Role of Time Preference in Explaining Burden of Malnutrition: Evidence from Urban Delhi

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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. We use quasi-hyperbolic discounting, which allows for the fact that individuals' preferences may change over time and nests exponential discounting, which occurs with time-consistent preferences. Our theory results demonstrate that time preference has a bearing on health - 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). To empirically validate these predictions, we undertook a primary survey of 885 adults (25-60 years) in area of West Delhi. As none in our sample was undernourished, our empirical results pertain only to overweight or healthy individuals and find that they are consistent with our theory results. The regressions indicate that a low discount factor/ higher bias for the present (or self-control issues) are predictive of identifying individuals who are overweight or obese. Moreover, the magnitudes of these coefficients are comparable to the magnitude of the more commonly recognized risk factors of rising body weight outcomes such as wealth/income. Finally, our results suggest that time preferences are not correlated with age, implying that psychometric tests based on eliciting these behavioral parameters could assist in identifying individuals early on who might be at the risk of becoming overweight in the future.

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

Acknowledgement: I am thankful to Professor Sebastian Vollmer at the Center for Modern Indian Studies (CeMIS), Georg-August-Universität Göttingen, who provided funding for this study. I greatly acknowledge the contribution of my supervisors, Professor J.V. Meenakshi and Dr. Parikshit Ghosh, for their continuous support and guidance. I also want to thank Professor Abhijit Banerji and Dr. Anirban Kar for their useful suggestions. Lastly, I am indebted to the field enumerators and supervisors, who worked really hard in collecting good quality data.

2.1 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) and the prevalence of undernutrition, and especially among children and women, is still high. However, overweight and obesity, generally considered problems of richer, western countries, has emerged as a major problem in India, too. 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).

The prevalence of overweight and obesity, also an aspect of malnutrition (overnutrition), is amplifying in India, and affects almost 1 in 5 adults (National Family Health Survey (NFHS)-4, National Fact Sheet, 2016).[1] Relatively little attention has been paid by policy makers and researchers to the emerging problem of overnutrition and related non-communicable diseases in developing economies. This paper attempts to contribute to the limited literature by examining the role of time preference in identifying individuals who are overweight or obese. It has two main objectives: firstly, using a theoretical 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 burgeoning problem of overweight. Secondly, we take theory to data, and empirically test its predictions.

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 for decisions that are farther in

[1] Overnutrition among adults in NFHS is measured by percentage of individuals with a Body Mass Index (BMI) is 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%.

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. The empirical analysis of this paper is based on a primary survey conducted in West Delhi during June-July 2018. The data consists of adults who were in the age group of 25-60 during the time of survey. In our survey, we elicit individuals’ rates of time preferences using questions involving choices about different monetary amounts at different points in time. We also measured the respondents’ heights and weights to compute their Body Mass Index (BMI) as a metric of their health, further details are in section 2.4.

Much of the literature on modeling the determinants of overweight relates to developed countries. For example, Philipson and Posner (1999) (using static framework), Lakdawala et al. (2005) and Lakdawala 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.[2] Levy (2002) also develops a dynamic model of rational, non-addictive, eating and show that the steady state for a lifetime expected-utility maximiser is a state of being overweight and a small deviation from this rationally-optimal stationary weight leads to explosive oscillations in weight. Furthermore, an increase in elasticity of utility and time preference of an individual increases the rationally optimal stationary level of overweight.

[2] 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 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.

The literature focusing on time preference 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 preference to model various health choices such as smoking and alcohol consumption. More relevant to this paper are the studies by Kolmos 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 preference. An implication is that food intakes and weight are increasing (decreasing) in the discount rate (discount factor).[3] 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. [4]

We now provide a brief review of the literature that quantifies the relationship between time preference and health, specifically, body mass index (BMI). Most of these studies focus on developed countries.

The earlier work relies on proxies for time preferences. Kolmos et al. (2004) utilizing national-level time-series data, use the national savings rate and consumer debt as a proxy for time preference 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

[3] 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

[4] 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

Survey of Youth, utilize savings and dissavings information to capture time preferences among American youth (aged 24-32), finding some evidence of association between time preference and BMI.[6] Borghans and Golsteyen (2006) use both financial indicators (assets and liabilities) and attitude, as well as indirect measures (based on will-power) of the discount rate among the Dutch.[7] They observe that differences in BMI at a given point in time are correlated with the ability to manage income or expenditures. Their analysis also suggests that the upward trend in BMI over time cannot be attributed to discount rates, as it turns out that the average individual discount rate did not change over time. Zhang and Rashad (2008) also make use of will-power as an indicator of time preference in the U.S, finding that conditional on covariates, there is a positive association between BMI and time preference for men.[8]

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.[9]

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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.

[6] As before, respondents reporting dissaving would have higher time preference (lower discount factor) than those who report savings.

[7] 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.

[8] Zhang and Rashad (2008) use two datasets - small Roper Center Obesity survey and the larger 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.

[9] 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.

Sutter et al. (2013) relate experimental measures of time preferences, risk aversion and ambiguity attitudes with BMI and other behaviour such as smoking, drinking, savings, and conduct at school among children and adolescents (aged 10-18) in Austria. They find that impatient children are more likely to (a) have higher BMI, (b) smoke, (c) consume alcohol, (d) misbehave in school and are less likely to save.[10]

None of the studies mentioned above distinguish between time-consistency and inconsistency. A few recent studies incorporate time inconsistency in teasing out the 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.[11] 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.[12] 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.[13] Their results are particularly strong for health. They observe that time preference coefficients i.e. 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

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

[11] 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.

[12] 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.

[13] 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.

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.

This paper builds on the theory literature and contributes to it in two significant ways. First, unlike much of the literature above, our model can help explain both underweight and overweight. Countries that are going through the nutrition transition rather rapidly are characterized by the coexistence of underweight and overweight individuals. A second contribution of this paper is that we employ quasi-hyperbolic discounting model that accounts for inconsistent or changed preferences. We show how individuals with self-control issues can tie themselves to commitments to alter their food choices, which can improve their welfare. Lastly, our model indicates that psychometric measures such as impatience and present bias can predict individuals with higher BMI or lower BMI (see section 2.2).

While a sizeable empirical literature from different parts of the developed world on time preference and body weight outcomes exists, there is no empirical evidence on developing countries. Therefore, our paper attempts to fill this gap, by estimating the link between time-discounting and BMI using data collected through a primary survey in Western Delhi. In addition to time-consistent discounting (which much of the literature adopts, except for Courtemanche et al., 2015; Ikeda et al., 2010 and Bradford et al., 2017), we also analyse whether connection between time preference and BMI is driven by present bias behavior. In taking the theory to data, however, we only focus on the overweight aspect, as it transpired that our sample had virtually no one who was underweight.

Our theory model indicates that time preference has a bearing on health through food. Assuming time-inconsistent preferences, our model predicts that individuals with lower self-control (who care more about present) have poorer health outcomes, that is, either they are underweight (lower BMI) or over-nourished (higher BMI). Similarly, under a time-consistent assumption, impatient individuals have adverse health outcome i.e. they are underweight or overweight. To test these predictions, we fielded our own survey and measured time preference using choice-based experiments. As it happened, our sample had a negligible proportion of underweight adults, therefore we could not test the predictions of the theory model pertaining to underweight. The empirical results for higher BMI/overnutrition are in line with our theory. They provide evidence that a low discount factor or low present bias is predictive of identifying individuals at risk, that is, those with elevated BMI levels. We also provide evidence that magnitudes of the coefficients of intertemporal discounting variables, as a risk factor for increased BMI, approximate to more commonly recognized risk factors such as education and wealth/income.

The remainder of the paper is organized as follows. The next section details the theory model we developed. Section 2.3 describes the dataset used for the empirical analysis of the study. Section 2.4 sets out the outcome variable, and describes the estimation of time and risk preferences. The empirical framework and descriptive statistics are detailed in section 2.5. Section 2.6 presents the empirical findings, and section 2.7 concludes.

2.2 Theory Model

Individuals make food choices which have a significant effect on their health. Food is an immediate source of pleasure because it provides flavor, texture and relief from hunger. But excessive intake results in obesity and hence obesity related health issues. On the other hand, insufficient food intake has adverse health consequences as well. To make a right food choice, either by choosing appropriate quantity or healthy food requires forgoing such pleasures in favor of better health outcomes. By better health outcomes we mean reduction in the possibility of mortality or morbidity because of diseases that can affect health in the future due to overeating/under eating in the present period.

This paper tries to describe the food choices of individuals using a theoretical model which involves intertemporal trade-off between the utility that the agent gets from food (or by consuming non-food) in the present, against the negative affect of eating more (eating less) on health in future. A dynamic framework using Quasi-hyperbolic discounting model is used, where agents have time inconsistent preferences or self-control issues. Quasi-hyperbolic discounting model nests exponential discounting model, which assumes time-consistent preferences of the agents. We also show how agents with self-control issues can use commitment devices to improve their welfare.

An agent chooses food consumption (f) which affects agent's weight which in turn affects agent's health in the future. The per period utility function of an agent is: $U(f_t, h_t) = u(f_t, c_t) + h_t$. Per period utility is a function of amount of food consumed, other consumption and health status. It is assumed to be separable in its health argument. U is assumed to be continuous, and linear in health. Value of food consumption is chosen by the agent but value of health status is not at agent's discretion and is determined by the equation of motion: $h_{t+1} = h_t(1-\lambda) + \varphi(f^{id} - f_t)$. Agent's health depreciates if the agent doesn't eat at all, where λ is the rate of depreciation (0< $\lambda \leq 1$) and φ tells how agent can build his health stock by eating food. φ shows health returns from eating food, returns are positive ($\varphi_f > 0$) till f^{id} level of food consumption and turns negative once f^{id} level of food consumption is crossed. In this model f^{id} is like the ideal food consumption from health perspective. In particular, suppose that for a given level of food and non-food consumption, the individual has an "ideal health", $h^{id}(say\ corresponding\ to\ f^{id})$.[14] Individual 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, agent spends all his income on food and non-food consumption i.e. agent doesn't save.

When we take the theory to data, we utilize BMI as an indicator of health because food intake affects weight or BMI of an individual. The predictions of the theory model henceforth will be interpreted in terms of BMI. If somebody starts with very low BMI (is undernourished), increase in BMI will improve his health, but after a point, increase in BMI depletes health because it might lead to a condition of excessive weight (overweight) and could result in obesity related health problems.

[14] All else equal Agent prefers to improve his health when he is below or above h^{id} and prefers to remain closer to the h^{id}. This can happen by reducing or increasing the food consumption.

Researches have modeled self-control issues using quasi-hyperbolic model originally developed by Phelps and Pollak (1968), and later used by Liabson (1994, 1997). Therefore, we use quasi-hyperbolic discounting, an elegant two parameter (β,δ) discounting function which takes into account self-control problems.

