer grid on the subjects' decisions, and thus produces a more refined estimate of the relevant utility function parameters. However, HL method is often found to be too complex for subjects to understand especially with individuals with poor cognition/education and those belonging to developing countries. A fair number of studies using HL method in developing countries report 40-60% of inconsistency in risk attitudes among subjects (Brick et al., 2012; Cook et al., 2013; Charness and Viceisza., 2015). Eckel and Grossman proposed a simpler task (EG task, henceforth), but even the EG task can be conceptually challenging and non-intuitive. Studies have found that GP task is simpler to understand than the EG and HL tasks, and is being increasingly used in developing countries with non-standard subjects (Cameron et al., 2013; Dasgupta et al., 2015; Gangadharan et al., 2016). During our pre-pilot we also found that GP task was easily understood by the non-standard subjects as compared to EG and HL task and hence, was used in our survey.

4 Evidence on the Relationship between Time preferences and Health Outcomes from a Primary Survey Conducted in West Delhi.

Primary survey contains a direct measure of time and risk preference. Furthermore, individual-specific information on food consumption is collected, a direct test of the channel through which behavioral parameters affect health outcomes is possible. In our sample 34% adults are overweight and 51% obese. The proportion of adults who are underweight (BMI <18.5) is negligible (1%), which means that only 13% are in healthy weight category.

Summary statistics on calculated time preferences are set out in Table 2. The average $\beta = 0.879$, which means on an average individual is present biased. The minimum value of β is 0.220 and the maximum is 1, while 0.774 and 0.997 are the minimum and maximum values of δ respectively. In our sample about 30% adults are present biased.[34] Our results are similar to Meier and Sprenger (2010) who find 36% of their sample as present biased.

Recall that the mediating factor between time preferences and BMI is food, the latter is measured using food score. We expect a positive relationship between β, δ and the food score (because higher score indicates that individual is consuming healthier diet). Figure 1 presents the non-parametric lpoly plots of the association between food score and time preferences. We observe a positive association between δ and food score (Panel B of figure 1). For the present bias term, we observe that for values less than or equal to 0.7, β is positively associated with food score, but beyond this value we find that increase in β is negatively associated with food score (Panel A of figure 1). Hence, these figures are suggestive of positive relationship between time-discounting and food score which are in line with our expectation.

Table 3 presents food scores by weight categories. We observe that individuals in the normal weight category have lower food score (and are statistically significantly different) as

[34] 43% of our sample have time-consistent preferences and 27% are future biased. Because of the reasons mentioned in section 4.1 we cap values of β at 1 if it is greater than 1.

compared to individuals who are overweight or obese which is contrary to our expectation. The reason could be that these are merely correlations and we haven't controlled for a lot of other factors, but in the regressions below we observe relationship in the expected direction.

The direct empirical counterpart to the theoretical relationships derived in section 2 is the following system of two equations:

$$food\ score_i = \gamma_0 + \gamma_1\beta_i + \gamma_2\delta_i + \gamma_3 X_{food\ score,i} + \mu_i \tag{16}$$

and

$$BMI_i = \eta_0 + \eta_1\, food\ score_i + \eta_2 X_{BMI,i} + \tau_i \tag{17}$$

Where $food\ score_i$ denotes $food\ score$ of individual i, β_i, δ_i are the variables of interest and $X_{food\ score,i}$ is a vector of control variables (such as age, wealth score, years of education, respondent's sex and risk preference). We control for risk preference because as discussed above, time and risk preferences may be intertwined, and not controlling for risk preferences of the respondents may bias the coefficient of interest. $X_{BMI,i}$ includes control variables such as age, wealth score, years of education, respondent's sex, dummies for type of occupation, dummy for exercise and dummy for menopause.[35] We expect a positive relationship between β, δ and food score in equation 16 and a expect negative relationship between BMI and food score in equation 17.

Table 4 presents simultaneous equations model (SEM) results corresponding to equations (16) and (17). As discussed above, we can test predictions of theory model under scenario 2 only, because the sample had only 1% of underweight adults. Column (1) and (2) of Table 4 starts with a simple regression of $food\ score$ on present bias term β, long run discount factor δ and age, and BMI on $food\ score$ and age respectively. We then systematically add the other controls to construct the full model in column (15) and (16) to see how the magnitude of coefficient of β, δ and $food\ score$ changes with specification.

[35] Employed full-time in work that involves medium or high physical activity, employed part-time, not working (includes home maker, student, unemployed/retired) relative to omitted category- employed in full-time light or sedentary work.

The sign of coefficient of both β and δ are in the expected direction but are not significant (column 1 and 2 of table 4). However, when wealth score is added in columns (3) and (4), the coefficient of δ and food score becomes significant with expected sign.

