Title

Influence of Time Preferences on Health Behaviors among Mexicans: Essays from Health Economics & Behavioral Economics Perspectives

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Publication Date
2014

UNIVERSITY OF CALIFORNIA
Los Angeles

Influence of Time Preferences on Health Behaviors among Mexicans: Essays from Health Economics & Behavioral Economics Perspectives

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Health Policy and Management

by

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2014

ABSTRACT OF THE DISSERTATION

Influence of Time Preferences on Health Behaviors among Mexicans: Essays from Health Economics & Behavioral Economics Perspectives

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Sandhya Venkatesha Rao Shimoga

Doctor of Philosophy in Health Policy and Management

University of California, Los Angeles, 2014

Professor Thomas Rice, Chair

This study explores the role of time preferences in determining health behaviors including diet, physical activity and smoking by combining traditional health economics concepts with behavioral economics perspectives. While there is extensive literature that conclusively show that high discount rates are associated with addictive behaviors, the conclusions are mixed for health producing behaviors including diet and physical activity. Our study utilizes population level data from Mexico with time discounting estimated from answers to hypothetical money choices.

The first study explores the relationship between time discounting and health behaviors by using Grossman's model of health capital by employing an instrumental variable approach to address the endogeneity in their relationship. We find that people who have low discount rates are more likely to report eating more vegetables per week, more likely to exercise and have more exercise minutes and are more likely to quit smoking. These results indicate that interventions to lower discount rates via education or social safety nets might improve health behaviors.

Our second study compares exponential, hyperbolic and quasi-hyperbolic functional forms of time discounting to investigate time-inconsistency in time discounting and its influence on health behaviors. While our data are found to be inadequate to fit a quasi-hyperbolic model, we find that in our data exponential form is strongly supported and hyperbolic form is weakly supported. We find also that people who have time-inconsistent hyperbolic preferences have worse health behaviors. Further, we find ‘Oportunidades’, a conditional cash transfer program in Mexico, helps people with hyperbolic time preferences in improving their diet related behaviors.

Our last study explores whether people assess their health relative to that of their peers and how such evaluation influences their health behaviors. We find that comparison to peers leads to assessing health from a loss-gain frame. People who think they have worse health tend to forecast better health behaviors and people who think they have better health than their peers forecast sub optimal behaviors. These results indicate that interventions aimed at peer groups would be more effective if those solutions take into consideration the comparison asymmetry within those groups.

This dissertation of Sandhya Venkatesha Rao Shimoga is approved.

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2014

DEDICATION

To

Charan, Mihir & Shruti

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ACKNOWLEDGEMENTS

I gratefully acknowledge the research support from AHRQ grant number R36HS022385 for Health Services Research Dissertation; UCLA Graduate Division's Dissertation Year Fellowship and by Health Initiatives of the Americas, UC Berkley & Programa De investigación en Migaracion y Salud (PIMSA), which made this dissertation possible.

I thank my committee chair, Tom Rice, for taking me under his wing, for encouraging and helping me in developing my slightly off-beat ideas and for gently prodding to be more thorough in my thinking and analysis. Every time I had a meeting with him, I came out with better clarity of thought, and a lighter heart which has kept me going throughout the past three years. Thanks are also due to my committee members - Fred Zimmerman for being my mentor for the past 5 years, for giving me a number of research opportunities and for being enormously supportive while I tried to find my research focus; Arturo Vargas Bustamante for pointing me to the data used for this study, for the opportunities to develop my research folio and for his friendly advice on all things academic; Suzanne Shu for helping me with developing this research and in analyzing the data, for encouraging me to pursue behavioral economics and for being a kind listener. My thanks are also due to my faculty advisor Ninez Ponce for her unwavering support and to my friends Jessica Williams, Jenna Jones, Selena Ortiz, Alice Villatoro, Audrey Jones, and Donglan Zhang for their listening ears and for just being there.

My heartfelt gratitude is to my family - my mother Vanaja Rao for her quiet strength, my father Venkatesha Rao who is my role model as a professor, my father-in-law Niranjan Singh for his enthusiastic support. My biggest thanks are to my children Mihir and Shruti who have been the source of utmost joy and who have made these years easy by doing their homework right next to me on the couch while I worked on my dissertation. Finally, none of this would have been possible without my husband Charan who encouraged me to change my career, helped me generate and develop research ideas, read my drafts, listened to my presentations, took care of children and finances. It is his fascination with future orientation that got me thinking of this research topic. Thank you Charan for being in my life, for being my muse and for being you!

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CHAPTER 1. INTRODUCTION

This dissertation study aims to understand how individual time preferences influence their health related behaviors. Time preferences indicate one's future orientation and propensity to invest in activities which are likely to produce future benefits but have immediate costs. Time preferences are used to explain a variety of such activities including inclinations to invest in education, retirement savings and in healthy behaviors.

While this idea is used to explain healthy behaviors which are an investment in the production of health, there are still outstanding questions on whether such relationships are endogenous. In other words, being future oriented might facilitate healthy behaviors resulting in better health and having better health might make one more future oriented by making them more optimistic about their future. We address this endogeneity in our study in chapter 4.

Health behaviors which have immediate costs are known to suffer from procrastination tendencies, where tasks such as starting an exercise or a diet regimen might get postponed when the time comes to act upon it. Such observed behaviors indicate that time preferences which cause such behaviors might be time-inconsistent. In other words, time preferences vary depending on whether the action is to be taken immediately or whether it is in the future. We explore this concept further in chapter 5, where we test whether time preferences have such inconsistency and if so, whether such inconsistency leads to worse health behaviors.

Time preferences are also modified based on whether the resulting actions are assessed from a reference point. We examine whether comparison of self-health to that of peers as a reference point influences health behaviors in chapter 6.

We study these questions in a Mexican population utilizing time preferences calculated via answers to hypothetical monetary choice questions. This study is one of the first to examine this relationship in Mexican population where rapidly increasing rates of obesity is one of the major emerging threats to population health. It is also relevant to the United States where Mexican immigrant subgroup is one of the largest and fastest growing minority groups which also faces increasing levels of chronic disease burden resulting from obesity and life style choices.

1.1 Background

Individual health has many determinants including market goods and services such as medical care; social determinants such as access to safe living conditions, access to affordable fresh foods, affordable housing; environmental conditions such as clean water, sanitation and low pollution; and individual factors such as education, income, location, race/ethnicity etc. In developing countries infectious diseases are largely responsible for morbidity and mortality at a population level. In contrast, chronic diseases arising from lifestyle factors and suboptimal health behaviors of individuals are some of the main causes of declining population health in many developed and emerging economies including the United States and Mexico. Some of the suboptimal behaviors responsible for declining population health include lack of regular physical activity, unhealthy diet, smoking, drinking, drug use as well as non-adherence to regular preventive care check-ups and screenings.

In an influential study, McGinnis and Foege estimate that almost 40 percent of all deaths in the US in 1990 were due to unhealthy behaviors, mainly comprising of tobacco use, poor diet, lack of exercise and excessive alcohol consumption (McGinnis and Foege 1993). Including other health-harming behaviors such as not obtaining recommended screening tests, regular preventive care check-ups, and lack of adherence to medications would increase their estimates. A decade later, an updated study by Mokdad et al. shows relatively few changes in the main causes or the percentage of deaths due to those causes (Mokdad, Marks et al. 2004). These estimates have to be interpreted with considerable caution as the sources of most of the deaths are multi-faceted and it is hard to elicit the independent effects of specific determinants. Still, this uncertainty notwithstanding, modifiable behaviors are important determinants of premature deaths. Also, morbidity associated with such behaviors should also be a warning signal to policymakers due to their increasing burden on health care systems.

Mexico, much like its northern neighbor, suffers from increasing levels of lifestyle induced illnesses including diabetes and chronic heart diseases. Adult obesity rates in Mexico rival those of the United States. Recently, Mexico surpassed the U.S. as the nation with highest prevalence of obesity with seven in ten adults designated as overweight or obese compared to 61% in the U.S. Mexico also has the highest per capita consumption of sugary beverages. Childhood obesity in Mexico has tripled over the last three decades with 17% of the children either overweight or obese. These problems in Mexico reflect similar trends in the U.S. where among disadvantaged and minority populations (including Mexican immigrant subgroup), there is a higher prevalence of diabetes, elevated blood pressure and chronic heart disease.

The reasons for individual suboptimal behaviors include many individual and societal factors that influence such behaviors directly and indirectly. For example, decision to choose what to eat depends on income, taste, habits as well as availability and affordability of food among other factors. It is a complex decision making process to sift through the available information, resist or accede influences and finally assess choices based on best interests for overall wellbeing. One of the recurring themes in all these decisions is that these decisions have delayed consequences that occur throughout the life course. The choice of education, work, savings, retirement, health, choice of residence as well as life events such as marriage, migration, or having children, produce consequences that are experienced over a lifetime (Loewenstein 1993) and affect one's health, wealth and happiness. Moreover, according to Adam Smith, how such decisions that have delayed consequences might determine economic prosperity of nations. Hence, understanding how we make such temporally distributed choices has attracted much academic attention.

Our particular interest in this paradigm pertains to how such decision making processes and resulting choices influence health behaviors and eventually overall health over a lifetime. Decisions that affect health – ones that have immediate consequences such as attending to a serious medical condition or decisions that lead to life-long consequences such as smoking, being continuously insured or eating fatty foods – have temporally distributed consequences. In particular, some of the decisions regarding health have consequences that last a lifetime and may affect the life expectancy. Such individual decisions related to health preserving or enhancing activities have consequences on the overall health and wealth of a society. Further, understanding this relationship might shape interventions or policies relating to health behaviors. People who have higher discount rates (or who are not future-oriented) tend to have self-control problems as they might not properly assess how indulgences in the short term would influence their health in the long term. In such cases, policies that offer help with pre-commitment to assist with self-control problems could help. Other areas of decision making where time preferences play an influential role such as savings have benefitted from having pre-commitment based savings programs specifically aimed for people with high discount rates (Ashraf, Karlan et al. 2006). Such programs can potentially benefit health behaviors too. But lack of consistent empirical support, lack of population level studies and studies specifically in minority and developing country contexts have hindered policy adoption when it comes to health behaviors. Social policies which normally undergo cost-benefit analysis use market interest rates (or sometimes even arbitrary rates assigned by bureaucrats) as discount rates to discount cost and benefits of competing policy options. While this method has been used as a matter of practicality, there is a growing interest in using a ‘social discount rate’ that is derived from population’s true time preferences as we improve our understanding of how individual time preferences influence many aspects of our lives. Thus, understanding this relationship pertaining to health behaviors might potentially inform and nudge policy makers to adopt a more realistic ‘social discount rate’ for cost-benefit analyses of competing health policies.

Traditionally, in economic analyses of temporally distributed choices, the discounted utility model is used to explain the values attached to delayed outcomes in terms of time discounting or time preferences. Time preference refers to an individual’s willingness to exchange utility today for utility later (Frederick, Loewenstein et al. 2002). Time preferences are formed over a lifetime, are influenced by factors including education, wealth, and family circumstances and are presumed to affect one’s behaviors in a variety of life domains including health behaviors, savings behaviors and risk taking. The traditional models to study investments in health and health care, including Grossman’s seminal model of Health Capital (Grossman 1972), utilize the discounted utility paradigm to evaluate choices over time. Having lower discount rates are expected to be associated with better health behaviors (Frederick, Loewenstein et al. 2002). In chapter 2, we describe current literature in this regard. However, having better health might make one to be more future oriented, leading to a problem of reverse causation (Becker and Mulligan 1997). In chapter 3, we investigate whether time preferences influence health behaviors by utilizing Grossman's model while accounting for the reverse causation using an instrumental variables approach.

While the above formulation might be an improvement over existing studies, the Grossman model and the Discounted Utility model both assume that time preferences are consistent over time. In other words, the discount rates are the same for tomorrow or for 10-years from now. For rational actors with time-consistent preferences this would be the case; but even rational individuals have limited capacity to project their future behaviors due to changes in preferences over time influenced by life events and also due to uncertainty associated with such forecasting (Gafni and Torrance 1984; Bleichrodt and Gafni 1996). While the assumption of rational time-consistent preferences provides a useful framework to study its relationship with health behaviors, it falls short when it comes to problems associated with health behaviors such as procrastination. Even with information on healthy lifestyles, means to do so implement that knowledge and correctly assessed future value of such behaviors, many of us postpone acting on them. This behavior pattern cannot be explained if preferences are time-consistent. Behavioral economics proposes an alternate explanation based on the premise that time preferences are inconsistent over time. It proposes that we discount utilities at a higher rate for the immediate future and at lower rates for the long term. Such inconsistent discounting may explain differences between individuals in their attempts to follow healthy behaviors and may point to interventions that might alleviate problems such as procrastination. In chapter 4, we explore alternate forms of discounting including exponential, hyperbolic and quasi-hyperbolic discounting in relation to health behaviors. Further, we investigate whether a social policy in Mexico called 'Oportunidades' facilitates healthy behaviors in people with time-inconsistent preferences.

Some of the differences in discounting may be due to viewing utilities from health behaviors as gains or losses. Prospect theory (Kahneman and Tversky 1979) proposes that gains and losses are valued differently over time from a reference point and consequently, gains or losses associated with health behavior are relative to a reference point. In chapter 5, we explore whether comparison of health with that of peers forms such a reference point and whether such assessment based on reference points influences future health behaviors.

We explore a variety of health behaviors in this study including diet, physical activity and smoking. The data are from the second wave of the Mexican Family Life Survey (MxFLS), a nationally representative longitudinal household survey from Mexico. The data are collected during 2005-06 and include a rich set of data on individual demographics and health behaviors, family and household characteristics as well as innovative measurement of individual time preferences. The population also includes a small sample of Mexican immigrants to the United States. Hence, this study adds to the literature by studying the relationships between time preferences and health behaviors in a developing country which is also a largely understudied population sub group in the United States. This study also is uniquely positioned to compare results from preference based measures and proxy measures of time preferences due to availability of such measures within the same dataset. Investigation of present bias at a population level adds to the current literature dominated by small sample studies. Assessment of health behaviors from loss-gain paradigm based on future expectations potentially contributes to framing policies promoting health behaviors. Chapter 6 summarizes and concludes the study.