Lifetime utility of an infinitely lived agent at time t can be written as:

$$V_t = u(f_t, c_t) + h_t + \sum_{i=1}^{\infty} \beta\delta^i \left[u(f_{t+i}, c_{t+i}) + h_{t+i} \right] ,$$

where $0 < \beta < 1$ and $0 < \delta < 1$.

It is a simple modification of exponential discounting. The β parameter brings in time-inconsistent preferences for immediate gratification and parameter δ is the standard discount factor representing time-consistent (long-run) impatience. 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. When $\beta = 1$, it reduces to exponential discounting, where agents have time-consistent preferences.

Under quasi-hyperbolic discounting, agents do not exhibit time consistency as explained in section 2.1 above. This happens because the decision maker's current choice at various dates will be different from what the earlier selves have planned for him. This conflict leads to inconsistency as the agent would like to change his choice, he had made previously instead of executing it. To find solution in such cases, the problem is modeled as a game between different selves at various decision point.[15] Since, agent can amend his choices in every period, the optimum solution that we get solving this game is termed as "non-committed" level of food consumption.[16] Agent knows that his future selves will change his plan when the time will come to implement the choices made. Therefore, he can resort to commitment devices where he decides to follow a stationary food consumption path and hence, we term it as "committed" level

[15] Agent is assumed to sophisticated i.e. he knows his future self is not going to stick to decisions made by the earlier selves.

[16] Choice variable in the model is food.

of food consumption. In the following sections, we solve for choices under non-commitment and commitment and find that agent can improve his welfare/health by using commitment devices.

2.2.1 Choice Under Non-Commitment

Agent at time period t will maximize:

$$V_t = \ u(f_t, c_t) + h_t + \sum_{i=1}^{\infty} \beta\delta^i \ u(f_{t+i}, c_{t+i}) + h_{t+i} \ \ w.r.t \ \ to\, f_t$$

$$s.t. \ to \ \ h_{t+1} = h_t(1-\lambda) + \varphi\big(f^{id} - f_t\big)\, and\, Y_t = \ pf_t + c_t$$

The first order condition is:

$$u_f(f_t, \ Y_t - pf_t) - pu_c(f_t, Y_t - pf_t) + \frac{\beta\delta \ \varphi_f(f^{id} - f_t)}{1-\delta(1-\lambda)} = 0 \rightarrow \ f_t^{nc}(\beta, \delta, \lambda, Y_t, p)$$

In case of quasi hyperbolic discounting, the agent can revise his plan in every period, $f_t^{nc}(\beta, \delta, \lambda, Y_t, p)$ is the (optimum) non-committed level of food consumption in time period t.[17] The optimum (non-committed) food consumption $f_t^{nc}(\beta, \delta, \lambda, Y_t, p)$ can lie above or below f^{id}. Therefore, there are two scenarios to consider here, first scenario is of undernutrition where food intake is so low that is it is insufficient to maintain healthy health(weight) status i.e. $f_t^{nc}(\beta, \delta, \lambda, Y_t, p) < f^{id}$.While the second scenario is of overnutrition, where food intake is higher than normal food consumption i.e. $f_t^{nc}(\beta, \delta, \lambda, Y_t, p) > f^{id}$.[18]

When the agent is choosing period by period (i.e. not sticking to the level of food consumption that he had planned), he ends up eating $f_t^{nc}(\beta, \delta, \lambda, Y_t, p)$. Suppose f_s^{nc} is the steady state level of food consumption, then, at the steady state $f_t^{nc} = \ f_{t+1}^{nc} = \ f_{t+2}^{nc} =$

[17] Under quasi hyperbolic discounting people struggle to stick to the choices made for future when the future becomes present.

[18] See appendix A2.1 for calculations.

$\cdots \ldots \ldots .. = f_s^{nc}$. Also, income stream will be constant i.e. $Y_t = Y_{t+1} = Y_{t+2} = \cdots \ldots \ldots . = Y$. Therefore, at the steady state, f_s^{nc} will satisfy the first order condition i.e.

$$u_f(f,\ Y - pf) - pu_c(f,\ Y - pf) + \frac{\beta\delta\ \varphi_f(f^{id} - f)}{1 - \delta(1-\lambda)} = 0 \qquad \rightarrow\ f_s^{nc}(\beta, \delta, \lambda, Y_t, p) \qquad (1)$$

The above equation indicates that marginal utility of other consumption must be equal to the overall marginal utility of food which equals to the marginal utility of eating plus discounted marginal utility of change in health induced by eating.

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

$$\frac{\partial f_s^{nc}}{\partial \delta} = \frac{-\ \dfrac{\beta\ \varphi_f\left(f^{id} - f\right)}{[1 - \delta(1-\lambda)]^2}}{u_{ff}(f, Y - pf)\ - 2pu_{cf}(f, Y - pf) + p^2 u_{cc}(f, Y - pf) + \dfrac{\beta\delta\varphi_{ff}(f^{id} - f)}{1 - \delta(1-\lambda)}} \qquad (2)$$

$$\frac{\partial f_s^{nc}}{\partial \beta} = \frac{-\ \dfrac{\delta\ \varphi_f\left(f^{id} - f\right)}{1 - \delta(1-\lambda)}}{u_{ff}(f, Y - pf)\ - 2pu_{cf}(f, Y - pf) + p^2 u_{cc}(f, Y - pf) + \dfrac{\beta\delta\varphi_{ff}(f^{id} - f)}{1 - \delta(1-\lambda)}} \qquad (3)$$

We are interested in knowing how change in $\beta\ and\ \delta$ affects health, this effect can be seen by evaluating the derivative ${\partial h_s^{nc}}/{\partial \delta}\ and\ {\partial h_s^{nc}}/{\partial \beta}$.[19]

$$\frac{\partial h_s^{nc}}{\partial \delta} = \frac{\varphi_f\left(f^{id} - f\right)}{1-\lambda} * \frac{\partial f_s^{nc}}{\partial \delta} \qquad (4)$$

and

$$\frac{\partial h_s^{nc}}{\partial \beta} = \frac{\varphi_f\left(f^{id} - f\right)}{1-\lambda} * \frac{\partial f_s^{nc}}{\partial \beta} \qquad (5)$$

[19] Refer to appendix A2.2 for calculations.

The denominator in (2) and (3) is always negative, while the numerator could be either be negative or positive depending on which side of f^{id} the steady state food consumption (f_s^{nc}) is.[20]

There are two scenarios:

Scenario 1: When $f_s^{nc}(\beta, \delta, \lambda, Y_t, p) < f^{id}$ i.e. agent is eating sufficiently low such that he is underweight. In this case, increase in food consumption has a positive return on health which means $\varphi_f > 0$. Hence the numerator of equation (2) and (3) is negative which implies that $\frac{\partial f_s^{nc}}{\partial \beta} > 0 \ and \ \frac{\partial f_s^{nc}}{\partial \delta} > 0$.[21] Lower β indicates higher present bias (agent gives lower weight to the future), cares more about present at the expense of health in the future and therefore, consume less food today and consume more of non-food items and has lower health outcome(in this case, lower BMI). Similarly, lower δ means lower patience, giving less weight to health which comes in future resulting in lower food consumption today and ultimately lower health status in the future (lower BMI).

Scenario 2: When $f_s^{nc}(\beta, \delta, \lambda, Y_t, p) > f^{id}$ i.e. agent's food intake is so high that it is considered excessive as it contributes to obesity. In this case, increase in food consumption has a negative return on health which means $\varphi_f < 0$. Hence the numerator of equation (2) and (3) is positive which implies that $\frac{\partial f_s^{nc}}{\partial \beta} < 0 \ and \ \frac{\partial f_s^{nc}}{\partial \delta} < 0$. Lower β indicates higher present bias, implying that the agent will worry less about health (that comes in the future) and will eat more today. Therefore, lower β leads to higher food consumption (i.e. further away from f^{id}) and hence lower health outcome (i.e. higher BMI). Similarly, lower δ means higher impatience meaning agent doesn't take into account the cost of eating more in the present period on health, which comes in future. This results in higher food consumption today and ultimately lower health status (in this case, higher BMI).

[20] Denominator is negative because we assume V_t to be quasi concave. Refer to appendix A2.1 for details.

[21] Recall that denominator is negative always.

2.2.2 Choice Under Commitment

To restrain from short term temptations, individuals can demand commitment devices which help them to adhere to their plans. Broadly, a commitment device is an arrangement entered into by an individual with the aim of helping fulfil a plan for future behavior that would otherwise be difficult due to intra-personal conflict stemming, for example, from a lack of self-control.

Agent is self-aware of the fact that his future selves will change his mind as future becomes present. So, the agent can constraint the behavior of his future selves by using commitment devices. When agent decides to pre-commit to a certain level of food consumption say f_c for every period i.e. he follows a stationary food consumption path, then the lifetime utility will look like:

$$V_t = u(f_C, Y - pf_c) + h_t + \sum_{i=1}^{\infty} \beta\delta^i \left[u(f_c, Y - pf_c) + h_{t+i}\right]$$

$where\ h_{t+i} = h_{t+i-1}(1-\lambda) + \varphi\left(f^{id} - f_c\right),\ h_t\ i$s the initial health status of the agent which is given at time period t.

The objective function would eventually boil down to:

$$u(f^c, Y - pf^c)\left(1 + \frac{\beta\delta}{1-\delta}\right) + h_t\left[1 + \frac{\beta\delta(1-\lambda)}{1-\delta(1-\lambda)}\right] + \frac{\beta\delta\varphi(f^{id} - f^c)}{[1-\delta(1-\lambda)](1-\delta)}$$

We are assuming that agent decides to commit from current period (i.e. t).[22]

The first order condition would be:

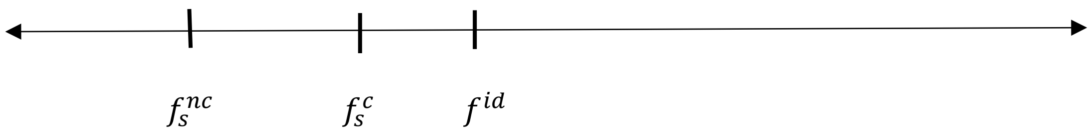
$$u_f(f,\ Y - pf) - pu_c(f,\ Y - pf) + \frac{\beta\delta\ \varphi_f(f^{id} - f)}{(1-\delta(1-\lambda))\ (1-\delta+\beta\delta)} = 0 \rightarrow\ f^c(\beta, \delta, \lambda, Y, p) \qquad (6)$$

[22] Refer to appendix A2.3 for details.