Our estimates stabilize once we control for years of education (column 7, 8 to column 13, 14 of Table 4). When we add risk preference in column (15), the magnitude of coefficients associated with $\beta\ and\ \delta$ increases from 0.30 to 0.40 and 2.97 to 3.80 respectively, and it has the correct (positive) sign, while the coefficient of food score decreases from -2.49 to -1.92. The results indicate that food does mediate the relationship between time preferences and BMI. Note that the signs and significance of coefficients of our variables of interest are stable across different specifications.[36]

For comparison, we also run OLS regression (using full specification) for equations (16) and (17) and the results are presented in Table 5. Though signs of coefficient of $\beta\ and\ \delta$ are in the expected direction, they are not significant (column 1 of Table 5), whereas coefficient of food score is significant but has a perverse sign (column 2 of Table 5). This is likely because the OLS regressions do not account for the correlations between the two error terms of the SEM.

5 Evidence from the Nationally Representative IHDS data.

The IHDS data has the advantage of being nationally representative, we use data from the second round of nationally representative IHDS survey to test the predictions of both the scenarios of our model. Overall, 36% of urban adults (25-60-year-old) are overweight and 20% are obese, while 9% adults are underweight and remaining 35%

[36] The results above use time preferences estimated from the last switching point. As a robustness check, we (a) utilize first switching point in case of more than one switching and (b) exclude respondents displaying multiple switches. Columns 1 to 4 of Table A2 in appendix show that our results are consistent across these specifications. The coefficient of $\beta\ and\ \delta$ is statistically significant and positively associated with food score and food score is negatively associated with BMI in both the SEM regressions. We also run regression by controlling for smoking and alcohol consumption. Coefficients are reported in column (5) and (6) of Table A2 in appendix. We find that our result is consistent. We don't control for these variables in our main regression as only 3% and 10% of our sample smoke or drink alcohol, respectively. Controlling for these variables could therefore lead to over controlling problem.

have BMI in the healthy range. These percentages are derived using the Asia-specific cutoffs to classify individuals into different weight categories.

To test relationship between time preferences and underweight and overweight, we run reduced form equations relating time preferences and BMI, using savings as a proxy for time preferences. This is similar to earlier work referred to in section 1 that has used savings rate, saving and dissaving information, financial indicators (such as assets and liabilities) and attitudes to proxy time preferences (see Smith et al., 2005; Borghans and Golsteyen, 2006 and Kolmos et al., 2004). Our hypothesis is that people with higher time preferences (or lower δ or lower β) in a household will tend to spend more rather than save to obtain pleasure now.

Households in IHDS report their income (earned through different sources) and expenditure (on different categories), based on which we calculate their savings (which is income - expenditure). Given higher likelihood of measurement error in income and expenditure variable, used for calculating savings, we created a dummy variable which takes value 1, if savings are positive, and 0 if a household dissaves (i.e. household expenditure is higher than household income).

Table 6 provides quantile distribution of BMI and associated proportion of households with positive savings. As we move up along the BMI distribution from 5th quantile to 20th quantile, proportion of households who are saving also go up slightly (from 46% to 49%). Similarly, if we look at the upper end of the BMI distribution from 75th quantile to 90th quantile, the proportion falls from 57% to 50%. These figures are indicative of the relationship we are expecting at the lower and upper ends of the BMI distribution.

We estimate quantile regressions with the following specification:

$$BMI_{i\theta} = \alpha_{0\theta} + \alpha_{\theta 1} Savings_i + \alpha_{\theta 2} X_i + \varepsilon_i \qquad (18)$$

where $\theta \in [0,1]$ denotes θ^{th} conditional quantile of the distribution of BMI.

The above equation is estimated at different values of θ. BMI_i denotes BMI of individual i, $Savings_i$ is a dummy variable as described above, is the variable of interest and X_i is a vector of control variables and state fixed effects.[37] Age in years, respondent's sex, years of education and type of occupation - blue collar jobs, not working relative to white collar jobs are included as control variables.

Scenario1 suggests that at the lower end of the BMI distribution, individuals with positive savings (i.e. lower time preferences or high $\delta\ or\ \beta$) are likely to have higher BMI, whereas scenario 2 suggests that individuals with positive savings will have lower BMI at the upper end of the BMI distribution. That is, we expect that the relationship between savings and BMI will change from being positive to negative as we move from lower to upper end of the conditional BMI distribution.

This is indeed the case, as seen in Table 7. The association between savings and BMI is positive for individuals who are at the lower end of the BMI distribution (column 1, 3, 4 and 5) while at the upper end of the BMI distribution, household with individuals who dissave are more likely to have higher BMI (column 6, 8 and 9). In other words, households with positive savings (patient individuals or individuals with self-control) are more likely to be healthy at both ends of the BMI distribution, supporting our theory prediction.

5 Estimation Sample and Estimates of Time preferences on Age

The results discussed so far are based on an estimation sample of 706 adults from 885 that were interviewed. We discuss here why sample was lost and the implications for the interpretation of results. First, since item non-response was possible, 99 individuals either did not have their weights/heights, did not answer the multiple price list module, did not answer food frequency module or did not answer questions used as controls in the regression.

Of the remaining 786 individuals, 80 gave inconsistent answers in the MPL questions: in other words, they switched from larger-later payments to smaller-sooner amounts in

[37] We do not control for household's wealth in the regression because of its possible correlation between savings. When we include it on our regression, we lose significance at the lower end of the BMI distribution, but signs are as expected.

at least one out of four series. Hence, we could not estimate time preferences for these individuals and hence these observations are dropped from regressions.