CHAPTER 2. LITERATURE REVIEW

This chapter presents a review of the literature on how economics and particularly the health economics literature have used the concept of time preferences to explain differences in individual health behaviors. It then reviews some of the anomalies that are not explained in the empirical literature that are based on traditional economic models and some of the alternate explanations explored in literature to explain them. Finally, the chapter describes some of the gaps in literature that we aim to address in this study.

2.1 Theoretical Background

One of the primary questions addressed by studies on risky health behaviors is why people fail to pursue healthy behaviors and continue unhealthy habits even as information regarding consequences of such behaviors becomes common knowledge. While overall health of the population over the past 4 decades is trending towards a better health (Cutler, Glaeser et al. 2009), some health behaviors have shown better trends than others. For example, while smoking prevalence fell by about half between 1994 and 2007, obesity has more than doubled in the same period. Further, there are differences among population sub groups by gender, race/ethnicity, and by socioeconomic gradient with the latter being shown as the most influential determinant of such differences (Cawley and Ruhm 2011).

The health economics literature provides several theoretical explanations (Cawley and Ruhm 2011)to the health behavior trends and differences including health capital theory (where health behaviors are treated as investments into health); the relationship between health and education; health behaviors and addiction (including rational addiction theory where addiction to risky behaviors is modeled as a rational choice); the price elasticity of behaviors (resulting from a variety of reasons including taxation policies, availability of goods and services including cheap calorie dense foods); income; the role of advertising and other external influencers of decision making; and lastly, time preferences leading to different healthy behavior choices. We will concentrate on further exploring the last explanation in this study.

Time preference or time discounting refers to an individual's willingness to exchange utility today for utility later (Frederick, Loewenstein et al. 2002); it is also defined as the marginal rate of substitution between current and future utility of a choice that has intertemporal consequences (Becker and Mulligan 1997). It measures one's propensity for patience for delayed rewards (i.e. self-control). Time preferences vary across individuals and it is hypothesized that such differences can help explain differences in behaviors (Fuchs 1982) including savings for retirement, indulgence in dietary habits that produce future health risks or investments into activities such as regular exercise or going to periodic preventive care checkups and screenings – the actions that have short term costs and long term benefits. One of the explanations for differences in health behaviors that has emerged over the years is that the perceived utility from such suboptimal behaviors may outweigh the perceived utility from healthy behaviors (Chapman and Coups 1999). This problem is exacerbated by the fact that the costs associated with healthy behaviors are immediate, whereas benefits occur in the future. Hence, the way individuals value short-term costs over long term benefits is an important determinant of their healthy behaviors. One of the first theoretical premises on relationship between investments into health in the production of health is described by Grossman's model of Health Capital where health is produced using various investments including education and medical care (Grossman 1972). As investments, by definition, incur current costs for future benefits, this model provides a convenient framework for thinking about how time preferences influence such investments in health by using a discounted utility (DU) function to establish the relationship between the decisions to invest in health and their intertemporal utilities as:

$$V_T = \sum_{\tau=t+1}^{T} D_\tau \,.\, v(h_\tau, Z_\tau) \quad \text{---------------} \; (2.1)$$

Here, v is the utility (or value) function, Z_t is the consumption of standard commodities at time t, h_t is the health stock at time t, and D_t (0<D<1) is the discount function used to discount future utilities at time t. When a person makes investments in health that yield utility in the future time periods, she is expending time and resources in the current period for future utility. Such investments by a rational person are expected to maximize the present discounted value of lifetime utility. Thus, an individual's health related decisions in the current period correspond to the degree to which future utility is discounted. Time discounting captures the reasons for caring less about a future consequence, including factors that diminish expected utility generated from a future consequence, including uncertainty and changing tastes (Frederick, Loewenstein et al. 2002). [1] The discount function - the relative weight attached to utility in period t, relative to utility in period t+k, can be written as:

$$D_t\,(k) = \left(\frac{1}{1+r}\right)^k \qquad \text{---------------------------}(2.2)$$ where r is the discount rate.

The discount rate r represents the collective effects of various factors including psychological factors. Note that the rate of discount here is same for all future time periods and hence, does not depend upon the decision time horizon itself. The utilities for an immediate

[1] Time preferences correspond to the degree of preference for immediate utility over delayed utility. They correspond to health related decisions including whether to invest time and resources into healthy behaviors or prevention activities. Study of time discounting and preferences fall into 2 categories – one that investigates the role of discounting and one that concentrates on the utility function itself. In this section, we concentrate on the former category.

future period are always assumed to be reevaluated at each time period, implying a time-consistent behavior (Becker and Mulligan 1997).

Using this model, Victor Fuchs, in his pioneering empirical study, hypothesized that individual differences in health and in turn in health behaviors can be explained by individuals' inability or unwillingness (which is an expression of their time preferences) to take up those behaviors (Fuchs 1982). Using time preferences calculated from survey based hypothetical gamble questions, Fuchs' study reported a weak negative correlation between higher time discounting and health promoting behaviors. However, this study does not distinguish the potential simultaneous determination of health behaviors and time preferences via variables such as schooling. It also lacked explanatory power due to a small (~300) sample and measurement issues that did not differentiate between perceptions of uncertainty, lack of knowledge and time preferences. Still, as an exploratory study, it pioneered the use of hypothetical gamble measures in a telephone survey to elicit individual time preferences. Most importantly, it provided the first significant empirical indication of the influence of time preferences on health behaviors, inspiring numerous future studies.

In Grossman's model, time preferences are exogenously determined and remain unaffected by education or other variables in the model, but they do shape both education and health outcomes. Further theoretical developments into this topic by Gary Becker and Casey Mulligan advocated that time preferences are endogenously determined by factors (or resources, S) that also influence investments in health (Becker and Mulligan 1997); their influential study placed special emphasis on the mediating role of time preferences in determining the influence of education on health. They advocated that lower rates of time preferences may cause better health and more education and also more education can cause lower rates of time preferences. There is also substantial evidence that suggest that education, age, income, life expectancy and parental transfers are some of the other factors that influence time preferences and health behaviors [(Kenkel 2000); (Ehrlich and Chuma 1990)] . While theoretically this model has gained increasing acceptance, it is scarcely tested empirically due to the difficulties in measuring how socioeconomic factors influence time preferences (Ehrlich and Chuma 1990; Picone, Sloan et al. 2004; Adams 2009; Adams and Nettle 2009). In the next chapter, we review key empirical literature which were influenced by Fuchs' study and which set the trend for research using the premise of time preferences as an explanation for health behaviors.

2.2 Empirical Evidence

There is extensive empirical literature seeking to establish the relationship between time preference and health behaviors – both at individual and at the aggregate level over the past four decades. At a macroeconomic level, increasing obesity rates over the past five decades has been correlated with decreasing savings rates which are indications of declining time preferences as people are more willing to spend than save for future as reported by Komlos, Smith and Bogin (Komlos 2004). They find that personal savings rate in the U.S. fell by 83% whereas obesity increased by 112% between 1970 and 2000. Consumer debt also showed similar trends during the same time period. Similar trends are observed in other developed nations including Spain and Finland, which have savings rates comparable to those of the U.S. On the other hand, countries such as Switzerland and Belgium, which have higher savings rates, also have lower obesity rates. While such correlations by no means imply causality, and personal savings and obesity are both influenced by multitude of other factors, it is worth investigating whether the implied rise in marginal rate of time preference may also be a contributing factor to increasing obesity epidemic. Use of better proxies for time preference, controlling for other factors that influence the outcome, as well as using data at individual level rather than using aggregate data, are suggested in literature as next logical steps into such investigation.

Empirical evidence at an individual level suggests a weaker and inconsistent relationship. For example, Zhang and Rashad report a small, positive association between lower rates of time preference and lower body mass index (BMI) in a study using Behavioral Risk Factor Surveillance System (BRFSS) combined with data from Roper Center(Zhang and Rashad 2008). However, their use of self-reported will power as a proxy for time preference is a weak measure at best. There is some evidence that individual time preferences formed as a result of education and upbringing do not change significantly over time as found in a longitudinal study of Dutch nationals (Borghans and Golsteyn 2006) over a decade spanning 1994-2005. While individual discount rates over the decade did not change significantly, increases in BMI were more pronounced in people with high discount rates. However, many other factors that contribute to obesity such as diet and physical activity levels were not controlled in this study. Hence, this study could not establish the direct relationship between health behaviors and time preference. A study of vaccine uptake and time preferences found a weak correlation with influenza vaccine acceptors showing lower discount rates compared to those who rejected vaccination (Chapman and Coups 1999). In other studies no association was found between time preference and high cholesterol (Chapman, Brewer et al. 2001), exercise (Chapman and Coups 1999), or adherence to hypertension medication(Chapman, Brewer et al. 2001).

In contrast, studies on addictive behaviors show a stronger relationship between addiction and time preference [for a review, see Bickel & Marsch, 2001 (Bickel and Marsch 2001)].

Smokers are found to have higher discount rates compared to non-smokers (Fuchs 1982; Chapman, Brewer et al. 2001; Odum, Madden et al. 2002); heavy social drinkers and problem drinkers were found to have higher time discounting compared to light drinkers(Vuchinich and Simpson 1998). Moreover, the correlation depended upon the type of measurement method used for time preferences, with a weak correlation to discount rates measured using monetary rewards and no correlation to the discount rates measured using health outcomes as rewards. Most of these studies are case-control studies with small sample size ranging from 30-800 and include populations from developed countries [for a review see Chapman, 2005 (Chapman 2005)]. Stronger evidence would be provided by studies include large population level samples, which are almost non-existent in current literature. Moreover, most of these studies are conducted in developed countries on predominantly non-Hispanic White population samples. Many of the studies utilize population groups who are well-educated with at least some college level education.

Time preferences are also known to vary by SES including levels of education and income and also to some extent by race/ethnicity (Frederick, Loewenstein et al. 2002; Tanaka, Camerer et al. 2010). The differences in health behaviors that are due to education, SES and race/ethnicity would be better informed if the studies that aim to explain differences using time preferences take into account differences in population characteristics. Further, it would have more policy relevance if studies would draw out the differences between the population subgroups in terms of their time preferences.

2.3 Methodological Issues

The inconsistency in the empirical evidence is partly due to issues associated with measurement of time preferences as the studies are found to employ widely differing measurement methods. Measurement of time preferences follows two prevalent strategies as described by Frederick, Loewenstein and O'Donaghue in their seminal article titled 'Critical Review of Time Preferences and Time Discounting' (Frederick, Loewenstein et al. 2002). Those strategies include – i) field methods in which discount rates are inferred from actual economic decisions that people make in their normal lives such as choice of pension plans, and ii) experimental methods, in which people are asked to evaluate stylized intertemporal prospects involving real or hypothetical outcomes. Field studies have the advantage of estimation based on real behavior which improves their ecological validity. However, they are susceptible to a number of real life confounders, such as lack of information, liquidity constraints, and disbelief about future outcomes, all of which cannot be controlled in any single study. On the other hand, experimental studies control for some of those confounders but suffer from biases introduced by procedural nuances and stylized treatments of actual behaviors. Studies relating to health behaviors and time preferences utilize one of the above methods in accordance with the literature and the resulting implicit discount rates vary widely based on the method used. In the current literature, the conclusions from both of these types of studies do not always agree (Chapman and Coups 1999; Chapman 2005). Most of the studies which utilize proxy measures based on field methods (Komlos 2004; Smith, Bogin et al. 2005; Borghans and Golsteyn 2006; Zhang and Rashad 2008) show weaker relationships between health behaviors and time preferences whereas studies which utilize experimental methods show stronger relationships (Fuchs 1982; Chapman and Coups 1999; Bickel and Marsch 2001; Epstein, Salvy et al. 2010). The former studies suffer from face validity for the measurement of time preferences as they use a broad proxy measure for time preferences although they include population level samples, whereas the latter suffers from a lack of external validity due to limited convenient samples albeit having more precise measurements of time preferences. Hence, it would add to literature and would be a worthwhile exercise to compare results from different measurement methods on the same population sample to understand whether and how measurement methods might be the cause of differing conclusions.

2.4 Need for Additional Explanations

Inconsistent empirical evidence also might be due to the predominant theoretical models based on Discounted Utility (DU) theory that underlie current empirical studies. The standard DU model utilizes a single exponential discount rate to represent time preferences. It also assumes that people continuously evaluate new alternatives by integrating them into existing models, utilities are independent across time periods, utility in a time period t+k is independent of consumptions the previous periods, and preferences that are time-consistent. Exponential discounting used in DU models does not take into account changes in probabilities of occurrence of events over time, changes in their magnitude, changes due to utility of anticipation, memory and other psychological factors which are incorporated in behavioral models. And, there are some observed behaviors that do not conform to DU assumptions such as procrastination in following health behaviors, aversion to loss which leads to assessing utilities as losses or gains from a reference point, and addictive behaviors that are due to habit formation (Frederick, Loewenstein et al. 2002).

Time preference literature has expanded over the past two decades to include alternative discounting forms such as hyperbolic or quasi-hyperbolic discounting[2] (Ainslie and Haslam 1992; Laibson 1997; Laibson, Repetto et al. 1998; Angeletos, Laibson et al. 2001; Diamond and Köszegi 2003) and emerging literature applies this paradigm to health behaviors. Cutler et al. assume hyperbolic discounting to explore the issue of self-control in eating behaviors and conclude that such discounting would explain self-control problems (while not explicitly measuring the discounting based on hyperbolic form) (Cutler, Glaeser et al. 2003). Similarly, several studies on smoking and obesity and their relation to discounting utilize hyperbolic functional forms (Odum, Madden et al. 2002; Gruber and Kőszegi 2004; Scharff 2009; Ikeda, Kang et al. 2010) and conclude that hyperbolic discounting explains their behaviors. These studies again either utilize an experimental method to measure discounting with limited samples or assign hyperbolic discounting based on answers to questions on procrastination tendencies. Interestingly, results from both methods indicate hyperbolic discounting as a potential explanation for health behaviors; however, samples usually are limited to White, college-educated populations. Other alternative explanations include whether time preferences are influenced by utilities being assessed as losses or gains from a reference point. This paradigm has ample policy implications for health behavior modification interventions and the research in this area is still nascent.