2.2.3 Comparing Non-Committed and Committed Food Consumption

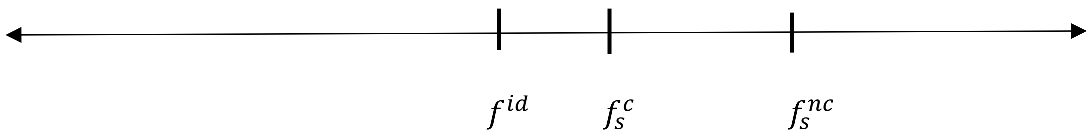
Since there are two cases, effect of use of commitment devices will be different under two cases:

Scenario 1: When $f_s^{nc}(\beta, \delta, \lambda, Y_t, p) < f^{id} \rightarrow \varphi_f > 0$



If an underweight agent decides to commit, he will end up eating more compared to his non-committed food consumption. This would help in improving agent's welfare because he is already eating less than what is ideal from health perspective, and if he uses commitment device, it will help him to stick to his decision to eat more which will be beneficial for his health.

Scenario 2: When $f_s^{nc}(\beta, \delta, \lambda, Y_t, p) > f^{id} \rightarrow \varphi_f < 0$



In scenario 2, agent is eating excessively than what is required to maintain healthy weight i.e., agent is over nourished. When agent can revise his plan in every period, he ends up eating more as compared to his pre-committed level of food consumption. This suggests that agents with self-control issues can resort to commitment devices which would help him control his eating desires and would lead to improved health status.[23] Hence, time

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23 The first order condition (6) shows that φ_f has higher weight (because $\frac{1}{1-\delta+\beta\delta} > 1$) vis-à-vis φ_f in equation (1) i.e. the first order condition in case of non-committed food choice. This indicates that agent gives higher preference to health in case of committed food choices and therefore, will make food choice which is closer to the ideal food consumption in both the scenarios.

inconsistent agents would value commitment devices as it might help in improving their welfare.[24]

Therefore, our theory model demonstrates that health is affected by psychometric measures such as discount factors (long run under quasi-hyperbolic and discount factor under exponential discounting) and present bias. As individuals discount the future more over the long run (lower δ) or as consumers become more present-biased (lower β), health of the individuals deteriorates (lower BMI or higher BMI).

Policy implications for agents with time inconsistent and time consistent preferences are different. Government doesn't need paternalistic justification for agents with low $\boldsymbol{\beta}$ that is agents with time- inconsistent preferences. Hence, government has a very strong reason to intervene because as shown above, inconsistent agents will value commitment devices and government can provide those commitment devices to them which will improve their health and welfare. While in case of time-consistent preferences, people with low $\boldsymbol{\delta}$ already have committed food consumption stream and are satisfied with what they are eating. Thus, if the government wants to respect their preferences then they need not intervene, but, if the government does intervene, then it will require strong paternalistic justification.[25]

2.3 Sampling strategy

The data for this paper was collected through a primary survey during June-July 2018.[26] Rohini, a locality in West Delhi, was chosen as it consists of dwellings representing

24 In exponential discounting, food choice under commitment will coincide with the food consumption if agents decide period by period because agents are already committed (they have consistent preferences i.e. whatever they decide for future period, and when that future period becomes present, they choose what they had decided). Therefore, agents with time-consistent preferences will not demand commitment devices because they end up consuming what they had committed to. Refer to appendix A2.4 to see what happens when $\beta = 1$ i.e. when individuals have time-consistent preferences.

25 Paternalism is defined as an action that infringes a person's liberty and is performed without their consent, but is intended to improve a person's welfare.

26 The survey was funded by Georg-August-Universität Göttingen, Center for Modern Indian Studies (CeMIS) courtesy Professor Sebastian Vollmer.

diversity in terms of living standard, ranging from people living in slums to large penthouses.[27] The sample for this paper consists of 885 adults.

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.[28] 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. Table 2.1 shows that realized sample proportions were not very different from the population proportions.

From each stratum, apartments were randomly selected (using Rohini's electoral roll of 2018). 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. Where approval was given (permission was denied only 5 percent of the time), households were then randomly selected (once again using addresses from the electoral roll). It was difficult to find electoral roll addresses in stratum 1 (slums); in this case, we took a random start, and then interviewed every 5th household in the east direction until the desired sample size was reached. In apartments, we drew a random sample twice that was necessary to account for potential non-response at the household level. Non response rates were 51%, 44% and 47% in strata 2, 3 and 4 respectively; non-response was negligible in the slum area (stratum 1).[29]

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27 In the part of Rohini we surveyed, there are no independent houses or floors, only apartments or slums.

28 Property dealers in the area were interviewed to obtain real estate values for ranking the apartments.

29 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.

Table 2.1: Proportion of Adults in Sample and Population by Strata

Strata based on Property Values	**Population** Proportion of population from each stratum	**Sample** Frequency (sample based on probability proportional to size)	Frequency (Target sample from each stratum)	Frequency (sample collected from each stratum)	Proportion of sample collected from each stratum
1	5%	40	100	137	15%
2	28%	224	204	202	23%
3	54%	440	420	422	48%
4	13%	104	104	124	14%
Total	100%	808	808	885	100%

Source: Based on primary survey data collected in West Delhi in June-July, 2018
Notes: Stratification was done on the basis of property value. Data refer to adults aged 25 to 60 years.

Once the household was selected and had given their consent to be interviewed, we checked if there was an adult 25-60 years of age; if not, that household was dropped (households consisting only of senior citizens were dropped, for example). We then selected one adult to interview using the following criteria: if there were no children in the age group 5 to 15 years of age, then a random adult (from those listed as living in the household) was selected. If they were unavailable, the next person was chosen. If there were children in the age group 5 to 15, then the mother was chosen (this was done to meet the data needs for the next paper, as detailed there). Thus, this survey gathered information from 885 adults in the age group of 25-60 belonging to 885 households. An additional 212 children were surveyed and these mother-child pairs are the basis of the analysis in the next paper.

In our sample, 22% respondents were male while 78% were female. Our sample is heavily biased towards females on two accounts: the first was the decision to interview the mother if the household had a 5-15-year-old child. Secondly, as the survey was conducted on all days of the week, we were more likely to encounter women, given their much lower labor force participation rates. Most men were interviewed on their non-working days (which was not necessarily the weekend—for example traders/shopkeepers would be off on a week day if that was the day the market was closed).

The questionnaire administered to the adult consisted of eleven modules: (i) information on respondent's background (such as age, education, marital status, occupation); (ii) demographic details of household members; (iii) a module to elicit time and risk preferences (detailed later); (iv) and (v) garnered information on characteristics of the household's dwelling unit (such as ownership of various durable goods, ownership status of house, source of water, water treatment, type of toilet facilities and employment of helpers/drivers etc); (vi) household's monthly expenditure under various categories (such as food, non-food, energy etc.); (vii) questions on respondent's time allocation to various activities in a typical day; (viii) and (ix) collected information on respondent's lifestyle (smoking and alcohol consumption status) and health (current and past morbidity); (x) food consumption through a food frequency questionnaire; lastly, (xi) the biomarker module, covered measurements of height, weight, waist and hip measurements of the adults. There were large measurement errors in collecting waist and hip circumference, therefore, they were not used in the analysis.

All surveying instruments such as height measuring machines, weighing machines and measuring tapes used in the survey were calibrated. The questionnaire was designed using Kobotoolbox software which provided a platform to collect data offline using smartphones and tablets. Extensive training was provided to the enumerators to equip them with the software. Training was also imparted on how to identify the eligible respondent and how to ask questions. Furthermore, enumerators were also taught how to take height, weight, waist and hip measurements and got first-hand experience of taking these anthropometric measurements during a pilot survey conducted in another locality in Delhi.

2.4 Construction of Variables

2.4.1. The Dependent Variable

The primary outcome variable is BMI. The Asian cut-offs are used to group individuals on the basis of BMI into underweight (BMI < 18.5), normal weight (18.5 ≤ BMI <23), overweight (23 ≤ BMI <27.5) and obese (BMI ≥ 27.5) categories, is the one defined by

World Health Organization (WHO, 2004). We use the continuous measure of natural logarithm of BMI as the dependent variable in the regressions and make use of BMI categories in the summary statistics.

2.4.2. Estimating Time Preferences

We measure both $\beta\ and\ \delta$ assuming time-inconsistent preferences and also just δ under the assumption of time-consistent 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 used four different time frames: today and one month ($t = 0$ and $\tau = 1$) , three months and four months ($t = 3$ and $\tau = 1$), today and six months ($t = 0$ and $\tau = 6$) and six months and twelve months ($t = 6$ and $\tau = 6$). Each respondent was asked to make 32 binary choices. However, in this paper we utilize 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 both time-consistent and time-inconsistent regime.[30] Therefore, all summary statistics on time preferences and regression results presented below are based on (two) series with $\tau = 6$.

Table 2.2 below lists two series. Each series includes eight binary choices i.e. option A and option B. Respondents were asked to choose one option for each of these eight payoff alternatives. It is expected that the respondents would opt for smaller sooner amounts and will switch to larger later amounts because the difference between smaller sooner and delayed amount increases as we go down from Rs 870 to 390. The switch from smaller sooner payment to larger later amount helps in identifying the range of

[30] 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.

values of time preference parameter because the shift implies that the respondent was indifferent at some point along the interval between the two (smaller sooner) amounts.

Table 2.2 reports proportion of respondents choosing later larger amounts. For instance, in first series, 11% respondents choose Rs 900 in six months over Rs 870 today. In both the series we can observe that the proportion of respondent choosing larger delayed option increases as we move down from Rs 870 and Rs 390 which is in line with our expectation. Comparing the two series, we do find evidence of time-inconsistency i.e. bias for the present. Given identical rate of return and same time delay, under time-consistent assumption one would expect respondents to choose same option for each row in both the series. However, 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.[31]

Table 2.2: 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.

[31] 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.

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

For exponential discounting, let the present value of the smaller sooner amount is given by:

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

The present value of the larger later amount is given by:

$PV(B) = \delta^{t+\tau} Y$

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

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

For option B present value can be written as:

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

We estimate monthly discount factor under exponential discounting framework by observing a smaller sooner amount at which the respondent switches 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.We can calculate discount factor by equating $PV(A) = \delta^0 720$ and $PV(B) = \delta^{0+6}$ 900. Therefore, monthly discount factor for series 1 in this case is $\delta_{0,6} = (720/900)^{1/6}$. Similarly, we can calculate monthly discount factor ($\delta_{6,12}$) for the second series. We then take the average of monthly discount factors of the two series, and call it δ_{exp}, and use in our analysis.[32]

[32] Where $\delta_{exp} = \frac{\delta_{0,6} + \delta_{6,12}}{2}$

In order to calculate β and discount factor δ under quasi-hyperbolic discounting, we use both the series simultaneously. Because unlike exponential discounting we have two parameters, therefore, we must have two equations to be able to calculate $\beta \ and \ \delta$. We label the present bias and long run discount factor under quasi-hyperbolic discounting function as $\beta_{qh} \ and \ \delta_{qh}$ respectively. For instance, say in first series the respondent switches at 750, while in 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 $\delta^6 = \frac{855}{900}, \delta_{qh} = (855/900)^{1/6}$.[33] Similarly, in first series we can equate $PV(A) = \delta^0 720$ and $PV(B) = \beta^1 \delta^{0+6}\, 900$, which will give $\beta_{qh} = \frac{720}{855}$.[34] Note that β_{qh} 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_{qh} for the respondent will be less than 1, which suggests that the respondent is present biased. And if a respondent switches at the same amount (or has same indifference point) in both the series, value of β_{qh} in this case will be equal to 1 which means he/she is time-consistent.[35]

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.[36] 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

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[33] 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 $\delta_{qh} = (855/900)^{1/6}$. Note that $\delta_{qh} = \delta_{6,12}$.