To examine whether there are systematic differences between those who are dropped from the estimation sample and those who remain, we ran two sets of probit regressions. In the first, we examine if the 80 respondents who gave inconsistent answers to MPL questions were different from those 706 individuals who did not. These results (refer to column 1 of Appendix Table A3) suggest that younger and less educated respondents are more likely to give inconsistent responses. In addition to this, women as compared to men have higher chances of giving inconsistent responses. However, there are no differences on BMI and wealth grounds. In a second probit regression, we examine if those with item non-response were systematically different from 706 observations. Results of this regression indicate no significant differences in terms of gender and age (see column (2) of Appendix Table A3) but less educated people are more likely to not respond to the questions/controls used in the regressions. Therefore, our remaining sample consists of relatively older adults, more educated respondents and relatively more men. Our regression results thus should be interpreted keeping this limitation in mind.

We also run regressions of our variables of interest $\beta\ and\ \delta$ on age (see Table A4). Age is not correlated with time preferences variables, therefore, there is no evidence that individuals are becoming systematically less patient over time (which might explain rising BMI levels); in other words, discount factors or time preferences variables are stable over time. Percoco and Nijkamp (2009) in a meta-analysis observe no change in the time preferences. Borghans and Golstyen (2005) using proxy of time preferences variable observe the average discount factor (or discount rate) did not change over time. Similarly, Merier and Sprenger (2009) find no evidence of discount factor/time preferences changing over time (people becoming less patient) which could explain rising BMI levels. Our results thus corroborate what has been observed in the literature, indicating that present bias (β) or long run discount factor (δ) are not correlated with age. Although conclusive evidence that these behavioral parameters do not change with age would require repeated observations on the same individuals as they age, nonetheless, this lack of relationship has useful implications for policy as outlined below.

6 Summary and Conclusions

This paper investigates the link between time preferences and BMI. Using quasi-hyperbolic discounting which takes into account change in preferences as time passes, our simple model predicts that lower patience or higher preference for present either increases BMI or decreases BMI. Utilizing data from primary survey of 885 adults in West Delhi our empirical results pertain only to overweight or healthy individuals. We then estimate the relationship between time preferences, food and BMI using a system approach. We find that time preferences have significant effect on food choices which in turn has a significant impact on BMI, reinforcing our theory results. In the second exercise, using IHDS dataset we find that the predictions of our theory model are validated empirically i.e. impatience or lack of self-control is associated with being underweight or overweight.

It is worth noting that our paper provides first evidence that food is the channel that explains relationship between time preferences and BMI using direct measures of time-discounting. Our paper also embarks on accounting for time-inconsistency, therefore, corroborating findings of Courtemanche et al., 2014. The evidence of significant relationship between present biased and BMI, has certain policy implications. Ikeda et al., (2010) and Courtemanche et al., 2014 argue that policies such as raising the costs of overeating in the current period such as tax on unhealthy foods might be effective. Further, Ikeda argues that to restrain present biased people from overconsuming, “nudging policies” that is changing the default option could be useful, for example, Wansink and Cheney (2005) and Wansink (1996) find that being served from a larger portion sizes results in larger consumption of calories among consumers. Similarly, Schwartz et al. (2012) find that when consumers were offered the choice to “downsize” the portion of a menu item’s side dish, those who opted for the reduction consumed less calories. However, for developing countries there is limited evidence and therefore needs further investigation.

While much of the literature on overweight focuses on changing macro level factors (such as falling food prices) as the primary reason for rising BMI levels, our study shows that individual behavioral factors can also explain the heterogeneity in BMI levels. In fact, both changing economic incentive and variation in time preferences can explain the changes in body weight as impatient or present biased individuals are more likely to react intensively to changing environment (Courtemanche et al., 2014).

Given absence of evidence on decreasing discount factor over time or changing present bias with age as discussed in section 5. Similarly, Borghans and Golstyen (2005) and Merier and Sprenger (2009) using panel data find no evidence of time preferences changing over time. The major implication of our results is that the psychometric or behavioral measures such as impatience or present bias tend to be very stable and are potentially powerful predictors of dietary and lifestyle choices, and consequently, BMI. These measures can potentially be used clinically to detect individuals who might be at risk (higher BMI) in the future at an early stage. Hence, targeting individuals at the lower tail of discount factor (or present bias) distribution at an early stage may mitigate the rise in overweight and obesity.

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Table 1: Payoff Table for 6 Month Time Horizon in the Time Preference Experiments

	Series 1			Series 2		
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Row	**Amount today Option A**	**Amount in six months Option B**	**Percent choosing Larger amount**	**Amount in six months Option A**	**Amount in twelve months Option B**	**Percent choosing Larger amount**
1	870	900	11	870	900	17
2	840	900	14	840	900	19
3	810	900	18	810	900	23
4	750	900	31	750	900	33
5	690	900	41	690	900	45
6	600	900	52	600	900	56
7	510	900	61	510	900	67
8	390	900	70	390	900	76

Source: Based on primary survey data collected in West Delhi in June-July, 2018.
Notes: Data refer to adults aged 25 to 60 years. Column (4) and (7) report proportion of respondent choosing later option in series 1 and 2 respectively.