2.5 Potential Contribution to Literature

We can infer from literature that time preferences influence health behaviors, but the empirical evidence is not conclusive with some of the strength of relationships seem to arise

[2] Hyperbolic or quasi-hyperbolic discounting forms have been developed to describe the behaviors that are time-inconsistent where people have high discount rates in the short term and low discount rates for the long term.

from the methodology used to measure time preferences. Most of the studies deal with addictive behaviors such as smoking or drug dependency. Studies are mainly confined to developed country samples with White college educated population. Further, alternate explanations such as different discounting for present and future (hyperbolic or quasi-hyperbolic discounting), reference dependent preferences are just beginning to be explored. Additionally, interventions that might alleviate time discounting related problems are rarely studied with respect to health behaviors.

This study potentially contributes to the understanding of the relationship between time preferences and health behaviors by – i) using traditional theory but controlling for endogeneity using instrumental variables; ii) enriching traditional empirical models with a behavioral economics paradigm to incorporate some of the alternative explanations; iii) studying the question using a population level sample from Mexico; iv) including measures of time discounting based on hypothetical gambles as well as proxy measures; v) including a variety of health behaviors; and vi) examining whether a successful Mexican social policy such as 'Oportunidades' might specifically address problems associated with higher short term discount rates.

The proposed study utilizes a conceptual framework based on Grossman's model of health capital for assessing the demand for health and health care, by incorporating the endogeneity in the relationship between time preferences and health behaviors (chapter 3). While such a model is theoretically supported, empirical evidence of the theory, especially relating to health behaviors, is not established in literature and rarely pursued due to difficulties in finding appropriate data. The proposed study also borrows concepts from behavioral economics to investigate time-inconsistent discounting models (chapter 4) and to explore reference dependent preferences (chapter 5). While these theoretical concepts have been discussed in literature as possible explanations for health behaviors, empirical testing is usually limited to small, select samples. Hence, utilizing a population level representative data source with a rich set of measures related to health, demographics, and socioeconomic variables as well as data on expectations and preferences would be a new contribution to literature. The proposed data on Mexicans and Mexican immigrants to the US addresses the relationships of time preferences and health behaviors. While this subpopulation has seen large increases in rates of obesity and life style related chronic conditions, the relationships of health behaviors and time preferences in such minority populations is rarely addressed in literature. Understanding discounting in minority populations may also be useful in economic analyses of minority targeted programs. This study uses hypothetical gamble questions to calculate time discounting rates and compares the results to models using commonly used proxy measures of time discounting (such as savings behavior) as a validity check. Analyzing the same data with different measures for time discounting would potentially explain some of differences in discount rates reported in literature.

CHAPTER 3. INFLUENCE OF TIME PREFERENCES ON HEALTH BEHAVIORS: AN INSTRUMENTAL VARIABLES APPROACH

This chapter explores the role of time preferences in determining health behaviors by taking into account the endogeneity in the relationship between time preferences and health behaviors. It also compares different measurement methods of time preferences and their relationship to health behaviors.

Current literature indicates that time preferences influence addictive health behaviors such as smoking, alcoholism or substance abuse, but the evidence is not consistent on health producing behaviors such as healthy diet or physical activity. Most of the studies include either health producing behaviors or addictive behaviors and results seem to depend upon the method of measurement of time preferences. Most of the studies use small, predominantly White samples from developed countries. None of the studies take into consideration the fact that several factors including education, income, age and gender affect time preferences as well as health behaviors leading to under or overestimation of results. Further, no studies exist to our knowledge which address the endogenous relationship between time preferences and health behaviors. To address some of these shortcomings, our study employs an instrumental variables approach with multiple measures of time preferences (based on hypothetical gambles and also proxy measures) to assess a variety of health behaviors (diet, physical activity and smoking) in a nationally representative Mexican sample using Mexican Family Life Survey of 2005.

3.1 Research Questions and Hypotheses

Research Question 1.A.: *Can differences in time preferences between individuals explain differences in their health behaviors taking into consideration the endogeneity in their relationship?*

Hypothesis 1.a.: People who have *lower* rates of time discounting would - i) be more physically active, ii) keep healthier diets (more fruits & vegetable consumption, less soda and less junk food consumption) and iii) be less likely to smoke and more likely to quit smoking compared to people with *higher* rates of time discounting, controlling for all else.

Research Question 1.B.: *Can the different measurement methods of time preferences explain different health behaviors within individuals?*

Hypothesis 1.b.: The estimated coefficients of time discounting from the models using hypothetical measures and from those using proxy measure for discounting do *not* differ.

3.2 Conceptual Model

Michael Grossman's Health Capital model (Grossman 1972) and its subsequent extensions (Grossman 2000) provide a formal model for demand for health, taking into account the fact that time preferences are influenced by several factors that also influence health behaviors, resulting in an endogenous relationship between them. In other words, time preferences influence health behaviors, health behaviors influence health and health status influences time preferences. Hence, we can write:

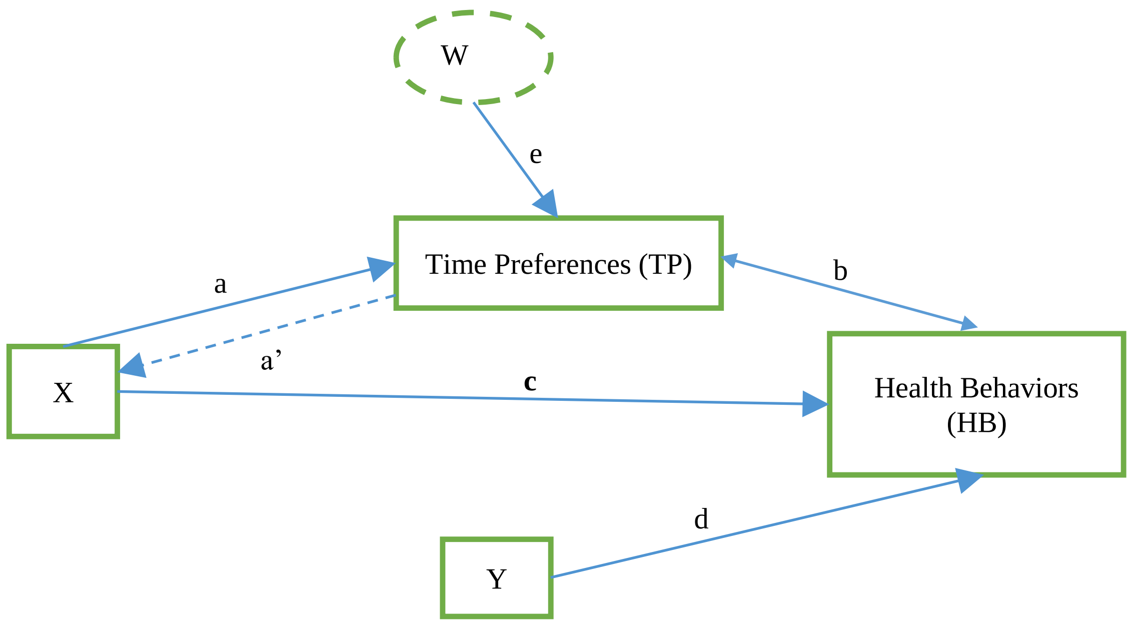
$$HB=f\,(TP, X, Y, \varepsilon) \text{ and } TP = g\,(HB, X, W, \eta) \quad \text{---- (3.1)}$$

Substituting equation 3.2 in 3.1 and simplifying, we can write health behaviors as:

$$HB = f(X, Y, W, \varepsilon, \eta) \quad \text{----} \ (3.2)$$

This relationship is represented pictorially in Figure 3.1 below.

Figure 3.1: Time Preferences and Health Behaviors



As seen from Figure 3.1, the factors (vector X) influence time preferences (path a) and also influence health behaviors (path c); some other factors (vector Y) influence health behaviors but do not influence time preferences (path d); and some other factors (vector W) influence only time preferences (path e). Path b represents the endogeneity between time preferences and health behaviors. ε and η in equations 3.1 and 3.2 represent error terms that comprise errors due to unobservables, omitted variables (such as parental influences on time preferences and health behaviors), measurement errors as well as random errors. It is possible that the error terms are correlated with health behaviors as they may include unobserved behaviors such as specific tastes and preferences (such as health beliefs or cultural factors) that are not reported or measured.

<u>Factors affecting health behaviors and time preferences (vector X)</u>

Age - Literature shows that older adults discount time preferences more heavily (i.e. have higher discount rates) than younger adults. This is postulated to be due to the shorter remaining life expectancy in old age. Also, older adults depending on their remaining life expectancy may indulge in habits that they abstained from in the younger ages, whereas middle aged persons may be more aware of the possibilities of ill health and may start developing healthier behaviors.

Gender –Women have lower rates of discounting (Tanaka, Camerer et al. 2006) and they are also known to invest more in preventive and protective health behaviors.

Education –Education is associated with healthy behaviors including better diet, regular physical activity and higher uptake of preventive services (Cutler, Deaton et al. 2006; Cutler, Lleras-Muney et al. 2008). This may be due to better information, better assimilation of knowledge and may be due to better expectations for future. More education is associated with lower rates of discounting which may be due to better expectations for future or in Becker’s words due to higher ‘imagination capital’ (Becker 2007).

Income – Low income, lack of regular income or seasonal income fluctuations have substitution effects on foods leading to diets that are cheaper which are usually not very healthy. Such effects are more pronounced in households with lower income levels. Necessity to work longer to be able to earn sustenance wages may leave little time for exercise; lack of liquidity may lower uptake of preventive services leading the poor to wait till they get sick to seek care. Lower incomes are also associated with less patience and higher discount rates.

Marital Status – Married people may pursue healthy behaviors due to spousal influence or may be due to additional expectations to be healthy to be able to support their families. They also tend to have lower discount rates as observed in literature probably due to having better expectations for future (Tanaka, Camerer et al. 2006).

Current Health Status – People who are in better health are more likely to be following health producing behaviors compared to people in poorer health. They are also more likely to have lower discount rates (following the GBM model).

Risk Preferences – A risk-averse person may be more careful about her health and may pursue more health producing activities compared to a risk seeker. Moreover, risk-taker may be more willing to pursue risky health behaviors such as smoking or drinking. A risk-taker also has a higher discount rate as she may not value future utilities as evidenced by her perusal of risky activities.

Location – Place where one grows up may influence discount rates. A bustling city may enhance impatience whereas a rural location with a slow pace of life may make one more patient. On the other hand, people who live in rural areas may have higher discount rates as they may not have access to credit or services that ensure returns on investments into their future such as lack of savings instruments, access to credit or safety net health services (Tanaka, Camerer et al. 2006). Health behaviors also depend on location in many ways. Urban areas have a variety of food choices (healthy and unhealthy) while rural areas may depend on local produce. Local cultures and attitudes towards eating, exercising or smoking might influence behaviors to a larger extent in close-knit rural communities than in more heterogeneous urban environments. On the other hand, cities may have more fast food restaurants and transportation leading to worse dietary patterns and lower levels of physical activity; villages may have lesser access to health facilities and more chances for being physically active.

<u>Factors affecting healthy behaviors and NOT time preferences (vector Y)</u>

Income Shocks – Changes in family income can change healthy habits. Loss of employment and subsequent loss of family income may induce one to substitute healthy diet with a cheaper, non-healthy diet. The need to take up additional work and longer hours of work may limit time for physical activities. Loss of insurance may change preventive care uptake. Stress may induce smoking or drinking. However, temporary shocks do not have long lasting effects on time preferences unless they are irreversible or long lasting.

Serious Health Shocks to self, family or at the population level may change healthy behaviors. (While such shocks may alter also time preferences, the change may be more gradual than changes to health behaviors.) For example, having to deal with a close family member's ill health or death or one's own health issues may serve as wake-up calls which may translate into positive investments into health producing activities. There may also be societal level shocks such as incidences of bird flu or H1N1 breakouts affecting communities at large that may tempt one to get a flu shot that she may otherwise have avoided.

Migration – When people move to a new place, they may change their food habits, primary care physicians or lose some of the familiar routines that they had developed earlier leading to changes in health behaviors. However, changes to time preferences due to temporary migration may not be immediate or lasting. [On the other hand, permanent migration may have a slow but lasting effect on time preferences.]

<u>Factors affecting time preferences only (vector W)</u>

Some of the factors that affect time preferences include past experiences and future expectations. Among those, only a few may not influence health behaviors.

Optimism about society's prospects– People who are optimistic about their society's prospects may also have a patient outlook, waiting for better times. However, such outlook may not influence their health unless there are discernible problems related to public health services that are expected to get better over time.

Probability of saving for the future- People who are more likely to think about future and about saving for a better future are more likely to have lower discount rates which may lead to behaviors that would enhance their future utilities compared to people who are less likely to think about future.

3.3 Study Design

3.3.1 Data

The data for this study are from the second wave of Mexican Family Life Survey (MxFLS) sponsored by the National Institute of Child, Health and Development (NICHD), Ford Foundation, Mexico's Department of Social Development (SEDESOL), and Mexican State Department of Health. Research support is provided by research collaboration between

University of California, Los Angeles (UCLA), Duke University and Universidad Ibero-Americana (UIA). MxFLS is an ongoing longitudinal multi-thematic survey started in 2002 and is nationally and regionally representative. The data are available in the public domain for waves from 2002-05 and 2005-06. The baseline sample was chosen by INEGI, the Mexican Statistical Institute, to be representative of the entire Mexican population at the time of the baseline survey (2002). The primary sampling units are chosen to be representative of national, regional and urban[3]-rural populations, with an oversampling for rural communities to provide adequate samples. The survey employs a probabilistic, stratified, multi-stage, cluster design. All the sampling units have a known, non-zero probability of being selected; stratification is by geography and by socioeconomic characteristics; and clustering is by sampling units. Sampling weights are available at the individual and household levels and are adjusted for non-response. Proxy interviews do not have survey weights.

The current study utilizes the second wave of the data collected in 2005-2006 (MxFLS-2, henceforth referred to as MxFLS unless otherwise specified) as preference measures required for this study are not collected in the first wave of the survey. MxFLS survey sample comprises of household level data from 8,440 households within 147 communities in Mexico with approximately 20,600 individuals including adults and children. MxFLS also collects data on household members who migrate to the United States by gathering contact information on those migrants and contacting them in the United States. The data include a rich set of socioeconomic and demographic data at the household and individual levels. The survey also includes data at the community level on access to services and facilities. In addition, it collects biometric data including height, weight, waist circumference, blood sugar and cholesterol levels. An innovative

[3] Urban community is defined as a community with a population above 2,500 inhabitants.

approach in the second wave of data collection was to include measures on risk and time preferences using questions on hypothetical money gambles. These measures (which are explained in detail in the following chapter) are one of the distinct features of this survey, providing preference data on a large representative sample.