[34] Equating $PV(A)$ and $PV(B)$ would give us $\rightarrow 720 = \beta^1 \delta^6\, 900 \rightarrow \beta = (\frac{720}{900})(\frac{1}{\delta^6}) \rightarrow \beta_{qh} = (\frac{720}{900})(\frac{900}{855})$. β_{qh} is nothing but the ratio of $\delta_{0,6}^6 \ to \ \delta_{6,12}^6$ i.e. $\frac{\delta_{0,6}^6}{\delta_{6,12}^6}$.

[35] It is possible that respondent switches at higher amount in series 1 as compared to series 2 which means that β_{qh} in this case will be greater than 1 i.e. they are future biased. In our theory model if we relax the assumption of β being less than equal to 1, then our model will not converge at the steady state. Therefore, in our sample if we observe these responses, we cap them at 1.

[36] Not switching at all is consistent with preference monotonicity.

delayed option and switched to sooner options from our analysis.[37] 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.[38] 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).

2.4.3 Eliciting Risk Preferences

Typically, linear utility is assumed for identification of time preferences, however, in an important recent contribution, Andersen et al. (2008) show that if utility is assumed to be linear in experimental payoffs when it is truly concave, estimated discount rates (discount factors) will be biased upwards(downwards). Measuring time preferences without controlling for risk preferences can lead to misleading results (Andersen, et al., 2008; Andreoni, et al., 2013). Therefore, we adopted a strategy which is similar to that of using double multiple price lists (DMPL, henceforth) i.e. also eliciting risk preferences in order to reduce the possibility of incorrect inference.[39]

Andersen et al. (2008) use the Holt and Laury task (HL, henceforth) to measure risk preferences which is widely used in laboratory experiments for eliciting the range of risk attitudes. This mechanism 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

[37] There were 80 respondents whose responses were inconsistent and hence were dropped as they violate preference monotonicity.

[38] 99% of respondents displayed zero or one switch in both the series.

[39] 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.

countries.[40] 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. Gneezy and Potters (GP task, henceforth) provided a simpler task of eliciting risk where respondents are asked to allocate/invest an amount between a risky and a safe option, the expected returns in case of risky option are always greater than the amount invested. 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; Dagupta et al., 2015; Gangadharan et al., 2016). Dasgupta et al. (2016) find that faced with field constraints related to time, cognition or comprehension, the GP task can provide stable and comparable measures of risk attitudes elicited using the EG task.[41] There is a consensus that the risk elicitation task must be simple to understand, to avoid adding noise to the data, especially in contexts in which the numeracy of the subjects is an issue. On this account, HL might be troublesome. However, once individuals with inconsistent decisions are excluded, HL shows similar noise levels of other tasks, nonetheless, it does result in data loss. It is not very clear how confident one should be in making policy recommendations when one must eliminate most of the data due to inconsistent choices. So, comprehension is a very serious issue, as there seems to be no good way to account for inconsistency (Charness and Viceisza, 2012).

In our survey we used GP task because of its relative simplicity as compared to other tasks. 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. Therefore, one

[40] During our pre-pilot we found it difficult to comprehend HL task to non-standard subjects.

[41] 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.

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.[42] The amount invested in the risky option provides a good metric for capturing differences in attitude toward risk between individuals.

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.

2.5 Empirical Framework and Summarizing the Data

The second objective of this paper is to test for significant association between time preference and BMI. We use natural logarithm of BMI as the dependent variable.[43] We run two specifications – the first specification assumes time-consistent preferences and use monthly discount factor δ_{exp} , and the second specification employs the quasi-hyperbolic discount factors and utilizes the present bias term β_{qh} and monthly long run discount factor δ_{qh}.

As noted later in the summary statistics, there were hardly any underweight adults in our sample. We therefore focus on the predictions of the model in section 2.2 relating to overweight only. We estimate regressions of the following form:

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[42] Only 10% of our sample chose to invest entire Rs 500.

[43] We utilize natural logarithm of BMI as a dependent variable because residuals estimated using equation (7) and (8), Shapiro –Wilk test do not reject the null hypothesis of residuals following normal distribution, while using just BMI as a dependent variable, rejects the null.

$$ln\ BMI_i = \alpha_0 + \alpha_1\delta_{exp,i} + \alpha_2 X_i + \varepsilon_i \quad (7)$$

and

$$ln\ BMI_i = \gamma_0 + \gamma_1\beta_{qh,i} + \gamma_2\delta_{qh,i} + \gamma_3 X_i + \mu_i \quad (8)$$

Where $ln\ BMI_i$ denotes natural logarithm of BMI of individual i, $\delta_{exp,i}$ and $\beta_{qh,i}$, $\delta_{qh,i}$ are the variables of interest and X_i is a vector of control variables. A large body of research documents various other covariates contributing to higher BMI or overweight and obesity in India and the control variables included in the estimations are guided by these prior studies. Studies have shown that basal metabolic rate decreases almost linearly with age resulting in higher BMI as one ages, therefore, it is important to control for age (see Kulkarni et al., 2017; Kulkarni et al., 2014). It is important to control for sex as clearly there are physiological differences between males and females. Also, in general, studies in India show that females have slightly higher prevalence of overweight and obesity than males (see for example Ramachandran, 2013; Subramanian et al., 2009).

Socio-economic status reflected by income or wealth as well as education is an important predictor of overweight and obesity. Many studies provide evidence of the positive association (as opposed to negative association in developed economies) between socio-economic status and BMI/overweight in India (see for example, Griffiths and Bentley, 2001; Subramanian et al., 2009; Kulkarni et al., 2017). Given evidence on education playing an important role in facilitating good health as observed in developed countries, one would expect a negative correlation between education and probability of being overweight. Contrary to developed countries, Griffiths and Bentley (2001) and Kulkarni et al. (2014) find positive association between BMI and education among Indian women. It is likely that this positive association is a reflection of socio-economic status because of possible correlation between income/wealth and educational attainment and perhaps low education levels for women in India in general.

Furthermore, for both developed and developing countries, there are studies that provide evidence of link between energy expenditure at work and BMI. These studies find that being employed in an occupation entailing low physical activity is associated with significantly higher BMI and hence is included as a control (see Lakdawalla and Philipson, 2009; Paeratakul et al., 1998).

Given other covariates described in the literature and discussed above, we include five categories of control variables. The first are demographic: age and gender. The second set includes the respondent's human capital as captured by years of education; the third category consists of dummies capturing the household's wealth quintile as an indicator of socio-economic position. The fourth category is again individual-specific and includes dummies for type of occupation- employed full-time in light or sedentary work, employed part-time, home maker, student, unemployed/retired relative to omitted category- employed in full-time work that involves medium or high physical activity. Finally, 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.

2.5.1. Summary Statistics

Using the Asian benchmark to categories adults in weight categories, Table 2.3 indicates that 34% adults in the sample are overweight and 51% are obese. The proportion of adults who are underweight (BMI <18.5) is negligible (1%), which means that only 13% are in healthy weight category.

Table 2.3: Cross -Tabulation of Adults (25-60-year-old) by Anthropometric Outcomes and Wealth Quintile (percent of individuals)

Wealth Quintile	**1**	**2**	**3**	**4**	**5**	**Total**
BMI Category						
Underweight	3	1	1	2	1	1
Normal-Weight	29	10	9	9	9	13
Overweight	34	37	34	31	37	34
Obese	35	52	56	58	54	51
Total	100	100	100	100	100	100

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

Notes: Data refer to adults aged 25 to 60 years. Underweight is defined adult as an adult with BMI<18.5 kg/m^2, normal weight is defined as an adult with 18.5 $kg/m^2 \leq$BMI <23 kg/m^2, and overweight as 23 $kg/m^2 \leq$BMI <27.5 kg/m^2 and obese as BMI $\geq$27.5 kg/m^2.Wealth index for number of assets owned constructed using PCA and was divided into quintiles.

Table 2.3 also presents the proportion of individuals in different BMI categories by wealth quintile.[44] Individuals belonging to wealth quintile 1 have the lowest proportion of adults who are overweight or obese (69%) and the highest proportion of individuals who are normal weight (29%), while other quintiles (2nd, 3rd and 4th) have similar proportion of individuals who fall in these categories (89%-91% overweight or obese and 9%-10% normal-weight). Also note that obesity is above or equal to 35% in all quintiles. These numbers indicate that though overnutrition is highest in the upper quintiles but it has percolated among urban poor as well. Our analysis is in line with Luhar et al. (2018), who, using NFHS data, find convergence of overweight/obesity prevalence across socio-economic position in urban areas among both men and women. In fact, they find that between 1998-99 and 2015-16, the increase in overweight and obesity was greater among lower wealth group than in the higher. Since our sample have almost negligible proportion of underweight adults, we could not test for predictions of theory model under scenario 1.

Table 2.4 presents summary statistics on calculated time preferences. Under time-consistent preferences, adults on an average discount any future outcome with monthly discount factor of 0.909, while the range of δ_{exp} is 0.774-0.997. These are suggestive of a high level of impatience and are consistent with values commonly observed in the literature. For instance, Bradford et al (2017) report monthly discount factor of 0.89 and Meier and Sprenger (2010) obtained 0.83. In case of time-inconsistent specification, β_{qh}= 0.879 which means on an average individual is present biased. The mean of δ_{qh}= 0.916 is greater than the mean of δ_{exp}= 0.909. The minimum value of β_{qh} is 0.220 and the maximum is 1, while 0.774 and 0.997 are the minimum and maximum values of δ_{qh} respectively. In our sample about 30% adults are present biased.[45] Our results are similar to Meier and Sprenger (2010) who find 36% of their sample as present biased.

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[44] Using information collected on ownership of household assets (or appliances) we constructed a wealth index, based on that individuals/households were divided into five wealth quintiles, where first quintile represents the lowest wealth quintile.