Table 2: Distribution of calculated discount factors and present bias term

Time preference variables	Average (standard deviation)	Range
	(1)	(2)
β	0.879 (0.235)	0.220-1.000
δ	0.916 (0.081)	0.774-0.997

Source: Based on primary survey data collected in West Delhi in June-July, 2018.
Notes: Data refer to adults aged 25 to 60 years. Column (1) reports mean of value and standard deviation in parenthesis of the specified parameter. Column (2) displays range of the distribution.

Table 3: Average Food Score by Weight Categories

BMI category	Average Food Scores
Normal weight	69
Overweight	77
Obese	78

Source: Based on primary survey data collected in West Delhi in June-July, 2018.

Notes: Data refer to adults aged 25 to 60 years. Adult is categorized as normal weight if 18.5 $kg/m^2 < BMI < 23\ kg/m^2$, overweight if 23 $kg/m^2 \leq BMI < 27.5\ kg/m^2$, and obese if $BMI \geq 27.5\ kg/m^2$.

Table 4: Estimates of Simultaneous Equation Models (SEM) of Food Score and BMI.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Dependent variable	**Food score**	**BMI**	**Food score**	**BMI**	**Food score**	**BMI**	**Food score**	**BMI**	**Food score**	**BMI**	**Food score**	**BMI**	**Food score**	**BMI**	**Food score**	**BMI**
Explanatory variables																
β	1.22 (3.08)	-	0.48 (0.29)	-	0.35** (0.15)	-	0.33** (0.16)	-	0.33** (0.16)	-	0.31** (0.14)	-	0.30*** (0.11)	-	0.40** (0.17)	-
δ	8.65 (14.66)	-	4.03*** (1.43)	-	3.01*** (1.09)	-	2.96*** (1.10)	-	2.99*** (0.96)	-	2.99*** (1.03)	-	2.97*** (1.05)	-	3.80*** (1.26)	-
Food score	-	-0.75 (1.65)	-	-1.82*** (0.54)	-	-2.45*** (0.09)	-	-2.45*** (0.05)	-	-2.46*** (0.20)	-	-2.47*** (0.03)	-	-2.49*** (0.02)	-	-1.92*** (0.14)
Age	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wealth Score	-	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Education in Years	-	-	-	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sex	-	-	-	-	-	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Type of occupation	-	-	-	-	-	-	-	-	-	✓	-	✓	-	✓	-	✓
Dummy for exercise	-	-	-	-	-	-	-	-	-	-	-	✓	-	✓	-	✓
Dummy for Menopause	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	-	✓
Risk preference	-	-	-	-	-	-	-	-	-	-	-	-	-	-	✓	-
Cov(μ_i and τ_i)	190.69		421.12***		561.30***		561.42***		562.67***		565.68***		569.23***		440.94***	
Observations	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**	**706**

Source: Estimates from a primary survey data collected from West Delhi in June-July, 2018.

Note: Data refer to adults aged 25 to 60 years. Last switching point is used as an indifference point in case of multiple switches to elicit time preferences. Type of occupation includes dummies for employed full-time in high and medium physically intensive job, employed part-time, not working and employed in low physically intensive job (reference category). Clustered standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table 5: Ordinary Least square Regression (OLS) of food score on time preferences and BMI on food score.

	(1)	(2)
Dependent variable	**Food score**	**BMI**
Explanatory variables		
β	2.104 (2.852)	-
δ	2.898 (10.916)	-
Food score	0.051 (0.037)	0.029* (0.010)
Age	✓	✓
Wealth Score	✓	✓
Education	✓	✓
Sex	✓	✓
Type of occupation	-	✓
Dummy for exercise	-	✓
Dummy for Menopause	-	✓
Risk preference	✓	-
Observations	**706**	**706**

Source: Estimates from a primary survey data collected from West Delhi in June-July, 2018.
Note: Data refer to adults aged 25 to 60 years. Last switching point is used as an indifference point in case of multiple switches to elicit time preferences. Type of occupation includes dummies for employed full-time in high and medium physically intensive job, employed part-time, not working and employed in low physically intensive job (reference category). Clustered standard errors in parenthesis. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p <0.01$.

Table 6: BMI values and proportion of Households who have positive savings by BMI percentiles

	5th quantile	10th quantile	15th quantile	20th quantile	70th quantile	75th quantile	80th quantile	85th quantile	90th quantile
BMI Value	17.4	18.6	19.5	20.2	25.8	26.6	27.4	28.5	29.9
Proportion who are saving	46%	45%	49%	49%	57%	52%	53%	50%	50%

Source: Author's estimates from IHDS 2011-12.

Note: Data refer to urban adults aged 25 to 60 years. Households with Income > expenditure is defined as households who are saving.