Analytical Sample - The analytical sample includes all adults (aged 18 or older) from the sample who participated in the preference measure questionnaire (Book IIIB). Proxy interviews, if any, are excluded from the analysis as the responses to preference measure questions require respondent's direct involvement with the surveyor. The sample size for this analysis is approximately 18,000 adult individuals from approximately 7,350 households from approximately 135 communities. This sample also includes around 150 individuals who migrated and currently reside in the United States.

Merging data from various tables – MxFLS has multiple questionnaires (called "books"). There are three books for household information, economy and consumption; two books for individual information and health behavior; two books for community level information; and other books for diet (at a household level), anthropometrics, cognitive test, reproductive history, and for detailed data on children. Each of these books has multiple sections for related questions with 5-30 sections in each book and each section within a book corresponds to a data table. Hence, to construct the analytical sample, approximately 150 tables are merged.

Individual level data from various tables are merged for analysis using the "folio" (which identifies the household to which the individual belongs) and "ls" (which identifies the individual with a household) variables. While most of the data used for analysis are at individual level, we also use household level variables (as explained below). Household level data are merged with the individual level data using the "folio" variable. Community level variables are merged using "id_loc" (identifying the location) variable.

3.3.2 Variables

<u>Dependent Variables</u> – Health behaviors are measured in terms of healthy as well as unhealthy dietary choices, physical activity and extent of physical activity, current/ex-smoking status and whether quit smoking (to test hypothesis 1.a.).

Physical Activity – Physical activity is measured using – i) a dichotomous measure of regular physical activity based on the answer to a question on whether the individual gets a routine weekly exercise or not and ii) the number of minutes of exercise per day among people who report regular physical activity which is a continuous measure.

Diet – Diet is measured in terms of two continuous measures – i) number of days per week fruits and vegetables are consumed and ii) number of days per week soda, chips or cookies are consumed. It is to be noted that the diet measures are at a household level. To assess the weekly consumption of fruits and vegetables, the answers to questions on the weekly consumption of different fruits and vegetables are combined and to assess the consumption of soda, chips or cookies, responses to the weekly consumption of those are combined into two single measures.

Smoking – Smoking is measured in terms of – i) a dichotomous measure of whether the respondent is a current or an ex-smoker and ii) a dichotomous measure of whether the individual has quit smoking.

Independent Variables

Time Discounting – The independent variable of interest is time discounting as specified in the conceptual model section. MxFLS-2 utilizes an experimental approach to elicit time preferences using hypothetical rewards presented using series of hypothetical monetary choices. The first series of questions include choice of 'now or later' rewards with increasing reward amounts for the same time delay. This method is more precise than using a single response, but is prone to 'anchoring effects' where the first set of questions influences subsequent choices (Frederick, Loewenstein et al. 2002). In other words, a person is more likely to choose 1,200 pesos[4] in a month over 1,000 pesos today if he first chose 1,100 pesos in a month versus 1,000 pesos today than if he first chose between 10,000 pesos in a month over 1,000 pesos today. Also, there may be an implicit recommendation provided to respondents to discount as the rewards increase with each subsequent questions (going from 1,000 to 2,000 pesos in a month compared to a 1,000 pesos today). These may bias discount rates upwards (Frederick, Loewenstein et al. 2002). A second series of questions varies both amount and time delay (the time at which the respondent receives the reward), thereby, providing an opportunity to test the propensity to prefer 'smaller-sooner' rewards versus 'later-greater' rewards. Comparing the discount rates from both of these questions would ensure the internal consistency of measures.

Calculation of discount rate - All the hypothetical monetary choices are presented in Mexican Pesos. There are a series of questions where the respondent is first asked to choose between 1,000 pesos now or 1,100 pesos in a month. Then the delayed reward amount is varied from 1,100 to 1,200, 1,500 and 2,000 pesos holding the time delay constant at one month.

[4] Currency used in the data is Mexican Pesos and at the time of the survey the currency exchange rate was approximately 12 Mexican Pesos per U.S. Dollar.

Depending upon how the respondent feels about waiting for a larger reward, switching occurs. For example, one may prefer 1,000 pesos now to 1,200 pesos in a month but when the amount is increased to 1,500 pesos she may decide to wait. In that case, the switching occurs when the value changes from 1,200 to 1,500 pesos. We can write the corresponding value functions as

V_{1200} = 1200*(ρ ^t) and V_{1500} = 1500*(ρ ^t) , where t= 1 month=1/12 or 0.083 years ----(3.3)

Now, as the switching happens between these two values, we can say that $V_{1200} < 1000 < V_{1500}$. The actual discount rate lies between the above values. Hence, we will use the midpoint of the above values as is the practice in literature, namely, discount rate ρ that corresponds to V_{1350} where the implicit annual discount rate is 35% [1000=1350/(1+ρ) => ρ=35%]. The details of the questions and their sequences of questions are presented in Appendix A (questionnaires and flowchart). The discount rate calculations are also described in detail in Appendix A.

<u>Other Proxy for Time Preferences</u>

MxFLS also provides some of the common proxy measures that are used in literature that utilizes actual behaviors as proxies for time preferences. One such proxy measure used often in literature is the time horizon used in making decisions about health and savings. This analysis uses *Time horizon used for decision making* as a proxy for time preference, which is a categorical variable with values of few days, few weeks, few months, 1 year, 5 years and 10 years. People with longer decision making time horizons are deemed to have lower time preference.

Other RHS Variables

Other control variables include individuals' demographic variables – age, sex, location (urban, semi-urban or rural), marital status, education, current health status, and current employment status. In addition, life change events such as permanent migration, and shocks including loss of employment, accidents, serious health issues/ diseases/ hospitalization of family members, death in the family and losses due to natural disasters in the past 4-5 years.

As we find that annual household or individual incomes are missing for most of the population, we utilize the data on household assets to build a household asset index variable to indicate family wealth status, which we use as a proxy measure for household wealth. The data on household assets include farm equipment, appliances, motor vehicles and livestock, reflecting both urban and rural households. A factorial analysis based on the methodology is used to construct the asset index which is commonly used for assessing household wealth in developing countries (Rutstein 2004).

Additionally, *risk preference* is included as a control variable. Risk preference is calculated based on answers to a set of 6 gambles with different expected values and different amount of risk. The questions used, a flowchart detailing categorizing risk and a table with expected values of outcomes are presented in Appendix B.

We include several control variables in specific analyses as they influence those outcome measures. We include household size, gender and education of the head of household and percentage of children in household as additional control variables in the analysis of dietary habits. This is because diet is measured at a household level and household's food choices are influenced by the size and composition of the household, as well as by the characteristics of the household decision maker (i.e. head of the household) following the previous literature on household decision making studies [Deaton et al.].

Instruments

Optimism about society's prospects is measured by the answer to the question "Compared with the standards of living in this community today, do you think that in three years they will improve, become worse, or remain the same?".

Probability of investing money in a savings scheme is a continuous measure.

Willingness to break laws/rules is measured by answers to questions – i) laws are made to be broken, ii) a person who does not cheat does not get ahead and iii) it is alright to do whatever we want as long as we do not hurt anyone. The answers to the above questions include completely agree, agree, disagree, and completely disagree.

The above instruments are tested as described in the methods section and the best instrument(s) are included in the final model (which is described in the results section 3.5).

Omitted Variables

There are several variables community level variables that are omitted from the analyses as they are not available in the dataset.

There are no measures of access to gyms, parks or bike lanes which might nudge people to exercise. Hence, effects of discounting on physical activity might be overestimated if there are no facilities. While there are measures on whether streets are perceived to be safe, these measures have a number of missing values which might not be missing at random and hence are not included in the analysis. Higher levels of crime might decrease the possibility of outdoor physical activities, especially for women. Family diet is dependent upon the availability of a variety of foods including fresh fruits, vegetables as well as stores that sell convenience foods. However, our dataset does not include data on food availability. We do not have access to the extent to which anti-smoking policies are enforced in communities, which if different in the surveyed communities, might lead to biased estimates of the effects of time discounting on smoking. Similarly, not accounting for access to anti-smoking programs might result in biased estimates of the effects of lower discounting on quitting smoking.

3.4 Methods

3.4.1 Measurement Model

The estimation equation based on the conceptual model can be written as:

$$HB_i = \alpha_0 + \alpha_{1i}\, \rho_i + \alpha_{2i}X_i + \alpha_{3i}Y_i + \varepsilon_i \text{ ---- } (3.4),$$

where ρ is the primary regressor of interest, discount rate; X is the set of exogenous variables that determine ρ as well as HB; and Y is the set of exogenous variables related to HB only. As discussed in the conceptual model, this simple model is subject to endogeneity bias due to potential simultaneous determination of HB and ρ. Econometrically, there are two components to this bias – i) ρ and HB are both determined by the set of variables X and ii) ρ may be related to other unobservable factors such as childhood, upbringing, parental habits that determine time preferences and in turn health behaviors. As we do not have information on all those variables, they are omitted from the above equation and will cause either positive or negative biased estimates (Wooldridge 2006) of the influence of ρ on HB. Hence, we will use an instrumental variables estimation, where ρ can be written as:

$$\rho_i = \xi_{0i} + \xi_{1i}X_i + \xi_{2i}W_i + \mu_i \text{ ----(3.5)}$$

Here, W represent the set of instruments (which are described in the 'Variables' section above). The identifying assumption is that the instruments are not correlated with the outcome variable HB (for all of the outcome variables). Hence, ρ is estimated first using equation 3.5 and then that ρ is substituted in equation 3.4 to estimate its influence on outcome variables.

3.4.2 Descriptive Statistics

All statistical analyses are conducted using Stata 12. Figure 3.2 shows the distribution of sample population over the six discount rate categories. Here, approximately half the sample population has discount rates of 100% or more and only 5% fall into the lowest discount rate category. This is consistent with discount rate distributions reported in literature (Wang 2011), where approximately 58% of Mexicans are reported to choose the gambles that had highest implicit discount rates.

The descriptive statistics are shown in table 3.1 which includes univariate means or proportions for the whole sample and bivariate comparisons of means/proportions by the 6 discount rate categories. As we see in table 1, 12% of the sample answered affirmatively to the question "Do you routinely engage in physical activity Monday through Friday?" and these physically active individuals report an average of 97 minutes of physical activity per day. 20% of the population in lowest discount category report regular physical activity compared to 11% in the highest discount rate category. The average minutes exercised varies from 106 minutes per week for the lowest discounters to 98 minutes for the highest discounters. The lowest discounters also report slightly higher consumption of fruits and vegetables and slightly lower consumption of soda and chips/cookies compared to highest discounters. Contrary to reported literature, lowest discounters are more likely to report being current or ex-smokers (19%) compared to highest discounters (12%); however, 37% of the low discounters have quit smoking compared to 27% in the highest discounters. All these differences are statistically significant based on chi-squared tests of group means. Lowest discounters are also younger, more educated (high school or more), more likely to report normal health, have slightly lower annual income, and are more likely to be employed. However, there are not any significant differences in terms of risk taking profiles between lowest and highest discounters.

Figure 3.2: Short Term Discount Rate Distribution

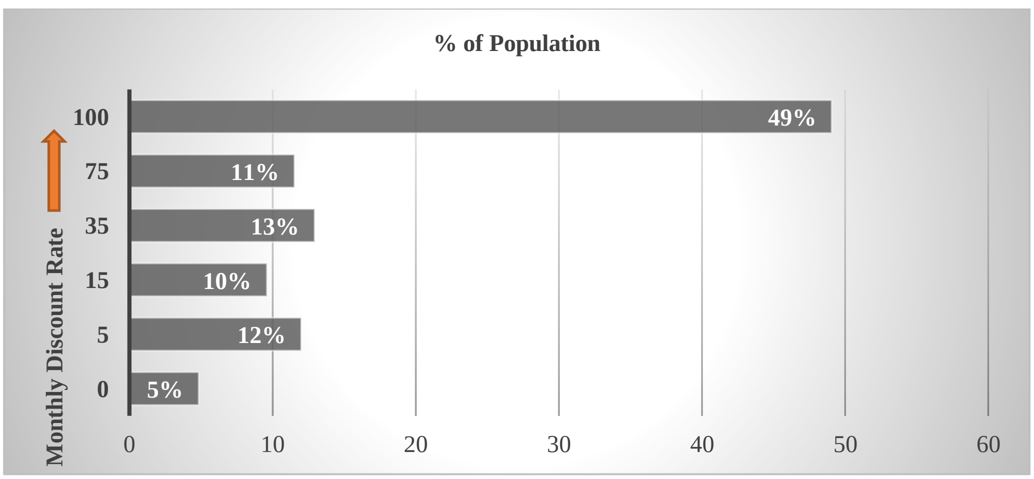


Table 3.1 Descriptive Statistics by Monthly Discount Rates

	Pop. Means / Per.	Means/Percent across Monthly Discount Rate Categories					
		0%	**5%**	**15%**	**35%**	**75%**	**100%**
Outcome Variables							
Diet							
Veg/Fruits (times per week)	30	31	31	30	31	30	30
Cookie/Chips/Soda (days consumed per week)	6	7	6	7	7	6	6
Physical Activity							
Routinely Exercise?	12%	20%	15%	13%	13%	12%	11%
Number of Mins Exercise Per Day	97	106	98	95	95	85	98
Smoking							
Current or Previous Smoker	13%	19%	13%	9%	14%	13%	12%
Quit Smoking	31%	37%	39%	36%	33%	30%	27%
Control Variables							
Age (years)	41	37	39	40	40	40	42
Sex							
Male	44%	44%	40%	39%	46%	47%	44%
Female	56%	56%	60%	61%	54%	53%	56%
Marital Status							
Single	23%	29%	26%	22%	24%	24%	22%
Divorced/Widowed	11%	9%	10%	10%	10%	10%	12%
Married	66%	62%	64%	68%	67%	67%	67%
Location							
Urban	38%	40%	40%	32%	39%	37%	38%
Semi Urban	22%	21%	21%	2469%	25%	24%	21%
Rural	40%	39%	40%	43%	36%	39%	41%
Education							
No Education	11%	9%	12%	13%	10%	8%	12%
Primary or Less	41%	37%	38%	43%	37%	38%	43%
Secondary	25%	24%	25%	24%	26%	29%	25%
High School	13%	17%	14%	12%	16%	14%	12%
College	10%	12%	12%	8%	11%	10%	8%
Graduate	0.4%	0.2%	0.4%	0.1%	0.8%	0.3%	0.3%
Health Status							
Very Good	7%	6%	6%	6%	10%	7%	7%
Good	49%	42%	45%	46%	49%	50%	50%
Normal	40%	49%	44%	42%	38%	41%	38%
Bad	4%	4%	5%	5%	4%	3%	5%
Very Bad	0.3%	0.4%	0.2%	0.4%	0.2%	0.2%	0.3%
Asset Index	5.36	5.31	5.28	5.30	5.38	5.40	5.38
Currently Employed?	50%	51%	49%	48%	54%	51%	48%