[45] 43% of our sample have time-consistent preferences and 27% are future biased. Because of the reasons mentioned in section 2.4.2 we cap values of β_{qh} at 1 if it is greater than 1. Our regression

Table 2.4: Distribution of calculated discount factors and present bias term

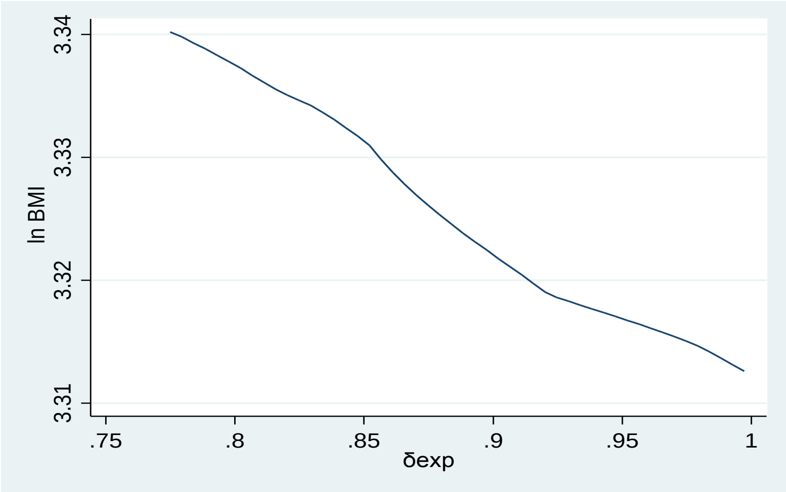
Time preference variables	Average (standard deviation)	Range
	(1)	(2)
δ_{exp}	0.909 (0.074)	0.774-0.997
β_{qh}	0.879 (0.235)	0.220-1.000
δ_{qh}	0.916 (0.081)	0.774-0.997

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.

Figure 2.1 presents the non-parametric lpoly plots of the association between $ln\ BMI$ and time preferences variables under exponential discounting framework for adults aged 25-60. We see that increase in δ_{exp} is associated with decrease in $ln\ BMI$ i.e. a relatively patient individual is more likely to have lower BMI vis-à-vis an impatient individual. Similarly, under quasi-hyperbolic framework, we observe a negative association between δ_{qh} and $ln\ BMI$ (see Panel B of figure 2.2). For the present bias term, we observe that for values less than or equal to 0.7, β is weakly negatively associated with $ln\ BMI$, but beyond this value we find that increase in β is associated with decrease in $ln\ BMI$ (see Panel A of figure 2.2). Hence, these figures are suggestive of negative relationship between time-discounting and $ln\ BMI$, which are in line with our theory prediction.

results are not sensitive to capping the β values at 1, as we find that our results are consistent even if we don't cap β.

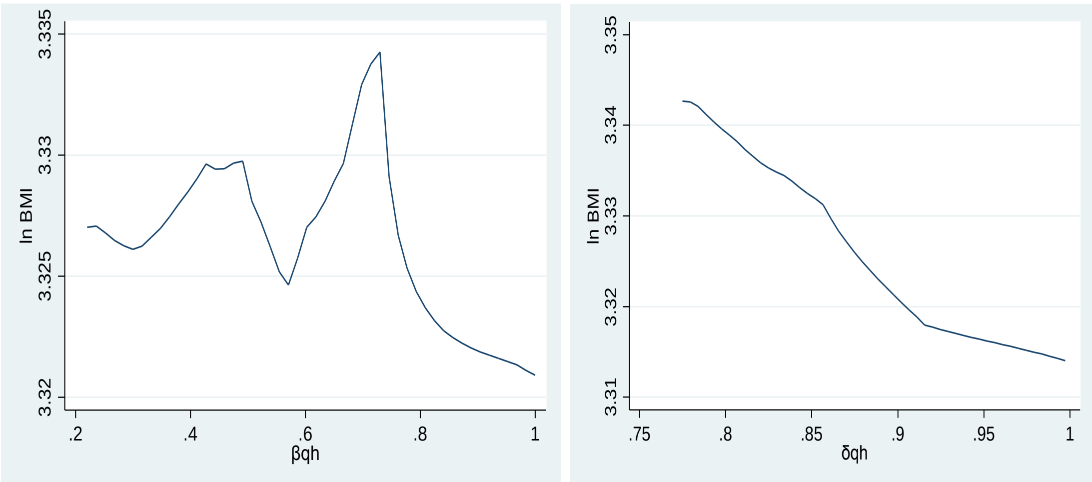
Figure 2.1: lpoly plots of ln BMI and discount factor (δ_{exp})



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.

Figure 2.2: lpoly plots of ln BMI and present bias (β_{qh}) and long-run discount factor (δ_{qh})

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.

2.6 Results

2.6.1 Results on the Role of Time Preference and Present Bias on Adult BMIs

We utilize 760 observations out of 885 in the regression analysis for the reasons explained in detail in section 2.6.2 below. Tables 2.5 and 2.6 present ordinary least squares (OLS) results corresponding to equations (7) and (8), respectively. As discussed above in section 2.4.2, in Tables 2.5 and 2.6, we report results using last switching point if respondent switches multiple times. Since time preference variables don't have a natural metric or scale, in column 7 of Tables 2.5 and 2.6, we also report standardized coefficients corresponding to the most comprehensive model (column 6). This enables us to compare the magnitude of $\beta_{qh}, \delta_{qh}, \delta_{exp}$ with other control variables (in terms of standard deviation differences).[46] Recall that we test predictions of theory model under scenario 2 because we do not observe underweight adults in our sample.

2.6.1.1 Estimates assuming Time-Consistent Discount Factor $\boldsymbol{\delta_{exp}}$

Column (1) of Table 2.5, starts with a simple regression of $ln\ BMI$ on discount factor (δ_{exp}) and risk preferences because of possible correlation between risk and time preferences. We then systematically add the other controls to construct the full model in column (6). Note that the risk preference variable has been controlled in all the specifications. Adding demographic controls in columns (2) and (3) doesn't change the coefficient estimate of α_1. However, including human capital variable and dummies for wealth quintile increase the magnitude of the coefficient from -0.155 to -0.191. The value of coefficient α_1 decreases when we add occupation type in the regression. Column (7) reports standardized coefficients for the full model presented in column (6). These results suggest that a one standard deviation (.074) decrease in δ increases BMI by an average of 1.3%. In other words, a one standard deviation (.075) decrease in δ increases weight by 0.832 kgs for individuals with BMI 25 and height 160 cm. One interesting thing to note here is the magnitude of the estimate of δ_{exp} as one of the risk factors for higher body weight

[46] Independent variables are standardized to a mean of zero and a standard deviation of 1. Therefore, one unit increase in X represents a rise of one standard deviation increase in X.

outcomes. The magnitude of δ_{exp} is close to the magnitudes of the coefficient on wealth quintile dummies or years of education (see column 7 of Table 2.5).[47]

The coefficients associated with the other controls have the expected sign. Consistent with the literature, BMI increases with age because metabolism slows with age and results in weight gain. In our sample BMI does not vary significantly across gender. Education is positively associated with $ln\ BMI$. However, wealth does not predict BMI once type of occupation is taken into account. We also run a specification without including years of education (see columns 1 and 2 of Table A2.1 in appendix) and observe that wealth quintiles become significant at 1% level and are positively correlated with $ln\ BMI$. For example, individuals residing in household in the fifth quintile on an average have 3% higher BMI vis-à-vis individuals belonging to the first wealth quintile. This suggests that education may reflect socio-economic status. The positive correlation of wealth and education is in conformity with previous studies (see Kulkarni et al., 2017; Subramanian et al., 2009)**.** Moreover, respondents employed in light or sedentary work, home makers, student and part-time employees on an average have higher BMI than respondents working in medium or high physically intensive jobs. This result is consistent with the fourth paper of this dissertation, where we observe a positive association between low physical activity at work and BMI. Finally, risk preference of individuals has insignificant effect on BMI across all specifications.[48]

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47 We use two other measures as a robustness check, where we (a) utilize first switching point in case of more than one switching and (b) exclude respondents displaying multiple switches. See column 3 to 6 of Table A2.1 in appendix, our results are consistent across these specifications. The monthly discount factor (δ_{exp}) is statistically significant and negatively associated with $ln\ BMI$ in both the regressions. The estimates of these regressions and the standardized coefficients are reported in Table A2.1 (column 3 to 6). Thus, the robustness of the link between discount factor and BMI increases our confidence that the relationship between BMI and time preference is not spurious.

48 We also run regression by controlling for smoking and alcohol consumption. Coefficients and standardized coefficients are reported in column (1) and (2) of Table A2.3 in appendix, respectively. 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.

Table 2.5: Correlates of ln BMI, under time-consistent discounting.

Dependent variable: natural logarithm of BMI	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
δ_{exp}	-0.155*	-0.158*	-0.155*	-0.175**	-0.191**	-0.181**	-0.013
	(0.085)	(0.084)	(0.084)	(0.082)	(0.082)	(0.082)	
Age (in years)		0.004***	0.004***	0.004***	0.004***	0.004***	0.042
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Male[a]			-0.022	-0.018	-0.016	0.010	0.004
			(0.015)	(0.014)	(0.014)	(0.019)	
Years of education				0.007***	0.005**	0.005**	0.020
				(0.002)	(0.002)	(0.002)	
Wealth quintile 2[b]					0.038	0.034	0.013
					(0.024)	(0.024)	
Wealth quintile 3[b]					0.040*	0.036	0.014
					(0.023)	(0.023)	
Wealth quintile 4[b]					0.036	0.034	0.014
					(0.024)	(0.024)	
Wealth quintile 5[b]					0.043*	0.037	0.015
					(0.023)	(0.023)	
Employed-fulltime in light or sedentary job[c]						0.136***	0.066
						(0.047)	
Employed part-time[c]						0.152***	0.036
						(0.052)	
House wife[c]						0.155***	0.077
						(0.047)	
Student[c]						0.123*	0.019
						(0.067)	
Unemployed/ Retired[c]						0.055	0.010
						(0.058)	
Risk preference#	-	-	-	-	-	-	-
Constant	3.458***	3.266***	3.273***	3.199***	3.223***	3.065***	
	(0.078)	(0.080)	(0.080)	(0.080)	(0.080)	(0.091)	
Observations	772	772	772	771	760	760	

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. $\delta_{exp} = \frac{\delta_{0,6} + \delta_{6,12}}{2}$. Last switching point is used as an indifference point in case of multiple switches. Independent variables are standardized to a mean of zero and a standard deviation of 1 and column 7 reports these standardized coefficients for the full model in column 6. #: All risk preference coefficients have value 0 and are (negatively) insignificant. Reference categories- [a]: Female; [b]: quintile 1 for wealth; [c]: employed full-time in medium and high physically intensive job. Robust standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

2.6.1.2 *Estimates assuming Quasi-hyperbolic Discounting*

This sub-section attempts to examine whether the association between time preference and $ln\ BMI$ operates through bias for the present or self-control issues. To investigate the same, we regress ln BMI on present bias term β_{qh} and on long run discount factor δ_{qh} along with controls mentioned above (equation 8). Results are presented in Table 2.6. As before, we add controls sequentially to see how the magnitude of coefficient of β_{qh} and δ_{qh} changes with specification. Risk preference is a control in all the specifications.