Table 7: **Quantile regression estimates of BMI on savings (proxy for time preferences) and other control variables.**

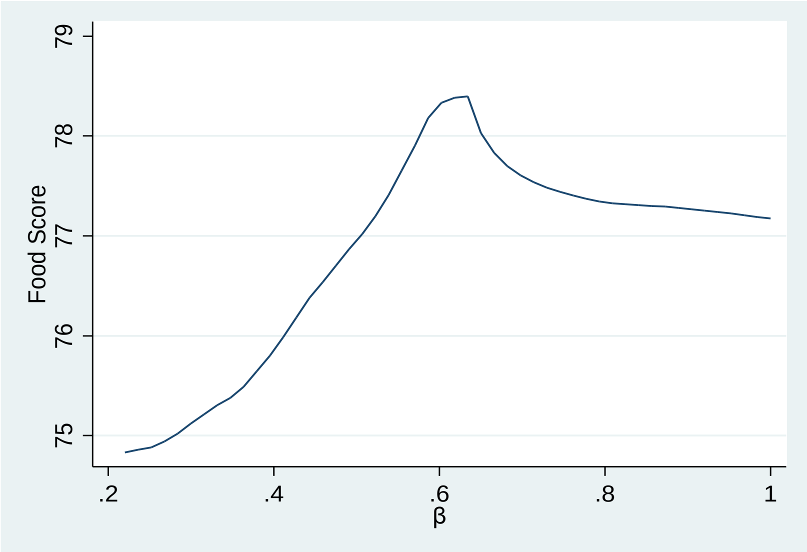
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable is BMI	**5th quantile**	**10th quantile**	**15th quantile**	**20th quantile**	**25th quantile**	**70th quantile**	**75th quantile**	**80th quantile**	**85th quantile**	**90th quantile**
Savings[a]	0.159*	0.076	0.169**	0.192***	0.144**	-0.144*	-0.129	-0.205*	-0.266**	-0.259
	(0.096)	(0.101)	(0.084)	(0.074)	(0.068)	(0.080)	(0.099)	(0.112)	(0.128)	(0.164)
Age	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Education (in years)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Type of occupation	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	20,447	20,447	20,447	20,447	20,447	20,447	20,447	20,447	20,447	20,447

Source: Author's estimates from IHDS 2011-12.

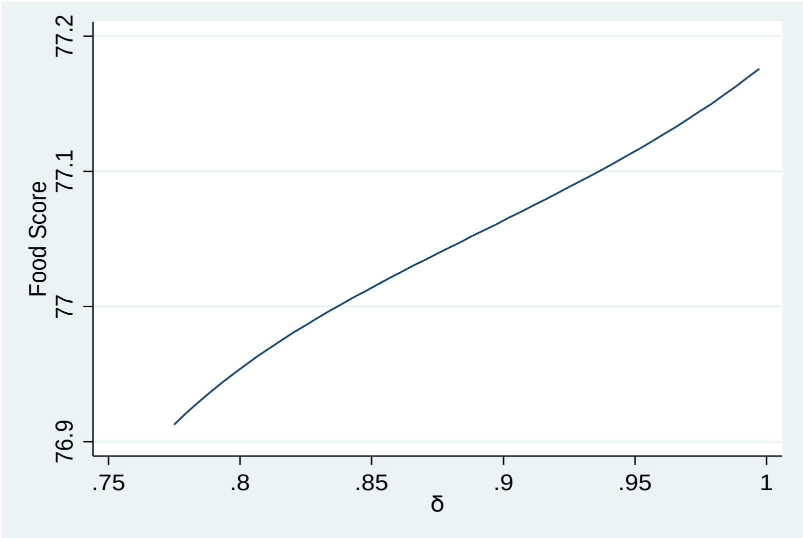
Note: Data refer to urban adults aged 25 to 60 years. Reference category- [a]: Dissaving. Type of occupation includes dummies for blue collar, white collar and not working (reference category). Standard errors in parenthesis. The regression also controls for state fixed effects. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Figure 1: lpoly plots of food score and present bias (β) and long-run discount factor (δ)

PANEL A



PANEL B



Source: Based on primary survey data collected in West Delhi in June-July, 2018
Note: Local polynomial bivariate regression results. Data refer to adults aged 25 to 60 years.

Appendix

Appendix A1

The objective function

$V_2 = u(f_2, c_2) + h_2 + \beta\delta[\, u(f_3, c_3) + h_3] \quad w.r.t \ \ to \ f_2$

$$s.t. \ \ to \ \ h_3 = h_2(1-\lambda) + \varphi(f_2) \ \ and \ Y_2 = pf_2 + c_2 \qquad 1(A)$$

Can be written as:

$$V_2 = u\big(f_2, Y_2 - pf_2\big) + h_2 + \beta\delta\big[\, u\big(f_3, c_3\big) + h_2(1-\lambda) + \varphi\big(f_2\big)\big] \qquad 2(A)$$

Maximizing $V_2 \ w.r.t \ to \ f_2$ will give the following first order condition (FOC):

$$\frac{\partial V_2}{\partial f} = u_f(f_2, \ Y_2 - pf_2) - pu_c(f_2, Y_2 - pf_2) + \beta\delta \ \varphi_f(f_2) = 0 \rightarrow \ f_2^*(\beta, \delta, Y_2, p) \qquad 3(A)$$

Now, we know that optimum food consumption is a function of time preferences. To obtain comparative statistics, we can derivate 2(A) w.r.t to $\beta \ and \ \delta$ and we can get (4), (5), (6) and (7) (see Section 2.3 above).