	Pop. Means / Per.	Means/Percent across Monthly Discount Rate Categories					
		0%	**5%**	**15%**	**35%**	**75%**	**100%**
Risk Categories							
Risk Neutral	9%	10%	7%	5%	8%	5%	11%
Risk Taker (Lowest)	2%	3%	2%	2%	3%	2%	2%
Risk Taker(Low)	8%	9%	9%	9%	10%	9%	7%
Risk Taker(Fair)	43%	37%	44%	46%	45%	42%	43%
Risk Taker (High)	5%	7%	7%	6%	6%	4%	4%
Risk Taker(Highest)	32%	34%	32%	31%	29%	37%	32%
Permanent Migration?	9%	11%	10%	9%	9%	9%	8%
Shocks							
Serious Accidents?	8.42%	12%	9%	9%	9%	9%	8%
Serious Health Problems in Last 4 Years?	12.84 %	16%	14%	12%	13%	11%	13%
Death in the family in the last 5 Years?	8.53%	9%	9%	9%	9%	8%	8%
Major Disease/Accident/Hospitalization in the last 5 Years?	11%	16%	14%	11%	11%	11%	10%
Unemployment in the past 5 Years?	7%	10%	9%	6%	8%	7%	5%
Faced natural disasters in 5 Years?	0.9%	0.8%	0.9%	0.6%	0.5%	0.8%	1.2%
Instruments							
Probability of Investing in Monthly Savings Scheme	13%	21%	18%	14%	15%	12%	11%
Planning Time Horizon (Alternate Primary Regressor)							
More Than 10 Years	41%						
5 Years	1%						
2-4 Years	4%						
Next Year	5%						
A Few Months	13%						
A Few Weeks	15%						
A Few Days	41%						
Do Not Think About Future	22%						
N	17,882	866	2,148	1,717	2,314	2,064	8,773

3.4.3 Statistical Methods

The analytical sample includes 17,882 adults who are 18 years or older and whose time preferences are positive. The analyses do not use sample weights as the sample weights for the data are not released at the time of this writing. The variables used in the analyses are checked for missing values in order to rule to out any systematic patterns of missing data[5]. As the data on most of the variables included in the regression analyses are missing for only a small number of cases and are determined to be missing completely at random, these data are not imputed and the regression analyses use the default option of list-wise deletion of incomplete cases. The variables are also tested for multicollinearity to ensure that the model is parsimonious and not over fitted.

The continuous outcome measures (diet measures, minutes of physical activity and years smoked) are tested using instrumental variables regression with two-stage least squares (2SLS) estimation with robust standard errors. OLS regressions of the same outcomes are also conducted for comparison. The post estimation tests check for endogeneity, overidentification and non-zero causal effects. The post estimation test for endogeneity tests whether the endogenous regressor in the model is in fact exogenous and reports a Woolridge's robust score which if significant indicates endogeneity. The test for overidentification provides Sargan's robust chi-squared statistic which if significant indicates that the instruments are not valid. The first stage regression

[5] The individual income variable was found to be missing for approximately 49% of the sample. It was also found to be systematically missing for female individuals in rural communities, which may be attributed to them being in informal work arrangements, or in non-income labor sector. As these data are not randomly missing, it is not recommended that these values be imputed. Hence, this variable was excluded from further analyses and education was used as a proxy for socioeconomic status.

coefficients of the instruments indicate whether the instruments have statistically significant effects on the endogenous regressor.

The dichotomous outcome measures (physical activity or not and smoking or not) are tested using instrumental variables regression with IV Probit estimation with robust option for standard errors. Probit estimations of the same models are also conducted for comparison. Here a significant Wald test statistic indicates that the endogenous regressor is indeed endogenous and that using instrumental variables estimation provides consistent estimates with correct standard errors. As above, the first stage regression coefficients of the instruments indicate whether the instruments have statistically significant effects on the endogenous regressor.

The same analysis is repeated using the alternate proxy measure for the primary regressor i.e. planning time horizon.

3.5 Results

A summary of results from different models are presented below (table 3.2.1) and detailed are described subsequently. Here the average marginal probabilities at the mean discount rate are shown for different models. Note that the results from OLS or Probit and the corresponding IV models show results that are similar in magnitude but the statistical significance is not always the same. This is discussed in detail in the subsequent sub sections. Table 3.2.2 shows the average marginal probabilities estimated from the IV models including average effects over a range of 0-100% monthly discount rates. It also shows a summary of average marginal probabilities at the mean discount rate from stratified analyses.

Table 3.2.1: Summary of Models with average marginal probabilities[6]

	Discount Rate				**Alternate Predictor: Planning Horizon**			
	OLS	2SLS IV	Probit	IV Probit	OLS	2SLS IV	Probit	IV Probit
Physical Activity (yes/no)	--	--	0.12*	0.19**	--	--	0.13	Did not converge
Physical Activity (minutes/day)	11.91**	11.92**	--	--	11.96	11.96	--	--
Vegetables/Fruits (times/week)[7]	30.07**	30.08**	--	--	30.08	30.09	--	--
Soda/Chips/Cookies [8] (times/week)[9]	6.37**	No Endogeneity	--	--	6.38	No Endogeneity	--	--
Smoker/Ex-Smoker (yes/no)	--	--	0.09	0.12**	--	--	0.09	Did not converge
Quit Smoking (yes/no)[10]	--	--	0.31**	No Endogeneity	--	--	0.31	No Endogeneity

** p <0.001   * p <0.05 --: Not Applicable

[6] Marginal means are reported for OLS and IV 2SLS; Average predicted probabilities are reported for Probit and IV Probit. **Highlighted models are the best specifications for the specific outcome measures**
[7] Household Level
[8] OLS Model as there is no endogeneity
[9]Household Level
[10] Probit Model as there is no endogeneity

Table 3.2.2 Average Marginal Means/Predicted Probabilities with Discount Rate as main predictor[11]

Average Predicted Probability	N	Overall Sample	Gender		Location		
			Male	Female	Urban	Semi Urban	Rural
Physical Activity (yes/no)	16,807	0.45 - 0.06**	0.23**	0.18**	0.24**	0.18**	0.14**
Physical Activity (minutes/day)	16,804[12]	30-2**	16.33**	8.48**	17.07**	10.60**	7.88**
Vegetables/Fruits (times/week)[13]	6,525	38-26 *	25.74**	30.37*	31.54**	31.22**	28.21**
Soda/Chips/Cookies [14] (times/week)[15]	6,574	6.7 – 6.2*	6.46	6.36	6.56	6.26	6.26
Smoker/Ex-Smoker (yes/no)	16,807	0.24-0.06**	0.18**	0.06**	0.15**	0.11**	0.09**
Quit Smoking (yes/no)[16]	2,130	0.38-0.27**	0.30**	0.35**	0.32**	0.28**	0.31**

** p <0.001   * p <0.05   NS: Not Significant at 5% level

[11] All Models are IV unless otherwise specified
[12] This sample includes people who have a non-zero predicted probability of exercising as determined from the IV Probit regression on exercise (y/n)
[13] Household Level
[14] OLS Model as there is no endogeneity
[15] Household Level
[16] Probit Model as there is no endogeneity

3.5.1 Physical Activity

Physical Activity (Yes or No)

The Probit regression of discount rates on any physical activity indicates that as the discount rates increase the marginal probability for having any regular physical activity decreases, as hypothesized (table 3.3 – second column). This result is statistically significant. Next, we repeat the same analysis with an ivprobit model with probability of investing monthly income in informal savings as the instrument (table 3.3 – column 3). The coefficients on the instrument is highly significant in the first stage IV regressions indicating that the instrument meets the non-zero causal effect test. The significant Wald-tests (chi-squared=32.19) after the IV regressions indicate that the primary (endogenous) regressor is indeed endogenous. Hence, we will use this instrumental variables probit (IV Probit) specification to further analyze the data.

Table 3.3 Physical Activity (Y/N) – Probit and IV Probit

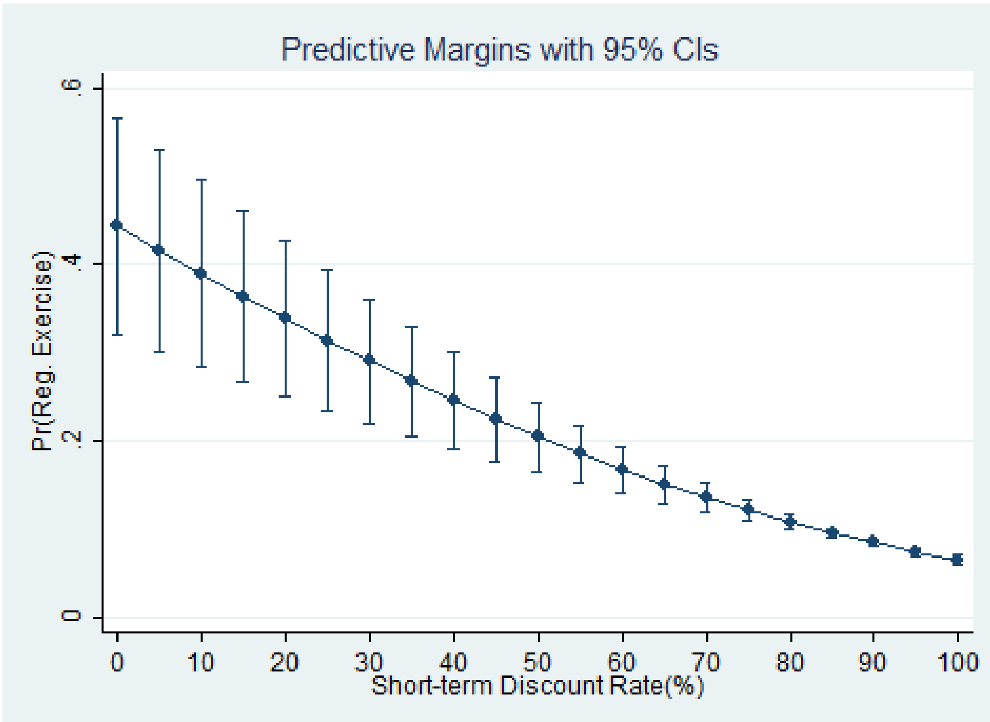
Physical Activity	**Probit**	**IV Probit**
Short-term discount rate	-0.002***	-0.015***
Age	0	0.003**
Female	-0.253***	-0.259***
Education (ref: no education)		
Primary or less	0.489***	0.483***
Secondary	0.850***	0.812***
High school	1.024***	0.919***
College	1.148***	0.988***
Graduate	1.389***	1.218***
Location (ref: rural)		
Semi-urban	-0.194***	-0.185***
urban	-0.286***	-0.258***
Health Status (ref: very good)		
Good	-0.110*	-0.091*
Normal	-0.061	-0.125**

Bad	-0.154	-0.184*
very bad	-0.021	-0.062
Asset Index	-0.047**	-0.020
Employed	-0.085**	-0.102***
Marital Status(ref: single)		
Divorced/widowed	-0.133*	-0.1
Married	-0.152***	-0.131***
Risk taking level (ref: neutral)		
Lowest	0.13	0.017
Low	0.06	-0.081
Fair	-0.019	-0.114*
High	0.131	-0.058
Highest	0.126*	0.023
Had accident	0.234***	0.153***
Permanent migration	0.078	0.031
Death in family	0.065	0.032
Illness	0.06	-0.01
Recent job loss	0.114*	0.021
Natural disasters	-0.138	-0.035
Constant	-1.361***	-0.337
N	16,946	16,807

* p<0.05, ** p<0.01, *** p<0.001

From table 3.3 above, we can see that the magnitude of the effect of time discounting on physical activity from IV model is larger than that from Probit model. Figure 3.3 below depicts the average marginal probability of regular exercise decreases (from 0.44 to 0.06) as the monthly discount rates increase (from 0% to 100%).

Figure 3.3: Predictive Margins for Regular Exercise: IV Probit Estimation



The average marginal probabilities of regular exercise by gender and by location are shown in figures 3.3.1 and 3.3.2 respectively. We can see from figure 3.3.1 that men are more likely to exercise than women at any given discount rate (21% for men compared to 17% for women); the difference is more pronounced at lower discount rates. At higher discount rates, men and women are equally likely to exercise and the probability of exercising becomes smaller as discount rates increase (8%-5% for men and women respectively at discount rates of 100% or more). Residents of rural areas have the lowest marginal probability of regular exercise (14%) compared to semi-urban (18%) and urban residents (24%) (table 3.4). These results are more pronounced at lower discount rates and tend to converge at high discount rates (figure 3.3.2).