The sign of coefficient of both β_{qh} and δ_{qh} are in the expected direction i.e. they are negatively correlated with $ln\ BMI$. As we move from column (1) to column (6), our result becomes stronger. The magnitude of the estimated γ_1 increases from -0.034 to -0.048, and for γ_2, it rises from -0.160 to -0.184. These estimates stabilize once we control for wealth and occupation. The coefficient of δ_{qh} is statistically (negatively) significant at the 5% level. The magnitude of the coefficient associated with δ_{qh} implies that a one-standard deviation (0.081) decrease in δ_{qh} leads to increase in BMI on an average by 1.5%. This result suggests that for individuals with BMI 25 and height 160 cm, a one-standard deviation (0.081) decrease in δ_{qh} leads to 0.960 kgs increase in weight.

The association of β_{qh} with $ln\ BMI$ becomes statistically significant (negatively) at 10% significance level after controlling for years of education and remains significant after adding wealth and occupation type. As β_{qh} decreases by one standard deviation (0.235), on an average BMI increases by 1.1%, this says that for adults with BMI 25 and height 160 cm, a one standard deviation (0.235) decrease in β_{qh}, increases weight by 0.704 kgs.[49]

The coefficient associated with β_{qh} is significant for our preferred specification (see Table 2.6) though significance is not consistent across specifications (see Table A2.2 in

[49] We calculated β_{qh} and δ_{qh} estimates using first switching point and only including respondents with no switching or one switching point, respectively as a robustness check. We find that our results are consistent i.e. though β_{qh} coefficient becomes insignificant but the sign (negative) is in the right direction, while long run discount factor is statistically negatively associated with BMI. The results of these regressions and the standardized coefficients are reported in Table A2.2 (see column 3 to 6 of Table A2.2). We also run a regression without capping β_{qh} variable at 1, to see whether it produces any different result, we find that our results are maintained and are presented in column (7) and the corresponding standardized coefficients are reported in column (8) of Table A2.2.

appendix), it has the correct (negative) sign. The results indicate that present bias does mediate the relationship between time preferences and BMI. Also, crucial are that the magnitudes of time preference coefficients, they are comparable with the most common and important factors such as wealth quintile dummies and years of education of rising BMI levels recognized in the literature (see column 7 of Table 2.6).

Table 2.6: Correlates of ln BMI, under quasi-hyperbolic discounting.

Dependent variable: natural logarithm of BMI	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
β_{qh}	-0.034	-0.042	-0.040	-0.049*	-0.049*	-0.048*	-0.011
	(0.031)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	
δ_{qh}	-0.160**	-0.168**	-0.163**	-0.182**	-0.196**	-0.184**	-0.015
	(0.081)	(0.079)	(0.079)	(0.078)	(0.078)	(0.078)	
Age(in years)		0.005***	0.004***	0.004***	0.004***	0.004***	0.042
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
Male[a]			-0.021	-0.017	-0.015	0.011	0.004
			(0.015)	(0.014)	(0.014)	(0.019)	
Years of education				0.008***	0.005**	0.005**	0.021
				(0.002)	(0.002)	(0.002)	
Wealth quintile 2[b]					0.038	0.033	0.013
					(0.024)	(0.023)	
Wealth quintile 3[b]					0.040*	0.035	0.014
					(0.023)	(0.023)	
Wealth quintile 4[b]					0.037	0.034	0.014
					(0.024)	(0.024)	
Wealth quintile 5[b]					0.042*	0.036	0.015
					(0.023)	(0.023)	
Employed-fulltime in light or sedentary job[c]						0.133***	0.064
						(0.048)	
Employed part-time[c]						0.150***	0.035
						(0.053)	
House wife[c]						0.152***	0.076
						(0.048)	

Student[c]						0.122*	0.019
						(0.067)	
Unemployed/Retired[c]						0.050	0.009
						(0.059)	
Risk preference[#]	-	-	-	-	-	-	-
Constant	3.494***	3.312***	3.316***	3.248***	3.269***	3.111***	
	(0.086)	(0.086)	(0.086)	(0.085)	(0.086)	(0.098)	
Observations	772	772	772	771	760	760	

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. $\beta_{qh} = \frac{\delta_{0,6}^{6}}{\delta_{6,12}^{6}}, \delta_{qh} = \delta_{6,12}$. Last switching point is used as an indifference point in case of multiple switches. Independent variables are standardized to a mean of zero and a standard deviation of 1 and column 7 reports these standardized coefficients for the full model in column 6. #: All risk preference coefficients have value 0 and are (negatively) insignificant. Reference categories- [a]: Female; [b]: quintile 1 for wealth; [c]: employed full-time in medium and high physically intensive job. Robust standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Turning to the other correlates of BMI, column (6) of Table 2.6 suggests that coefficient of age is positive, indicating that, on an average, BMI increases as the respondent ages. Education is positive and significantly correlated with ln BMI. Assets possessed by household seem to matter- coefficient is significant and positive for all the quintiles if we remove years of education (see column 1 and 2 of Table A2.2). Also, type of occupation is important in determining BMI- adults employed in inactive jobs, housewives, student and part-time employees, on an average, have higher BMI as compared to adults working in jobs that involve some physical activity.[50] These observations are in line with literature (see for example Kulkarni et al., 2017; Maitra and Menon, 2019).

2.6.2 Estimation Sample and Estimates of Time Preference on Age

The results discussed so far are based on an estimation sample of 760 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, 35 individuals

[50] Results including current smoker and drinker as a control are presented in column 3 of Table A2.3 in appendix. Coefficients and standardized coefficients are reported in column (3) and (4) of Table A2.3 in appendix, respectively.

either did not have their weights/heights, did not answer the multiple price list module or did not answer questions used as controls in the regression.

Of the remaining 850 individuals, 80 gave inconsistent answers in the MPL questions: in other words, they switched from larger-later payments to smaller-sooner amounts in 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. For remaining sample of 770 adults, for the preferred specifications (noted above) we ran various diagnostics tests, including the detection of influential observations. We found that 10 observations had dfbetas that exceed cutoffs: in other words, the inclusion of these observations, individually, significantly impacted the estimated coefficients of interest. Hence, these were not included, resulting in an estimation sample size of 760.

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 760 individuals who did not. These results (refer to column (1) of Appendix Table A2.4) 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 incorrect responses. However, the sample of inconsistent and consistent doesn't differ on BMI and wealth grounds. In a second probit regression, we examine if those with item non-response, or who had high dfbetas (45 observations) were systematically different from 760 observations. Results of this regression indicate no significant difference in terms of gender, education and age (see column (2) of Appendix Table A2.4). 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; incorporating the full sample into the analysis will be the subject of further research.

We also run regressions of our variable of interests i.e. time preference variables ($\delta_{exp}, \beta_{qh} and\ \delta_{qh}$) on age and other control variables (see Table A2.5). None of the variables are correlated with time preference variables, ruling out issue of collinearity with controls such as age, education, wealth, gender and risk preference. Further, 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 preference variables are stable over time. Percoco and Nijkamp (2009) in a meta-analysis observe no change in the time preferences. Similarly, Borghans and Golstyen (2005) using proxy of time preference variable observe the average discount factor (or discount rate) did not change over time. We tested this by regressing time preference on age and find that our results corroborate what has been observed in the literature, indicating that discount factor (δ_{exp}) or present bias (β_{qh}) or long run discount factor(δ_{qh}) are not correlated with age even after controlling for gender, education, wealth and individual risk preferences (see Table A2.5 in appendix). 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.

2.7 Summary and Conclusions

This paper investigates the link between time preference and BMI. Our theory model shows that time preference is relevant in explaining heterogeneity in health. Under both time-consistent and inconsistent regime, lower patience or higher preference for present increases BMI. We exploit data from a primary survey of 885 adults between 25-60 years from Western Delhi to empirically test these predictions. These behavioral parameters were elicited using incentivized choice experiments. Our results show that time preference predicts excess body weight. Under a time-consistent domain, after controlling for demographic characteristics, education, occupation type, wealth and risk preference, greater impatience (or low discount factor), on an average, results in higher BMI. This means that there is a negative association between patience and BMI. This result is in conformity with the findings of past studies exploring relationship between time-discounting and BMI (Courtemanche et al. 2015; Smith et al. 2005; Ikeda et al. 2010).

We also considered time-inconsistent preferences in order to check whether the connection between time-discounting and BMI is driven by present bias. The estimate of present bias is statistically significant at 10% level in one specification and in the other specifications has p-value less than 0.20, and, also have expected sign which suggests that present bias might be relevant in explaining increasing BMI. The long-run discount factor is statistically significant and negatively associated with BMI. Moreover, we find that the magnitude of the coefficients of intertemporal variables are quite large and comparable to more commonly recognized risk factors of increased BMI such as wealth and years of education.

Given absence of evidence on decreasing discount factor over time or changing discount factor with age as discussed in section 2.6.2, 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 cease rising overweight and obesity.

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Appendix on Theory Model

Appendix A2.1

The objective function

$$V_t = u(f_t, c_t) + h_t + \sum_{i=1}^{\infty} \beta\delta^i \, u(f_{t+i}, c_{t+i}) + h_{t+i} \;\; w.r.t \; to \; f_t$$

$$s.t. \; to \;\; h_{t+i} = h_{t+i-1}(1-\lambda) + \varphi\big(f^{id} - f_{t+i-1}\big) \; and \; Y_{t+i} = \; pf_{t+i} + c_{t+i}$$

Can be written as:

$$V_t = \; u(f_t, Y_t - pf_t) + \sum_{i=1}^{\infty} \beta\delta^i \, u(f_{t+i}, Y_{t+i} - pf_{t+i}) + \; h_t\left[1 + \frac{\beta\delta(1-\lambda)}{1-\delta}\right] + \sum_{i=0}^{\infty} \frac{\beta\delta^{i+1}\varphi(f^{id} - f_{t+i})}{1-\delta(1-\lambda)} \quad 1(A)$$

Maximizing $V_t \; w.r.t \; to \; f_t$ will give the following first order condition:

$$u_f(f, \; Y - pf) - pu_c(f, \; Y - pf) + \frac{\beta\delta \; \varphi_f(f^{id} - f)}{1-\delta(1-\lambda)} = 0 \rightarrow \; f_t^{nc}(\beta, \delta, \lambda, Y_t, p) \qquad 2(A)$$

We assume V_t to be quasi concave in $f_t \; and \; c_t$. Suppose H is a bordered Hessian then,

$$H = \begin{bmatrix} 0 & f_1 & f_2 \\ f_1 & f_{11} & f_{12} \\ f_2 & f_{21} & f_{22} \end{bmatrix}$$