We assume V_2 to be strictly concave in f_2 which means the following:

$$\frac{\partial^2 V_2}{\partial f^2} = u_{ff} - 2pu_{cf} + p^2 u_{cc} + \beta\delta \ \varphi_{ff} < 0 \qquad 4(A)$$

Hence, the denominator of equation (4), (5), (6) and (7) is negative.

Appendix A2

Agent at time period t=1 will maximize:

$$V_1 = u(f_1, c_1) + h_1 + \beta\delta\big[\, u\big(f_2(\beta, \delta, Y_2, p), Y_2 - pf_2(\beta, \delta, Y_2, p)\big) + h_2\big] + \beta\delta^2[\, u(f_3, c_3) + h_3] \ \ w.r.t \ \ to \ f_1$$

$$s.t.\ to\ \ h_2 = h_1(1-\lambda) + \varphi(f_1);\ \ h_3 = h_2(1-\lambda) + \varphi(f_2)$$
$$and\ \ Y_t =\ pf_t + c_t\ for\ t = 1,2\ \&\ 3 \qquad 5(A)$$

V_1 can be written as:

$$V_1 =\ u(f_1, c_1) + h_1 + \beta\delta\big[\,u\big(f_2(\beta,\delta,Y_2,p), Y_2 - pf_2(\beta,\delta,Y_2,p)\big) + h_1(1-\lambda) + \varphi(f_1)\big] +$$
$$\beta\delta^2[\,u(f_3, c_3) + h_1(1-\lambda)^2 + \varphi(f_1)(1-\lambda) +\ \varphi(f_2)]\quad w.r.t\ \ to\, f_1 \qquad 6(A)$$

The first order condition is:

$$\frac{\partial V_1}{\partial f} = u_f(f_1,\ Y_1 - pf_1) - pu_c(f_1, Y_1 - pf_1) + \beta\delta\ \varphi_f(f_1)[1 + \delta(1-\lambda)]=0 \rightarrow f_1^*(\beta,\delta,Y_1,\lambda,p) \quad 7(A)$$

If $V_1\ is$ assumed to be strictly concave then,

$$\frac{\partial^2 V_1}{\partial f^2} = u_{ff}\ - 2pu_{cf} + p^2 u_{cc} + \beta\delta\ \varphi_{ff}(1 + \delta(1-\lambda)) < 0 \qquad 8(A)$$

Hence, the denominator of equation (12) and (13) is negative.

Appendix A3

Assuming partially naive agent (who underestimates his present bias), sitting in time period t = 1, for time period t = 2, will maximize

$$V_2 =\ u(f_2, c_2) + h_2 +\ \hat{\beta}\delta[\,u(f_3, c_3) + h_3]\quad w.r.t\ \ to\, f_2$$
$$s.t.\ \ to\ \ h_3 = h_2(1-\lambda) + \varphi(f_2)\ \ and\, Y_2 =\ pf_2 + c_2, where\ , 0 < \beta <\ \hat{\beta} < 1 \qquad 9(A)$$

Maximizing $V_2\ w.r.t\ to\ f_2$ will give the following first order condition:

$$u_f(f_2,\ Y_2 - pf_2) - pu_c(f_2, Y_2 - pf_2) + \hat{\beta}\delta\ \varphi_f(f_2)=0 \rightarrow \hat{f}_2^*(\hat{\beta},\delta,Y_2,p) \qquad 10(A)$$

The difference from the sophisticated case is that the naive agent thinks in period 1 that, in period 2, he will eat $\hat{f}_2^*\big(\hat{\beta},\delta,Y_2,p\big)$, but actually, he eats $f_2^*(\beta,\delta,Y_2,p)$ in t=2. Whereas the sophisticated agent, correctly anticipates his bias for the present and therefore, his food consumption in time period t=2. In scenario 1, a partially naïve agent eats lower than what he had anticipated i.e. if $\hat{f}_2^*\big(\hat{\beta},\delta,Y_2,p\big) > f_2^*(\beta,\delta,Y_2,p)$. While in scenario 2, naïve individual ends up eating higher than what he had anticipated i.e. $\hat{f}_2^*(\hat{\beta}, \delta, Y_2, p) < f_2^*(\beta, \delta, Y_2, p)$. The comparative statistic results will remain unchanged.