Figure 3.3.1 Predictive Margins for Regular Exercise: IV Probit Estimation by Gender

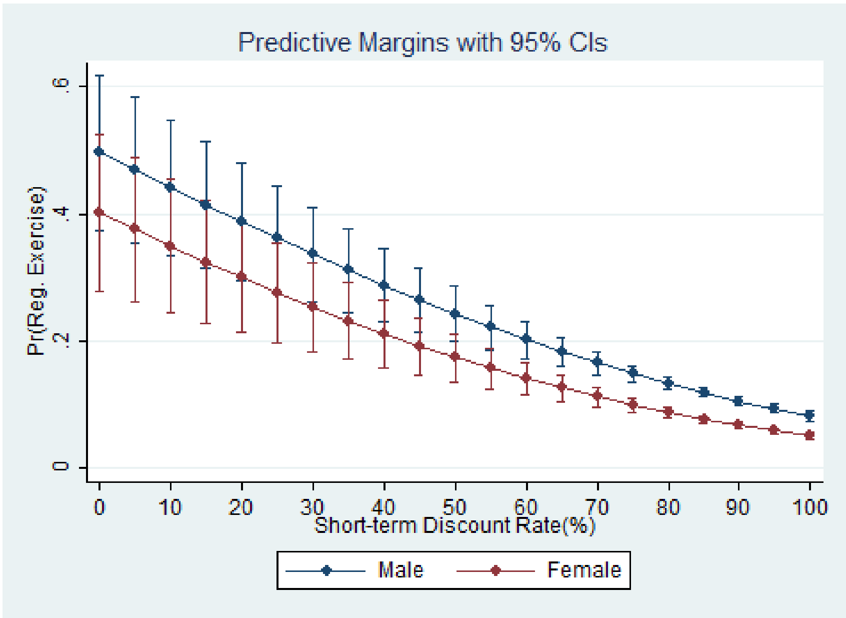
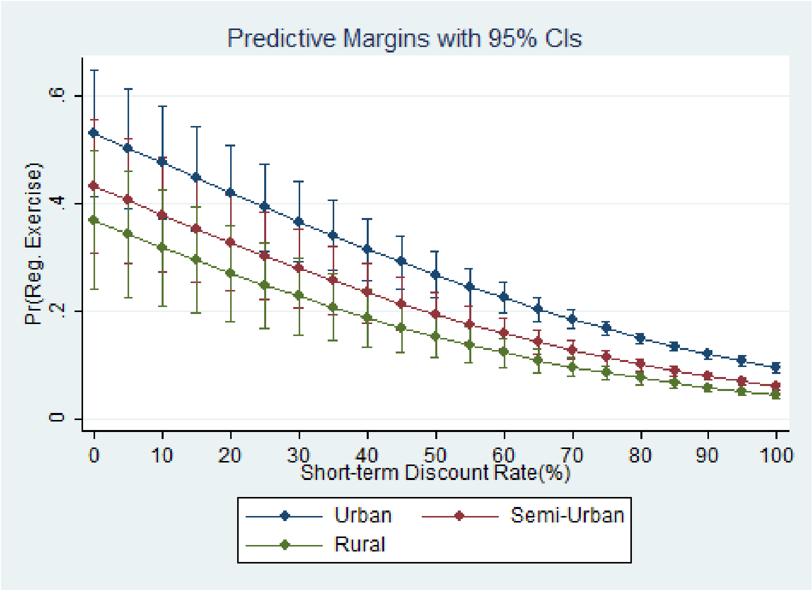


Figure 3.3.2 Predictive Margins for Regular Exercise: IV Probit Estimation by Location



Physical Activity (in minutes per day)

The results of the regression analyses of the continuous measure of number of minutes exercised per day[17] using OLS and IV two-stage least squares specifications are presented in table 3.4. We can see from the OLS regression of physical activity (minutes/day) on discount rates that as the discount rates increase the number of minutes of exercise per day decreases, as hypothesized. These values are statistically significant. Next, we can see from the same table that the estimation using IV 2SLS method with probability of investing monthly income in informal savings as the instrument also produces a similar result. The coefficient on the instrument (not shown) is significant at the 5% level in the first stage IV regressions indicating that the instrument meets the non-zero causal effect test. The post estimation test for endogeneity (Woolridge's robust chi-square test) is significant (F=10.8) indicating the primary (endogenous) regressor is indeed endogenous. Hence, we use this (IV 2SLS) to further analyze the data.

Table 3.4 Physical Activity (minutes/day) – OLS and IV 2SLS

Physical Activity (minutes/day)	**OLS**	**2SLS**
Short-term discount rate	-0.041***	-0.296***
Age	-0.091***	-0.027
Female	-8.279***	-9.302***
Education (ref: no education)		
Primary or less	2.664***	3.832***
Secondary	7.500***	8.954***
High school	12.538***	13.037***
College	16.264***	16.223***
Graduate	16.314*	16.719*
Location (ref: rural)		
Semi-urban	-5.083***	-5.364***
urban	-5.441***	-5.716***

[17] Using the predicted probability of exercising from the previous Probit & IV Probit analyses, we construct a sample of people who are likely to have any exercise and conduct the analysis of minutes of exercise/day.

Health Status (ref: very good)		
Good	-3.279	-3.257
Normal	-2.711	-4.207*
Bad	-3.929	-5.002*
very bad	-7.587*	-8.515*
Asset Index	-0.956*	-0.154
Employed	-2.756**	-3.514***
Marital Status(ref: single)		
Divorced/widowed	-1.828	-1.521
Married	-3.760***	-3.800***
Risk taking level (ref: neutral)		
Lowest	-0.312	-2.147
Low	-0.172	-3.158
Fair	1.124	-0.849
High	3.852	0.525
Highest	2.414*	0.73
Had accident	6.360***	5.018**
Permanent migration	-0.324	-0.939
Death in family	0.505	0.129
Illness	0.931	-0.532
Recent job loss	3.630*	2.282
Natural disasters	-3.485	-1.539
Constant	24.536***	41.469***
N	16,946	16,807

* p<0.05, ** p<0.01, *** p<0.001

As seen in figure 3.4 below, the average number of minutes of exercised per day decreases from 31 minutes to almost zero minutes as discount rates increase from 0% to 100%. The average marginal means of regular exercise (mins/day) by gender and by location are shown in figures 3.4.1 and 3.4.2 respectively. We can see from figure 3.4.1 that men are more likely to exercise for longer time periods compared to women at any given discount rate. However, as discount rates increase, women are least likely to report any exercise at all compared to men. As seen from figure 3.4.2 below, rural and semi-urban residents have lower levels of exercise (minutes/day) compared to urban residents and the differences between locations remains the same for all the discount rates from 0-100%. However, the magnitude of exercise decreases to zero for rural and semi-urban residents at discount rates higher than 90% while urban residents still show a small but positive physical activity level.

Figure 3.4: Average Marginal Means for Regular Exercise (mins/day): IV 2SLS Estimation

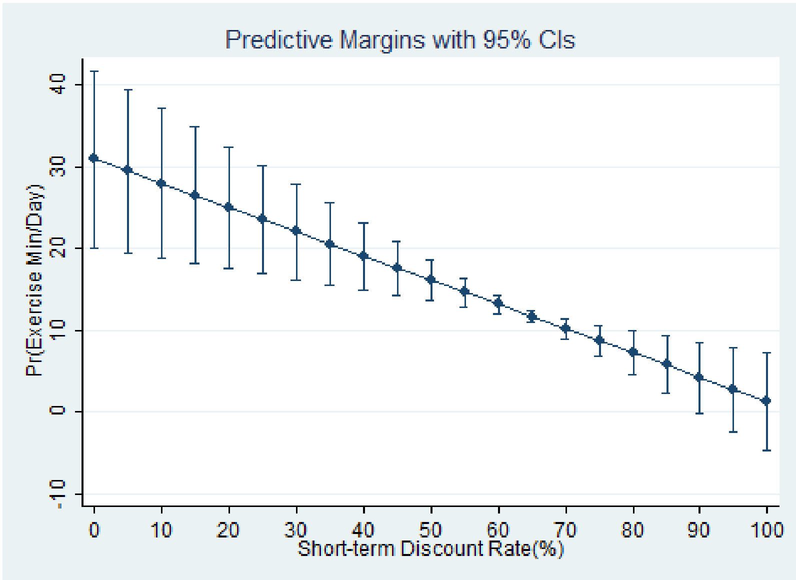


Figure 3.4.1: Average Marginal Means for Regular Exercise (mins/day): IV 2SLS Estimation by Gender

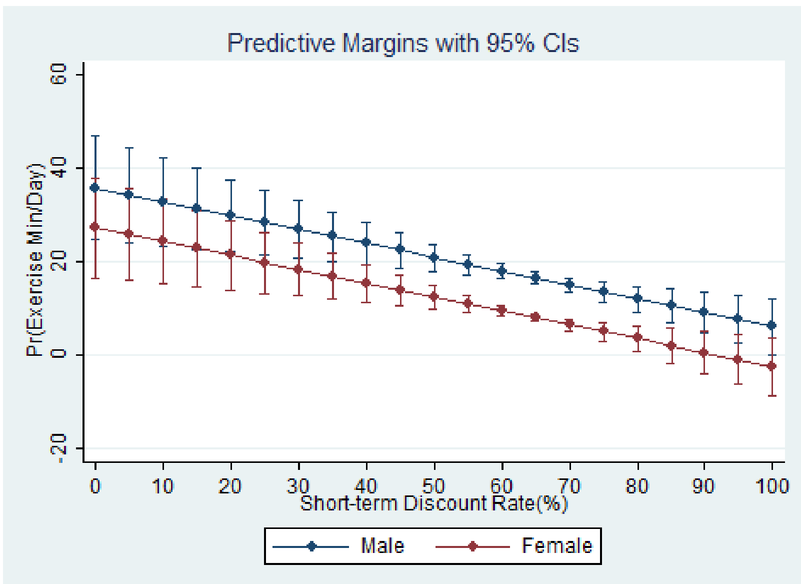
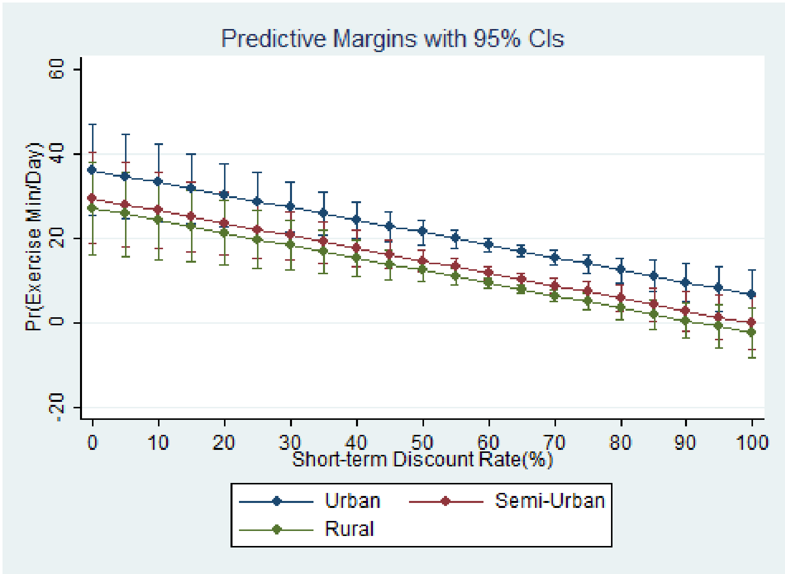


Figure 3.4.2: Average Marginal Means for Regular Exercise (mins/day): IV 2SLS Estimation by Location



Sensitivity Analysis

To test for the robustness of the above predictions, we conduct several sensitivity analyses. As health behaviors have long-term effects on health, it may be that the short term discount rates do not accurately reflect those behaviors. Hence, we re-estimate all of the above analyses using long-term discount rates which are also calculated using similar hypothetical gambles with a 3-year time delay. The results (in terms of statistical significance, magnitude of effects as well as their confidence intervals up to third decimal place) are very similar to those reported above. We also conduct the analysis of amount of physical activity (minutes per day) by excluding all the people who reported that they do not exercise in order to get a conservative estimate. The magnitude and significance of the results are similar those reported earlier.

3.5.2 Diet

Vegetables and Fruits (times consumed per week)

The analysis of diet measure of vegetables and fruits consumed per week on discount rates (of the person responsible for food preparation) using OLS and IV 2SLS specifications are reported in table 3.5. The OLS results indicate a small but statistically significant decrease in the consumption of fruits and vegetables as the discount rates increase. Next, we conduct the same analysis employing an instrumental variable (2SLS) method. Post estimation tests for this specification indicate endogeneity (significant Woolridge's robust chi2 statistic = 10.05) and the instrument probability of investing in savings satisfies the non-zero causal effect requirement. Hence, we will use this IV specification for further analysis. The IV model shows a larger and statistically significant negative effect (-0.12 compared to 0.02 from OLS) of increasing discount rates on the consumption of fruits and vegetables. We can see from figure 3.5. that the weekly consumption decreases from 38 times per week to 26 times as discount rates increase from 0-100%.

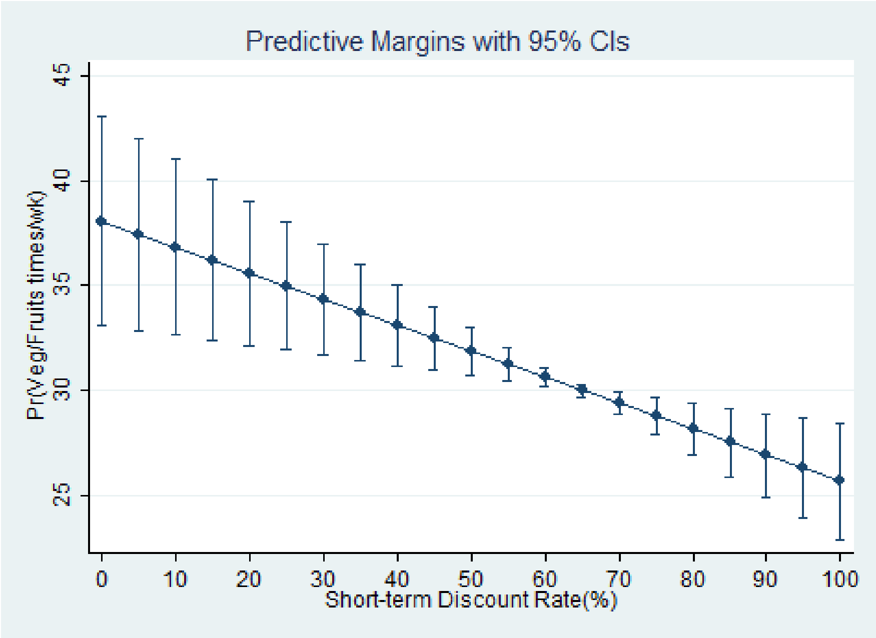
Table 3.5 Diet (fruits & vegetables: times/week) – OLS and IV 2SLS