If $V_t \; is$ assumed to be quasi concave then, $|H_1| < 0 \; and \; |H_2| > 0$. So, the bordered hessian matrix for V_t can be written in the following way:

$$H = \begin{bmatrix} 0 & u_f + \frac{\beta\delta\,\varphi_f\left(f^{id} - f\right)}{1-\delta(1-\lambda)} & u_c \\ u_f + \frac{\beta\delta\,\varphi_f\left(f^{id} - f\right)}{1-\delta(1-\lambda)} & u_{ff} + \frac{\beta\delta\,\varphi_{ff}\left(f^{id} - f\right)}{1-\delta(1-\lambda)} & u_{cf} \\ u_c & u_{cf} & u_{cc} \end{bmatrix}$$

$$|H_2| = -(u_f + \frac{\beta\delta\,\varphi_f(f^{id}-f)}{1-\delta(1-\lambda)})[u_{cc}\left(u_f + \frac{\beta\delta\,\varphi_f(f^{id}-f)}{1-\delta(1-\lambda)}\right) - (u_{cf}\,u_c)] + u_c\left[u_{cf}\left(u_f + \frac{\beta\delta\,\varphi_f(f^{id}-f)}{1-\delta(1-\lambda)}\right) - u_c\left(u_{ff} + \frac{\beta\delta\,\varphi_{ff}(f^{id}-f)}{1-\delta(1-\lambda)}\right)\right] > 0 \qquad 3(A)$$

Putting 2(A) in 3(A) would give us the following:

$$-pu_c[u_{cc}pu_c - u_{cf}u_c] + u_c\left[u_{cf}p\,u_c - u_c\left(u_{ff} + \frac{\beta\delta\,\varphi_{ff}\left(f^{id} - f\right)}{1-\delta(1-\lambda)}\right)\right] > 0$$

And finally, the above inequality can be written as:

$$u_{ff} - 2pu_{cf} + p^2u_{cc} + \frac{\beta\delta\varphi_{ff}\left(f^{id} - f\right)}{1-\delta(1-\lambda)} < 0$$

Hence, the denominator of equation (2) and (3) is negative.

Appendix A2.2

Since $h_t = h_{t+1} = \cdots \dots \dots \dots \dots . = h_s$ at the steady state, so health (at the steady state) can be written as:[51]

$$h_s = h_s(1-\lambda) + \varphi(f^{id} - f_s) \rightarrow h_s = \frac{\varphi(f^{id}-f_s)}{1-\lambda}$$

[51] If agent eats f^{id} his health status would be equal to $h_s^{id} = \frac{\varphi(0)}{1-\lambda}$.

Appendix A2.3

In case of committed choice, the lifetime utility will look like:

$$V_t = \ u(f_C, Y - pf_c) + \ h_t \ + \sum_{i=1}^{\infty} \beta\delta^i \ [u(f_c, Y - pf_c) + \ h_{t+i}]$$

$where \ h_{t+i} = h_{t+i-1}(1 - \ \lambda) + \ \varphi\big(f^{id} - f_c\big), \ h_t \ i$s the initial health status of the agent which is given at time period t.

$$\begin{aligned} V_t = \ & u(f_C, Y - pf_c) + \ h_t \ + \beta\delta \, [u(f_c, Y - pf_c) + \ h_{t+1}] \\ & + \ \beta\delta^2 \, [u(f_c, Y - pf_c) + \ h_{t+2}] + \ \beta\delta^3 \, [u(f_c, Y - pf_c) + \ h_{t+3}] \\ & + \ \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \end{aligned}$$

$$where \ h_{t+i} = h_{t+i-1}(1 - \ \lambda) + \ \varphi\big(f^{id} - f_c\big)$$

Now putting $h'_{t+i} \ s \ in \ above \ equation$

$$\begin{aligned} V_t = \ & u(f_C, Y - pf_c) + \ h_t \ + \beta\delta \left[u(f_c, Y - pf_c) + h_t(1 - \ \lambda) + \ \varphi\big(f^{id} - f_c\big) \right] \\ & + \ \beta\delta^2 \left[u(f_c, Y - pf_c) + \ h_{t+1}(1 - \ \lambda) + \ \varphi\big(f^{id} - f_c\big)\right] \\ & + \ \beta\delta^3 \left[u(f_c, Y - pf_c) + \ h_{t+2}(1 - \ \lambda) + \ \varphi\big(f^{id} - f_c\big)\right] \\ & + \ \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \end{aligned}$$

$$\begin{aligned} V_t = \ & u(f_C, Y - pf_c) + \ h_t \ + \beta\delta \left[u(f_c, Y - pf_c) + h_t(1 - \ \lambda) + \ \varphi\big(f^{id} - f_c\big) \right] \\ & + \ \beta\delta^2 \big[u(f_c, Y - pf_c) + \ h_t(1 - \lambda)^2 + (1 - \lambda)\varphi\big(f^{id} - f_c\big) \\ & + \varphi\big(f^{id} - f_c\big)\big] \\ & + \ \beta\delta^3 \big[u(f_c, Y - pf_c) + \ h_t(1 - \lambda)^3 + (1 - \lambda)^2\varphi\big(f^{id} - f_c\big) \\ & + (1 - \lambda)\varphi\big(f^{id} - f_c\big) + \ \varphi\big(f^{id} - f_c\big)\big] + \ \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \end{aligned}$$

$$V_t = \ u(f_C, Y - pf_c)[\ 1 + \beta\delta\ + \beta\delta^2 + \ \beta\delta^3 + \cdots \ldots \ldots . .]$$
$$+ h[\ 1 + \beta\delta(1 - \ \lambda) + \beta\delta^2(1-\lambda)^2 + \ \beta\delta^3(1-\lambda)^3 + \cdots \ldots \ldots \ldots \ldots . .]$$
$$+ \beta\delta\ \varphi\big(f^{id} - f_c\big)[1 + \delta + \ \delta^2 + \ \delta^3 + \cdots . \ldots \ldots \ldots \ldots]$$
$$+ \ \beta\delta^2\ (1 - \ \lambda)\ \varphi\big(f^{id} - f_c\big)[1 + \delta + \ \delta^2 + \ \delta^3 + \cdots \ldots \ldots \ldots \ldots \ldots]$$
$$+ \ \beta\delta^3(1-\lambda)^2\ \varphi\big(f^{id} - f_c\big)[1 + \delta + \ \delta^2 + \ \delta^3 + \cdots \ldots \ldots \ldots \ldots \ldots]$$
$$+ \cdots \ldots \ldots \ldots$$

$$V_t = u(f_C, Y - pf_c) + \ \sum_{i=1}^{\infty} \beta\delta^i\ u(f_c, Y - pf_c) +$$
$$h_t\left[1 + \tfrac{\beta\delta(1-\lambda)}{1-\delta(1-\lambda)}\right] + \ \textstyle\sum_{i=0}^{\infty} \tfrac{\beta\delta^{i+1}\varphi(f^{id}-f_c)}{1-\delta(1-\lambda)} \qquad 4(A)$$

And 4 (A) *can be written as*:

$$V_C = \quad u(f_c, Y - pf_c)[\frac{1 - \delta + \beta\delta}{1-\delta}] + \ h_t\left[1 + \frac{\beta\delta(1-\lambda)}{1-\delta(1-\lambda)}\right] + \ \frac{\beta\delta\ \varphi(f^{id} - f_c)}{[1 - \delta(1-\lambda)](1-\delta)}$$

Maximizing V_C w.r.t f_c will give us the following FOC:

$$u_f(f,\ Y - pf) - pu_c(f,\ Y - pf) + \frac{\beta\delta\ \varphi_f\big(f^{id} - f\big)}{(1-\delta(1-\lambda)\ )\ (1-\delta+\beta\delta)} = 0 \quad \rightarrow \ f^c(\beta, \delta, \lambda, Y, p)$$

Appendix A2.4

When we assume that preferences are consistent ($\beta = 1$), then the agent at time period t will maximize:

$$V_t = \ u(f_t, c_t) + h_t + \sum_{i=1}^{\infty} \delta^i\ u(f_{t+i}, c_{t+i}) + h_{t+i}\ \ w.r.t\ to\ f_t$$

$s.t.\ to\ \ h_{t+1} = h_t(1-\lambda) + \varphi\left(f^{id} - f_t\right)\ and\ Y_t =\ pf_t + c_t$

The first order condition is:

$u_f(f_t,\ Y_t - pf_t) - pu_c(f_t, Y_t - pf_t) + \frac{\delta\ \varphi_f\left(f^{id} - f_t\right)}{1-\delta(1-\lambda)}$=0 $\rightarrow\ f_t^{nc}(\delta, \lambda, Y_t, p)$ and then, we can look at how food consumption changes with change in δ at the steady state,

$$\frac{\partial f_s^{nc}}{\partial \delta} = \frac{-\frac{\varphi_f\left(f^{id}-f\right)}{[1-\delta(1-\lambda)]^2}}{u_{ff}(f,Y-pf)\ -2pu_{cf}(f,Y-pf)+p^2u_{cc}(f,Y-pf)+\frac{\delta\varphi_{ff}\left(f^{id}-f\right)}{1-\delta(1-\lambda)}} > 0 \text{ if } \quad f_s^{nc}(\delta, \lambda, Y_t, p) < f^{id}$$

$$\frac{\partial f_s^{nc}}{\partial \delta} = \frac{-\frac{\varphi_f\left(f^{id}-f\right)}{[1-\delta(1-\lambda)]^2}}{u_{ff}(f,Y-pf)\ -2pu_{cf}(f,Y-pf)+p^2u_{cc}(f,Y-pf)+\frac{\delta\varphi_{ff}\left(f^{id}-f\right)}{1-\delta(1-\lambda)}} < 0 \text{ if } \quad f_s^{nc}(\delta, \lambda, Y_t, p) > f^{id}$$

and

$\frac{\partial h_s^{nc}}{\partial \delta} = \frac{\varphi_f\left(f^{id}-f\right)}{1-\lambda} * \frac{\partial f_s^{nc}}{\partial \delta}$ > 0 (in both the scenarios)

This result suggests that if an individual is impatient (lower δ) then he is going to have poorer health outcome. By poorer health outcome we mean underweight if the agent is eating below f^{id} or obese if the agent is eating above f^{id}.[52]

[52] The food choice in case of consistent preferences is same in committed and non-committed case as the first order condition is exactly the same in both the cases. Intuitively also, when agent has time-consistent preferences, agent will not require any commitment device to keep him stick to his plans because he is already sticking to his plans.

Appendix Tables

Table A2.1: Correlates of ln BMI, under time-consistent discounting.