Appendix A4

We follow the framework of Meier and Sprenger (2010) to estimate time preferences:

For quasi-hyperbolic discounting, present value of option A can be written as:

$PV(A) = \delta^t X$ and 11(A)

For option B present value can be written as:

$PV(B) = \beta^{t0}\delta^{t+\tau} Y,\ \ where\ t0 = 1\ \ if\ t = 0(today)\ \ and\ \ t0 = 0\ if\ t \neq 0.$ 12(A)

In order to calculate β and monthly long run discount factor δ under quasi-hyperbolic discounting, we use both the series simultaneously. We must have two equations to be able to calculate $\beta\ and\ \delta$. We identify rows in both the series at which respondent switch from a smaller sooner amount to the larger delayed amount. For each series, we assume that individual is indifferent at the middle value. For example, in first series, suppose respondent chooses option A for first four rows and then switches to option B. This means he/she switches at 750, in this case we use Rs 720 as the indifference point which is the mid-point of Rs 750 and Rs 690. Similarly, for instance, in the second series he/she switches at 870. For the second series, the indifference point is 855 which is the middle value of 870 and 840. Therefore, in second series, we can equate $PV(A) = \delta^6 X$ and $PV(B) = \beta^0\delta^{6+6}$ 900 and can get $\delta^6 = \frac{855}{900}$, $\delta = (855/900)^{1/6}$.[38] Similarly, in first series we can equate $PV(A) = \delta^0 720$ and $PV(B) = \beta^1\delta^{0+6}$ 900, which will give $\beta = \frac{720}{855}$.[39] Note that β is the ratio of the indifference points of series 1 to series 2. So, if a respondent switches at lower amount in series 1 as compared to series 2, then, β for the respondent will be less than 1, which suggests that the respondent is present biased.

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[38] Equating $PV(A)$ and $PV(B)$ would give us: $\delta^6 855 = \delta^{12} 900 \rightarrow \delta^6 = \frac{855}{900}$. The monthly long run discount factor will be $\delta = (855/900)^{1/6}$.

[39] Equating $PV(A)$ and $PV(B)$ would give us $\rightarrow 720 = \beta^1\delta^6\ 900 \rightarrow\ \beta = (\frac{720}{900})(\frac{1}{\delta^6}) \rightarrow\ \beta = (\frac{720}{900})(\frac{900}{855})$.

And if a respondent switches at the same amount (or has same indifference point) in both the series, value of β in this case will be equal to 1 which means he/she is time-consistent.[40]

If a respondent didn't switch between earlier and delayed option, and say for example always chooses the smaller earlier option, then we assume that indifference point is the mid-point of Rs 390 and 0 which is 195. Similarly, if an individual always chooses the later option, the indifference point is 885 which is the middle value of 870 and 900.[41] If a respondent switches multiple times, we calculate their time preferences by utilizing their both first and the last switching point. We drop respondents who started with delayed option and switched to sooner options from our analysis.[42] Therefore, we have three kinds of time preferences estimates: first, where we include individuals who switched multiple times and utilize their last switching point, second, exploiting first switching point in case of multiple switching and lastly, only including individuals with no or one switching point.[43] In our analysis (both descriptive and regression) we include individuals who switch multiple times and use their last switching point as the point of indifference to calculate time preferences. Our results are robust to either using the first switch between smaller sooner and larger later choices, or to excluding subjects who switched multiple times (i.e. only including individuals with no or one switch per series).

[40] It is possible that respondent switches at higher amount in series 1 as compared to series 2 which means that β in this case will be greater than 1 i.e. they are future biased. In our theory model we assume that β is less than equal to 1, and therefore, in our sample if we observe these responses, we cap them at 1.
[41] Not switching at all is consistent with preference monotonicity.
[42] There were 80 respondents whose responses were inconsistent and hence were dropped as they violate preference monotonicity.
[43] 99% of respondents displayed zero or one switch in both the series.

Appendix Tables

Table A1: Components of Food Score.