Fruits & Vegetables (times/week)	**OLS**	**2SLS**
Short-term discount rate	-0.011**	-0.124**
Age	0.064***	0.092***
Female	4.408***	3.916***
Education (ref: no education)		
Primary or less	2.327***	2.802***
Secondary	3.465***	4.140***
High school	4.085***	4.366***
College	7.214***	7.434***
Graduate	10.430**	11.429**
Location (ref: rural)		
Semi-urban	0.172	0.229

urban	-2.331***	-2.363***
Health Status (ref: very good)		
Good	-0.176	0.055
Normal	-0.988	-1.425*
Bad	-3.321***	-3.679***
very bad	-8.223***	-8.190**
Asset Index	-0.492**	-0.315
Employed	1.094**	0.771*
Marital Status(ref: single)		
Divorced/widowed	-1.097	-0.704
Married	1.130*	1.287*
Risk taking level (ref: neutral)		
Lowest	-1.922	-2.740*
Low	-0.329	-1.324
Fair	-1.065*	-1.765**
High	-0.41	-1.758
Highest	-0.448	-0.963
Had accident	0.883	0.56
Permanent migration	-0.99	-1.058
Death in family	-0.381	-0.618
Illness	0.715	0.146
Recent job loss	-0.762	-1.410*
Natural disasters	-1.176	-0.27
Household size	0.406***	0.453***
Number of children	-0.301	-0.469**
Constant	21.060***	28.021***
N	6,574	6,525

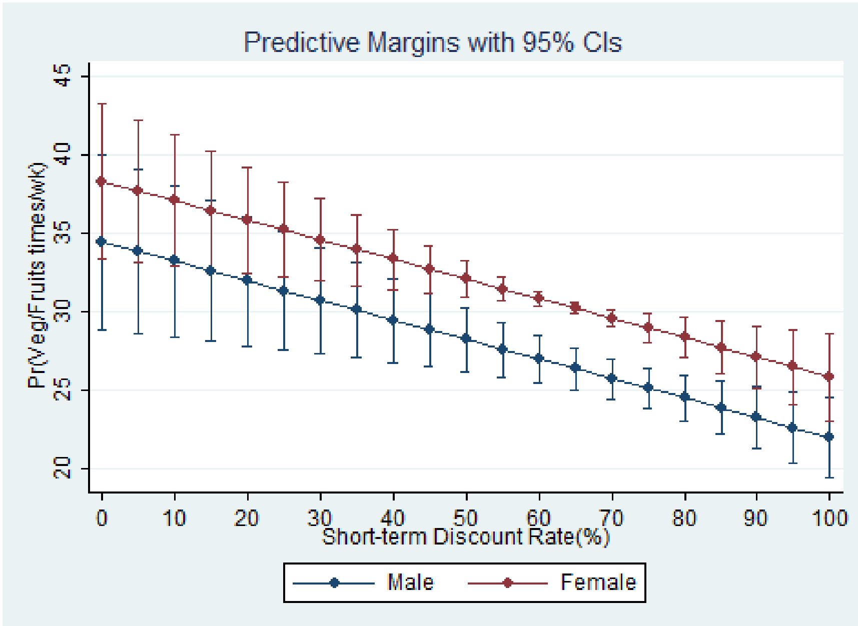
* p<0.05, ** p<0.01, *** p<0.001

Figure 3.5: Average Marginal Means for Weekly Fruit/Vegetable Consumption: IV 2SLS



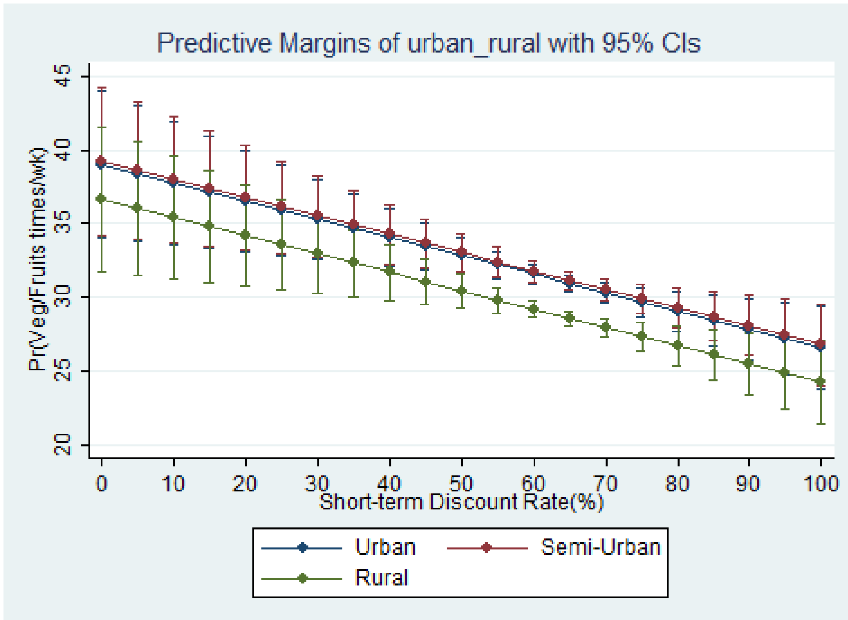
The marginal means by gender and location are presented below in figures 3.5.1 and 3.5.2 respectively. From figure 3.5.1, we can see that the households where women were responsible for household diet consume fruits and vegetables at an average rate of 30 times/week whereas it is 26 times for the households where men hold such responsibility.

Figure 3.5.1: Average Marginal Means for Weekly Fruit/Vegetable Consumption: IV 2SLS



The marginal means for fruit and vegetable consumption by location (figure 3.5.2 below) indicates the rural residents have lower average consumption of fruits and vegetables compared to urban and semi-urban dwellers (who show the same average consumption pattern).

Figure 3.5.2: Average Marginal Means for Weekly Fruit/Vegetable Consumption: IV 2SLS



<u>Cookies/Chips/Soda (times consumed per week)</u>

The analysis of diet measure of unhealthy foods (cookies, soda or chips) consumed per week on discount rates (of the person responsible for food preparation) using OLS and IV 2SLS specifications are reported in table 3.6. <u>The OLS results indicate a small but statistically significant decrease in the consumption of unhealthy foods with discount rates which runs contrary to our hypothesis.</u> While this result is statistically significant, the magnitude of the result (-0.003) is extremely small. The post estimations of the IV specification indicate no endogeneity which leaves us to conclude that OLS is a better fitting model for this data. Further analyses using the OLS model indicates that as discount rates increase, junk food consumption decreases by a small amount (table 3.6). However, large confidence intervals around the estimates indicate that the estimates may not be consistent (and hence the graphs are not reported). While female headed households have a lesser average consumption of junk food, the results are not significant. Similarly, urban households have a larger average junk food consumption, followed by semi-urban and rural households. These results are also not statistically significant.

Table 3.6 Diet (cookies/soda/chips: times/week) – OLS and IV 2SLS

Cookies/Soda/Chips	**OLS**	**2SLS**
Short-term discount rate	-0.003*	-0.014
Age	-0.020***	-0.004
Female	-0.099	-0.032
Education (ref: no education)		
Primary or less	0.838***	0.366**
Secondary	1.202***	0.572***
High school	1.410***	0.724***
College	1.484***	0.764***
Graduate	-0.263	-0.428
Location (ref: rural)		
Semi-urban	-0.309*	0.147
urban	-0.305*	-0.167
Health Status (ref: very good)		
Good	0.419	0.263
Normal	0.046	0.058
Bad	0.086	0
very bad	-1.3	-0.612
Asset Index	-0.183**	-0.166*
Employed	0.239	0.065
Marital Status(ref: single)		
Divorced/widowed	0.342	0.163
Married	0.398	0.257
Risk taking level (ref: neutral)		
Lowest	-0.146	-0.438
Low	-0.157	-0.485*
Fair	0.206	-0.439**
High	0.165	-0.608*
Highest	0.324	-0.320*
Had accident	0.039	0.09
Permanent migration	-0.277	-0.324*
Death in family	0.223	0.022
Illness	-0.227	0.121
Recent job loss	-0.154	0.093
Natural disasters	0.297	-0.275

Household size	0.047	0.012
Number of Children	0.134*	0.069
Constant	5.610***	3.768***
N	6,574	6,525

* p<0.05, ** p<0.01, *** p<0.001

Sensitivity Analyses

The above analyses use the discount rates of the person who prepares food in the household. However, family food choices would be influenced by household income, geographic location as well as by the decision making dynamics within households. As mentioned earlier, income is missing for more than half the households. Instead, we use alternate specifications that include education and gender of household head and state of residence as control variables. These specification produce results similar to those reported above. The preferences of the head of the household may dictate a family's dietary choices rather than that of the person who prepares food. In our sample, only 9% of the people who prepared family meals also were heads of their households and hence, it is possible that only a small fraction of the results reflected the true preferences of decision makers. Hence, we re-estimate the same models using the discount rates of the household heads as the main predictor. The results were similar to those reported in the original model. As the original specification has the highest sample size and as results from other specifications were similar, we report the results from the original specification.

3.5.3 Smoking

Smoking

The analysis of being a current smoker on short-term discount rates in a probit specification indicates no significant relationship between short term discount rates and being a current smoker. IV Probit regression of the same shows a significant Wald test (chi2 = 13.06) implying the endogeneity of short-term discount rates. Interestingly, results from this specification indicate that the marginal probability of being a current smoker decreases as discount rates increase (figure 3.6) which is in contrast with literature which indicates either no significant relationship or a small effect in the opposite direction (Chapman, Brewer et al. 2001; Odum, Madden et al. 2002). This result also contradicts our hypothesis 1.a.1. It should also be noted that magnitude of our results is small (with average predicted probability being 0.12) (table 3.7).

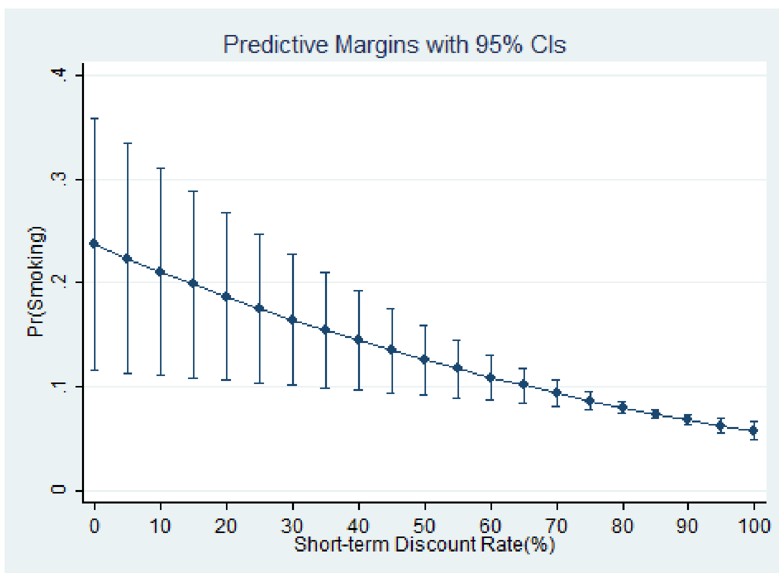
Table 3.7 Smoking – Probit and IV Probit

Smoking	**Probit**	**IV Probit**
Short-term discount rate	0.001	-0.009***
Age	-0.003**	-0.001
Female	-0.685***	-0.659***
Education (ref: no education)		
Primary or less	0.06	0.097
Secondary	0.077	0.128*
High school	0.078	0.095
College	0.011	0.005
Graduate	0.077	0.088
Location (ref: rural)		
Semi-urban	-0.238***	-0.234***
urban	-0.361***	-0.342***
Health Status (ref: very good)		
Good	-0.111*	-0.098
Normal	-0.029	-0.084
Bad	-0.071	-0.105
very bad	-0.132	-0.153
Asset Index	0.037*	0.051*
Employed	0.209***	0.168***
Marital Status(ref: single)		
Divorced/widowed	0.125	0.125*
Married	0.015	0.016
Risk taking level (ref: neutral)		

Lowest	0.230*	0.151
Low	0.112	0.011
Fair	-0.008	-0.077
High	0.062	-0.061
Highest	0.047	-0.013
Had accident	0.233***	0.178***
Permanent migration	0.142**	0.106*
Death in family	0.107*	0.075
Illness	0	-0.043
Recent job loss	0.169**	0.097
Natural disasters	0.194	0.248
Constant	-1.021***	-0.306
N	16,946	16,807

* p<0.05, ** p<0.01, *** p<0.001

Figure 3.6: Predictive Margins for being a Smoker: IV Probit Estimation



These results may be due to the fact that people who are smokers may be doing so to lose weight, or they may have more disposable income to spend on cigarettes or it may be related to cultural norms in specific groups or geographic locations. However, including control variables for BMI, income and state variables in the regression specifications did not change the results. Using alternate specifications using long-term discount rates in place of short term discount rates also produced results consistent with using short term discount rates. Hence, we present further analyses conducted using an IV Probit specification with short term discount rate as the predictor and do not include BMI, or state variables.

Further, women show lower marginal probabilities of being smokers compared to men, however, the negative sloping indicates that both men and women indicates that our hypothesis does not hold good with the current specification (figure 3.6.1). Urban dwellers show higher marginal probabilities of being current smokers compared to semi-urban or rural residents (figure 3.6.2). The differences get smaller at higher discount rates.