Dependent variable: natural logarithm of BMI	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
δ_{exp}	-0.175** (0.082)	-0.013	-0.181** (0.082)	-0.014	-0.180** (0.082)	-0.014
Age (in years)	0.004*** (0.001)	0.042	0.004*** (0.001)	0.042	0.004*** (0.001)	0.042
Male[a]	0.004 (0.019)	0.002	0.010 (0.019)	0.004	0.009 (0.019)	0.004
Years of education	-	-	0.005** (0.002)	0.02	0.005** (0.002)	0.02
Wealth quintile 2[b]	0.064*** (0.021)	0.025	0.034 (0.024)	0.013	0.037 (0.024)	0.015
Wealth quintile 3[b]	0.068*** (0.020)	0.028	0.036 (0.023)	0.015	0.032 (0.024)	0.013
Wealth quintile 4[b]	0.066*** (0.021)	0.027	0.034 (0.024)	0.014	0.033 (0.024)	0.013
Wealth quintile 5[b]	0.069*** (0.020)	0.028	0.038 (0.023)	0.015	0.035 (0.023)	0.014
Employed-fulltime in light or sedentary job[c]	0.158*** (0.049)	0.077	0.136*** (0.047)	0.066	0.136*** (0.048)	0.066
Employed part-time[c]	0.167*** (0.054)	0.039	0.152*** (0.052)	0.036	0.157*** (0.052)	0.037
House wife[c]	0.167*** (0.050)	0.084	0.155*** (0.047)	0.078	0.156*** (0.047)	0.078
Student[c]	0.148** (0.067)	0.023	0.123* (0.067)	0.019	0.126* (0.067)	0.02
Unemployed/Retired[c]	0.071 (0.060)	0.013	0.055 (0.058)	0.01	0.056 (0.058)	0.01
Risk preference#	-	-	-	-	-	-
Constant	3.090*** (0.091)		3.067*** (0.091)		3.065*** (0.091)	
Observations	761		760		745	

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. $\delta_{exp} = \frac{\delta_{0,6} + \delta_{6,12}}{2}$. Column (1) reports results without including years of education in the regression. First switching point is used as an indifference point in case of column (3) in case of multiple switches. Column (5) reports results only including individuals not switching or switching at most once. Independent variables are standardized to a mean of zero and a standard deviation of 1 and column 2,4 and 6 reports these standardized coefficients for the full model in column 1, 3 and 5 respectively. #: All risk preference coefficients have value 0 and are (negatively) insignificant. Reference categories- [a]: Female; [b]: quintile 1 for wealth; [c]: employed full-time in medium and high physically intensive job. Robust standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table A2.2: Correlates of ln BMI, under quasi-hyperbolic discounting.

Dependent variable: natural logarithm of BMI	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
β_{qh}	-0.045	-0.011	-0.046	-0.011	-0.041	-0.01	-0.004	-0.002
	(0.029)		(0.029)		(0.029)		(0.009)	
δ_{qh}	-0.178**	-0.015	-0.186**	-0.015	-0.188**	-0.015	-0.153*	-0.013
	(0.078)		(0.078)		(0.078)		(0.083)	
Age (in years)	0.004***	0.042	0.004***	0.042	0.004***	0.042	0.004***	0.041
	(0.001)		(0.001)		(0.001)		(0.001)	
Male[a]	0.005	0.002	0.010	0.004	0.010	0.004	0.010	0.004
	(0.019)		(0.019)		(0.019)		(0.019)	
Years of education	-	-	0.005**	0.02	0.005**	0.02	0.005**	0.02
			(0.002)		(0.002)		(0.002)	
Wealth quintile 2[b]	0.064***	0.025	0.034	0.013	0.037	0.015	0.033	0.013
	(0.021)		(0.023)		(0.024)		(0.024)	
Wealth quintile 3[b]	0.068***	0.028	0.036	0.015	0.032	0.013	0.035	0.014
	(0.020)		(0.023)		(0.024)		(0.023)	
Wealth quintile 4[b]	0.067***	0.027	0.034	0.014	0.033	0.013	0.033	0.013
	(0.021)		(0.024)		(0.024)		(0.024)	
Wealth quintile 5[b]	0.069***	0.028	0.037	0.015	0.034	0.014	0.037	0.015
	(0.020)		(0.023)		(0.023)		(0.023)	
Employed-fulltime in light or sedentary job[c]	0.156***	0.076	0.134***	0.065	0.134***	0.065	0.137***	0.066
	(0.050)		(0.048)		(0.048)		(0.046)	
Employed part-time[c]	0.165***	0.039	0.150***	0.036	0.155***	0.037	0.152***	0.036
	(0.055)		(0.053)		(0.053)		(0.051)	
House wife[c]	0.164***	0.082	0.152***	0.076	0.153***	0.076	0.156***	0.078
	(0.051)		(0.048)		(0.048)		(0.046)	
Student[c]	0.147**	0.023	0.122*	0.019	0.125*	0.02	0.124*	0.019
	(0.068)		(0.067)		(0.067)		(0.066)	
Unemployed/Retired[c]	0.068	0.013	0.051	0.009	0.052	0.01	0.056	0.01
	(0.061)		(0.059)		(0.059)		(0.057)	
Risk preference[#]	-	-	-	-	-	-	-	-
Constant	3.134***		3.113***		3.109***		3.046***	
	(0.099)		(0.098)		(0.099)		(0.096)	
Observations	761		760		745		760	

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. $\beta_{qh} = \frac{\delta^6_{0,6}}{\delta^6_{6,12}}, \delta_{qh} = \delta_{6,12}$. Column (1) reports results without including years of education in the regression. First switching point is used as an indifference point in column (3) in case of multiple switches. Column (5) reports results only including individuals not switching or switching at most once. Column (7) reports result by not capping β_{qh} values at 1. Independent variables are standardized to a mean of zero and a standard deviation of 1 and column 2, 4, 6 and 8 reports these standardized coefficients for the full model in column 1, 3, 5 and 7 respectively. #: All risk preference coefficients have value 0 and are (negatively) insignificant. Reference categories- [a]: Female; [b]: quintile 1 for wealth; [c]: employed full-time in medium and high physically intensive job. Robust standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table A2.3: Correlates of ln BMI, under time-consistent and quasi-hyperbolic discounting.

Dependent variable: natural logarithm of BMI	**(1)**	**(2)**	**(3)**	**(4)**
δ_{exp}	-0.189**	-0.014	-	-
	(0.083)			
β_{qh}	-	-	-0.046	-0.011
			(0.029)	
δ_{qh}	-	-	-0.189**	-0.015
			(0.079)	
Age (in years)	0.004***	0.042	0.004***	0.043
	(0.001)		(0.001)	
Male[a]	-0.002	-0.001	-0.001	0
	(0.020)		(0.020)	
Years of education	0.005**	0.02	0.005**	0.02
	(0.002)		(0.002)	
Wealth quintile 2[b]	0.034	0.013	0.033	0.013
	(0.024)		(0.024)	
Wealth quintile 3[b]	0.032	0.013	0.031	0.013
	(0.023)		(0.023)	
Wealth quintile 4[b]	0.031	0.013	0.032	0.013
	(0.024)		(0.024)	
Wealth quintile 5[b]	0.035	0.014	0.034	0.014
	(0.023)		(0.023)	
Employed-fulltime in light or sedentary job[c]	0.129***	0.062	0.126**	0.061
	(0.049)		(0.050)	
Employed part-time[c]	0.144***	0.034	0.143***	0.034
	(0.054)		(0.055)	
House wife[c]	0.148***	0.074	0.145***	0.073
	(0.049)		(0.050)	
Student[c]	0.118*	0.018	0.117*	0.018
	(0.068)		(0.068)	
Unemployed/Retired[c]	0.053	0.01	0.049	0.009
	(0.059)		(0.060)	
Risk preference[#]	-	-	-	-
Current smoker[d]	0.004	0.036	0.004	0.001
	(0.037)		(0.037)	
Current drinker[e]	-0.029	-0.169	-0.028	-0.009
	(0.021)		(0.021)	
Constant	3.105***		3.145***	
	(0.095)		(0.102)	
Observations	751		751	

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. $\delta_{exp} = \frac{\delta_{0,6} + \delta_{6,12}}{2}$, $\beta_{qh} = \frac{\delta_{0,6}^{6}}{\delta_{6,12}^{6}}$, $\delta_{qh} = \delta_{6,12}$. Last switching point is used as an indifference point in case of multiple switches. Independent variables are standardized to a mean of zero and a standard deviation of 1 and column 2 and 4 reports these standardized coefficients for the full model in column 1 and 3, respectively. #: All risk preference coefficients have value 0 and are (negatively) insignificant. Reference categories- [a]: Female; [b]: quintile 1 for wealth; [c]: employed full-time in medium and high physically intensive job; [d]: don't smoke currently; [e] : don't drink alcohol currently. Robust standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.

Table A2.4: 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 (1)**	**Dependent variable =1 if There was non-response or observation was an outlier (2)**
Age (in years)	-0.016**	0.000
	(0.007)	(0.007)
Years of education	-0.035*	-0.009
	(0.019)	(0.018)
Wealth quintile 2 [a]	0.013	-
	(0.240)	
Wealth quintile 3 [a]	-0.349	-
	(0.258)	
Wealth quintile 4 [a]	-0.033	-
	(0.249)	
Wealth quintile 5 [a]	-0.085	-
	(0.249)	
Male [b]	-0.430***	0.008
	(0.161)	(0.169)
BMI	-0.002	-
	(0.014)	
Constant	-0.384	-1.473***
	(0.413)	(0.392)
Observations	840	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]: quintile 1 for wealth; [b]: Female. Robust standard errors in parenthesis. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2.5: Ordinary Least square Regressions of behavioral parameters on age and other control variables.

Dependent variable: **Time preferences**	$\boldsymbol{\delta_{exp}}$ **(1)**	$\boldsymbol{\beta_{qh}}$ **(2)**	$\boldsymbol{\delta_{qh}}$ **(3)**
Age (in years)	-0.000	0.001	-0.000
	(0.000)	(0.001)	(0.000)
Male[a]	0.007	0.017	0.007
	(0.007)	(0.019)	(0.007)
Years of education	0.000	0.003	0.000
	(0.001)	(0.003)	(0.001)
Wealth quintile 2[b]	0.005	0.008	0.005
	(0.012)	(0.035)	(0.012)
Wealth quintile 3[b]	0.006	0.001	0.006
	(0.013)	(0.035)	(0.013)
Wealth quintile 4[b]	0.002	0.008	0.002
	(0.013)	(0.036)	(0.013)
Wealth quintile 5[b]	0.016	-0.032	0.016
	(0.012)	(0.037)	(0.012)
Risk preference[#]	-	-	-
Constant	0.905***	0.822***	0.905***
	(0.018)	(0.052)	(0.018)
Observations	760	760	760

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 and 3 is $\delta_{exp}, \beta_{qh}, \delta_{qh}$ respectively. $\delta_{exp} = \frac{\delta_{0,6} + \delta_{6,12}}{2}, \beta_{qh} = \frac{\delta_{0,6}^{6}}{\delta_{6,12}^{6}}, \delta_{qh} = \delta_{6,12}$. Last switching point is used as an indifference point in case of multiple switches. #: All risk preference coefficients have value 0 and are (negatively) insignificant. Reference categories- [a]: Female; [b]: quintile 1 for wealth. Robust standard errors in parenthesis. Significance: * p < 0.10, ** p < 0.05, *** p <0.01.