Dietary guideline	Components	Australian Guideline (recommended servings per day)	Maximum Score of each component is 10 & minimum is 0
Eat plenty of vegetables and fruits.	1. Fruits	≥ 2	10 if consuming recommended intake and intermediate amounts are scored proportionately
	2. Vegetables	Male≥ 6, Female≥5 (19-50-year-old) Male≥ 5.5, Female≥5 (51-70-year-old) (Vegetables + legumes)	10 if consuming recommended intake and intermediate amounts are scored proportionately
Eat protein rich foods such as lean meat, fish, pulses	3. Meat and meat alternatives: frequency of consumption of meats and alternatives per day	Male≥3, Female≥2.5 (19-50) Male≥2.5, Female≥2 (51-70) Includes: Lean meat, fish, poultry, nuts and legumes	10 if consuming recommended intake and intermediate amounts are scored proportionately
Include milks, yoghurts, cheeses, and/or Alternatives. Reduced-fat varieties should be chosen, where possible	4. Dairy products: frequency of consumption of dairy products per day	Male & Female ≥2.5 (19-50-year-old) Male≥2.5, Female≥4 (51-70)	10 if consuming recommended intake and intermediate amounts are scored proportionately
	5. Low fat milk	Use Low-fat/reduced-fat milk	10 if low-fat milk, 0 otherwise
Eat plenty of cereals, preferably whole-grain	6. Cereals	Male ≥6, Female≥6 (19-50-year-old) Male ≥6, Female≥4 (51-70-year-old) (rice, breads, chapati and other cereals)	10 if consuming recommended intake and intermediate amounts are scored proportionately
	7. Whole-grain cereals	proportion of whole-meal/whole-grain bread consumed relative to total cereals consumed (at least once a week)	Maximum score is 10 and intermediate amounts are scored proportionately
Eat variety of foods to ensure a balanced diet.	8. Dietary variety	proportion of foods for each core (fruits, vegetables, cereals, meat /protein, dairy) food group that are consumed at least once per week.	Each core group is given score out of 2 and total variety score is the sum of 5 core group.[1]
Reduced-fat varieties of dairy products should be chosen, where possible	9. Type of milk usually consumed	Use Low-fat/reduced-fat milk	10 if low-fat milk, 0 otherwise
Limit saturated fat and moderate total fat intake	10. Use of butter	Limit consumption of butter to restrict intake of saturated fat	Never or rarely =10 Sometimes=0, Usually=0
Limit salt intake	11. Consumption of salty intakes	Limit sauces, pickles, chutneys, ketchup to restrict intake of salty items	Never or rarely =10 Sometimes=0, Usually=0
Limit consumption of sugar and foods containing added sugar.	12. Frequency of consumption of soft drink, fruit juice drink, chocolate, confectionary(sweet) per day	Male ≤ 1.5, Female ≤ 1.25	10 if consuming within recommended intake and 0 if consuming more than recommended
Limit consumption of processed food	13. Extra foods[2]: frequency of consumption of extra foods per day	Male ≤ 3, Female≤ 2.5	10 if consuming within recommended intake and 0 if consuming more than recommended

Note: Use 2013 *Australian Dietary Guideline* for the recommended servings per day and is available at *https://eatforhealth.govcms.gov.au/sites/default/files/content/The%20Guidelines/n55g_adult_brochure.pdf*. Guidelines for added sugars and extra foods are presented as an upper limit. Because there is no quantitative guideline for added sugars in the guidelines, one-half the extras foods guideline is used which is consistent with other existing dietary indices.

Table A2: Simultaneous Equation Model of Food Score and BMI.

Dependent variable	Food Score	BMI	Food Score	BMI	Food Score	BMI
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variables						
β	0.33*** (0.12)	-	0.44* (0.24)	-	0.40** (0.17)	-
δ	4.00*** (1.39)	-	4.28*** (1.26)	-	3.79*** (1.15)	-
Food score	-	-1.85*** (0.09)	-	-1.71*** (0.14)	-	-1.95*** (0.09)
Age	✓	✓	✓	✓	✓	✓
Wealth Score	✓	✓	✓	✓	✓	✓
Education(in years)	✓	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓	✓
Type of occupation	-	✓	-	✓	-	✓
Dummy for exercise	-	✓	-	✓	-	✓
Dummy for Menopause	-	✓	-	✓	-	✓
Risk preference	✓	-	✓	-	✓	-
Current drinker	-	-	-	-	-	✓
Current smoker	-	-	-	-	-	✓
Cov(μ_i and τ_i)	424.42***		394.23***		447.59***	
Observations	**694**	**694**	**706**	**706**	**706**	**706**

Source: Estimates from a primary survey data collected from West Delhi in June-July, 2018.
Note: Data refer to adults aged 25 to 60 years. Column (1) and (2) reports results only including individuals switching at most once or not switching. Column (3) and (4) reports results using first switching point as an indifference points in case of multiple switches to elicit time preferences. Last switching point is used as an indifference point in column (5) and (6) in case of multiple switches. Type of occupation includes dummies for employed full-time in high and medium physically intensive job, employed part-time, not working and employed in low physically intensive job (reference category). Clustered standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table A3: Correlates of the probability of not being included in the sample on account of inconsistent or incomplete responses. (probit estimates).

Dependent variable is a binary variable	**Dependent variable =1 if respondent provided inconsistent responses in choice task**	**Dependent variable =1 if There was non-response**
	(1)	**(2)**
Age (in years)	-0.017*** (0.005)	-0.002 (0.004)
Years of education	-0.054*** (0.013)	-0.035*** (0.012)
Wealth Score	0.011 (0.013)	-
Female [a]	0.437*** (0.161)	0.006 (0.166)
BMI	-0.010 (0.008)	-
Constant	0.108 (0.144)	-0.599*** (0.122)
Observations	**786**	**804**

Source: Estimates from a primary survey data collected from West Delhi in June-July, 2018.
Notes: Data refer to adults aged 25 to 60 years. Base categories: Reference categories- [a]: Male. Clustered standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table A4: Ordinary Least square Regressions of behavioral parameters on age.

Dependent variable: Time preferences	$\boldsymbol{\beta}$ (1)	$\boldsymbol{\delta}$ (2)
Age	0.001	0.000
	(0.001)	(0.000)
Observations	**706**	**706**

Source: Estimates from a primary survey data collected from West Delhi in June-July, 2018.

Note: Data refer to adults aged 25 to 60 years. Dependent variable in column 1, 2 is β, δ respectively. Last switching point is used as an indifference point in case of multiple switches. Clustered standard errors in parenthesis. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.