Figure 3.6.1: Predictive Margins for being a Smoker: IV Probit Estimation by Gender

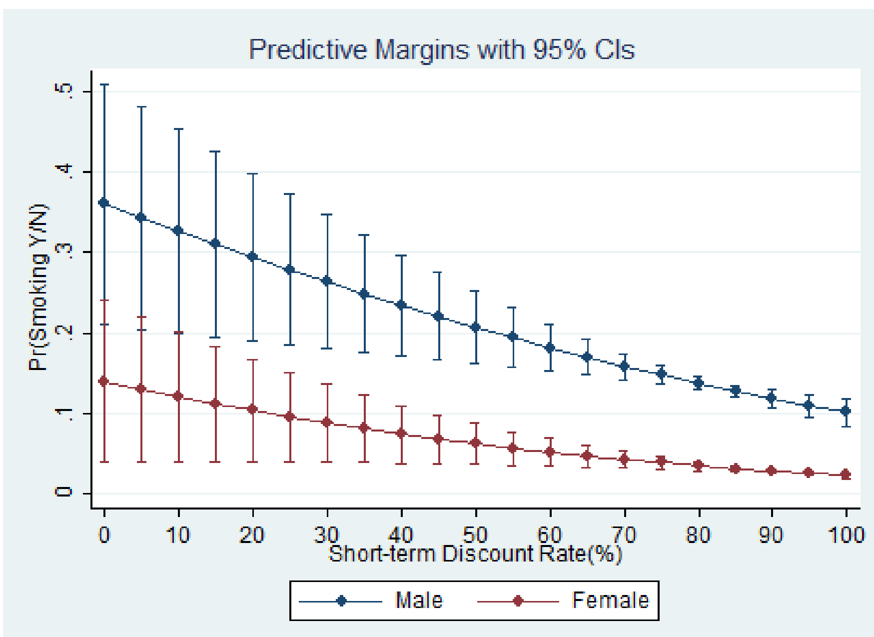
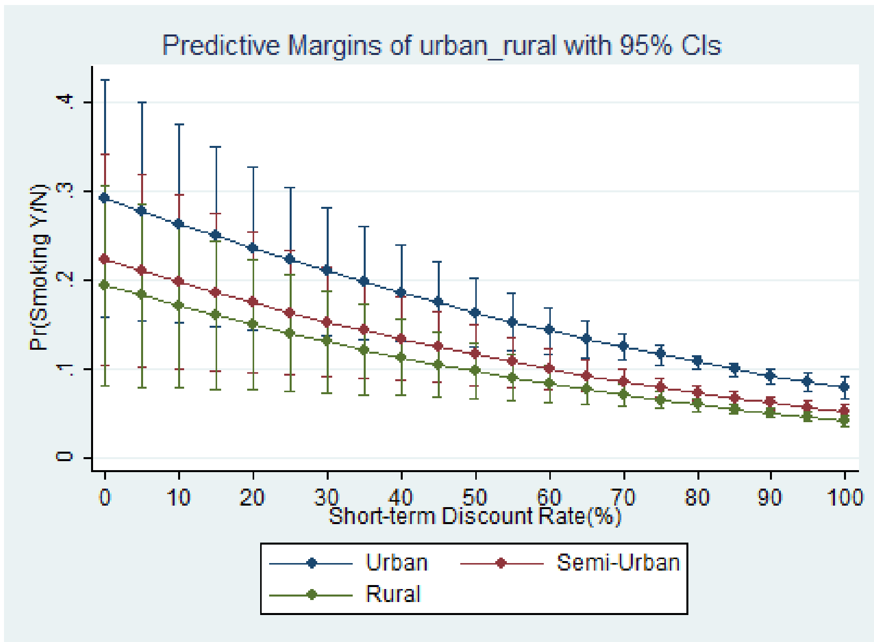


Figure 3.6.2: Predictive Margins for being a Smoker: IV Probit Estimation by Location



Quitting Smoking

Probit analysis of quitting smoking on short term discount rates indicates that as discount rates increase the marginal probability of quitting smoking decreases (figure 3.7) as hypothesized. These results hold in models where income, BMI and geographic locations are included as well as when long-term discount rates are used as predictors replacing short-term discount rates. IV probit specification indicates no endogeneity implying that results are more consistent under a regular probit model. Both probit and IV probit results are presented for comparison in table 3.8.

Table 3.8 Quit Smoking – Probit and IV Probit

Quit Smoking	Probit	IV Probit
Short-term discount rate	-0.003***	-0.007
Age	0.014***	0.014***
Female	0.159*	0.151*
Education (ref: no education)		
Primary or less	-0.033	-0.026
Secondary	0.027	0.025
High school	0.078	0.075
College	0.033	0
Graduate	-0.225	-0.246
Location (ref: rural)		
Semi-urban	-0.062	-0.053
urban	-0.035	-0.047
Health Status (ref: very good)		
Good	-0.035	-0.053
Normal	0.005	-0.026
Bad	0.18	0.147
very bad	0.686	0.647
Asset Index	-0.078*	-0.074*
Employed	-0.125	-0.126
Marital Status(ref: single)		
Divorced/widowed	-0.08	-0.075
Married	0.1	0.094
Risk taking level (ref: neutral)		
Lowest	-0.025	-0.05
Low	0.077	0.017
Fair	-0.038	-0.071
High	0.067	0.003
Highest	-0.002	-0.026
Had accident	0.317***	0.292***
Permanent migration	0.136	0.124
Death in family	0.047	0.06
Illness	0.204*	0.194*
Recent job loss	-0.009	-0.039
Natural disasters	-0.086	-0.055
Constant	-0.958***	-0.684
N		

* p<0.05, ** p<0.01, *** p<0.001

When the results are analyzed by gender, we see that men have a lower average probability of quitting smoking compared to women at all discount rate levels (figure 3.7.1). When we analyze results by location, we see that semi-urban dwellers have the least predicted probability of quitting smoking compared to rural or urban residents (figure 3.7.2).

Figure 3.7: Average Predictive Margin for Quitting Smoking: Probit Estimation

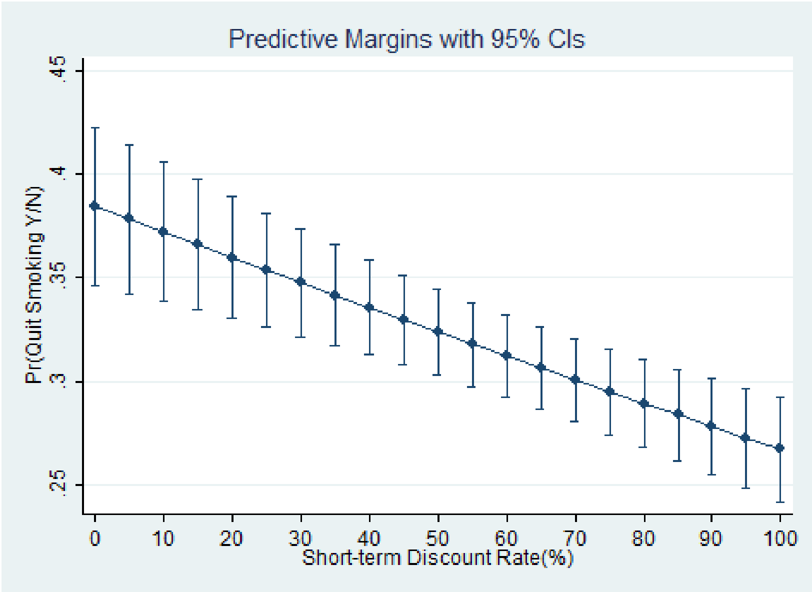


Figure 3.7.1: Predictive Margins of Quitting Smoking: Probit Estimation by Gender

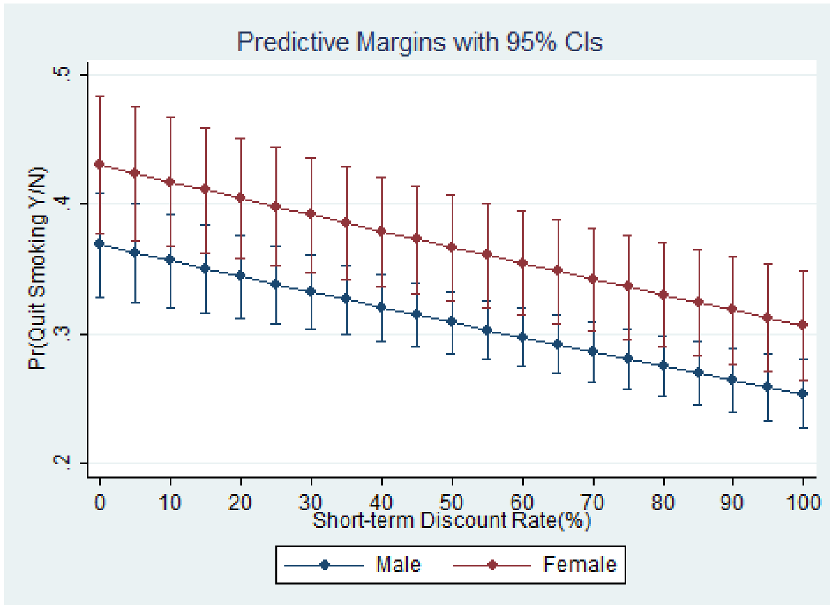
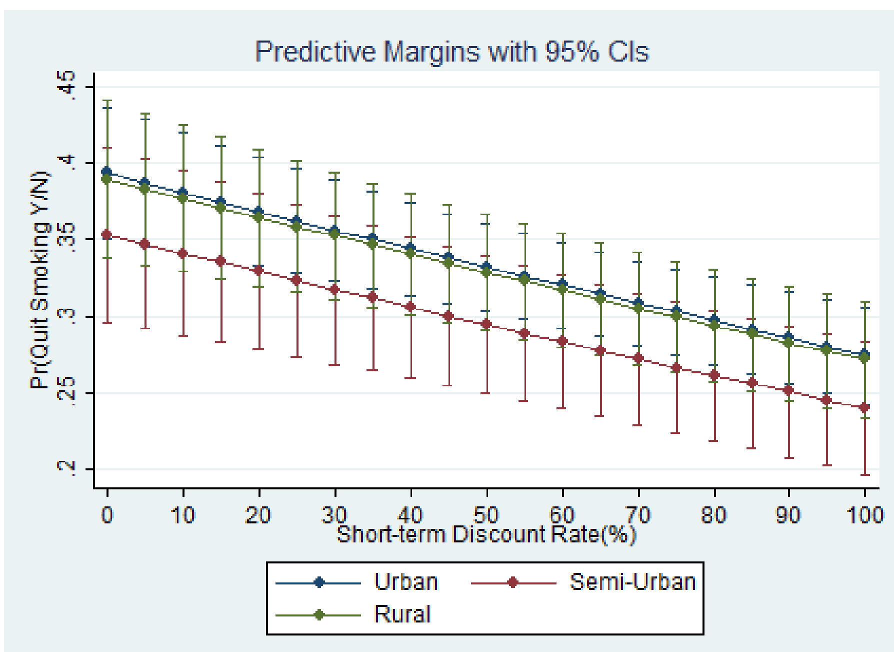


Figure 3.7.2: Predictive Margins of Quitting Smoking: Probit Estimation by Location



3.5.4 Analysis using Alternate Predictor

Using planning horizon as a proxy for discount rate produces mixed results (table 3.2.1). While we suppose that the instrument used in the IV specifications (i.e. probability of investing in savings schemes) is correlated with planning horizon, the models either do not converge or show any endogeneity. IV models of physical activities (minutes/day) and diet (fruits & vegetables per week) comply with IV model requirements. However, the coefficients on planning horizon in these cases is not significant although their magnitudes are similar to those from the analysis with discount rate as the primary regressor. In the case of probit or OLS analysis, none of the coefficients on plan horizon are significant though their magnitudes are similar to those from the analysis with discount rate as the primary regressor. Hence, we can conclude that the alternate regressor does not produce any significant results unlike discount rate calculated from hypothetical gambles; however the magnitudes of the results are similar. Hence, we cannot fully reject the hypothesis that both measures produce similar results.

3.6 Discussion

3.6.1 Health Behaviors

As seen from the summary table 3.2.2, the results for healthy behaviors including physical activity, vegetable/fruit consumption, quitting smoking (which can be construed as a healthy behavior among smokers) are in accordance with hypothesis 1.a, which posits that healthy behaviors are more likely to occur among people with low discount rates. These results agree with the reasoning that people who are future oriented tend to invest in their health by pursuing behaviors that are likely to yield results in the future; these results thus conform to the predictions from Grossman's theory of health as an investment.

Our study results show a stronger relationship between reported health behaviors and discount rates compared to those reported earlier in the literature (Fuchs 1982; Chapman and Coups 1999; Borghans and Golsteyn 2006). These differences may be due to the successful instrumental variables (IV) approach (in most of the analyses – see table 3.2.1 & 3.2.2) where we try to tease out the causal effect of discount rates on health behaviors. None of the studies that we came across our literature review employ IV approaches. While we cannot claim causality as we use cross sectional data and do not control for time trends including potential changes in time preferences over time, it is still a step in the right direction for eliciting the direct effects of time preferences on health behaviors.

The differences with previous literature may be also due to difference in population composition. Our results utilize population level data from Mexico whereas most of the literature is mainly on White population from the United States or from European countries. Most of the studies in current literature use sample sizes of 50 to a few hundred individuals compared to our sample size of approximately 18,000 (with analytical samples ranging from 18,000 for the analyses of diet and physical activity to approximately 2,500 for smoking). Wang et al. (Wang 2011) comparing population level discount rates from 45 countries report that Mexicans on the average have higher discount rates compared to more developed country counterparts. In our sample 49% of the population belongs to highest discounting category. Hence, the strong relationships reported here may be due to the population characteristics and composition in addition to the study design using instrumental variables approach.

Our results indicate that women have lower physical activity compared to men at all discount rates, One of the reasons might be a function of traditional gender roles assigned to women in Mexico, where they are expected to shoulder a majority of the housework and childrearing compared to men. Moreover, women may not consider housework as physical activity and may underreport their level of active life style. Among people with similar discount rates, urban area residents are more likely to get more exercise compared to their rural or semi-urban counterparts. This may be due to the perceptions of exercise patterns; people employed primarily in agriculture sectors may consider working in fields as part of their job rather than as a regular physical activity whereas people in urban areas who might walk to work or to bus stops may consider that to be regular physical activity.

Our results for diet holds good among men and women although women at all discount rates are more likely to report eating more fruits and vegetables. There might also be an element of social desirability bias which might result in more positive responses to healthy eating choices compared to choices of unhealthy foods. This might be especially pronounced among women and approximately 75% of the sample in the diet analysis were women. Fruits and vegetables consumption is much lower in rural households compared to urban or semi-urban households with similar discount rates which may indicate a problem with supply side factors such as availability and access as we control for many demand side factors including socioeconomic factors. People who work in rural agricultural economies may be forced to sell most or all of their produce to be able to take care of other needs. This is a common affliction among developing nations where demand on food products in urban areas due to faster urbanization and higher population densities create supply imbalances between rural and urban areas.

Our analysis indicates that people with lower discount rates in both urban and rural population are associated with better eating behaviors. However, lower education and socioeconomic levels in rural areas, which are also associated with higher discount rates, only work to exacerbate the problem in rural areas. The results for unhealthy behaviors show no association with discount rates in the case of junk foods. Mexicans consume more soft drinks per person than any other country and have more choices in terms of energy dense foods. While rural residents have higher discount rates compared to urban residents and hence should be choosing more unhealthy options (as per hypothesis), most of such consumption is occurring in urban areas and among relatively affluent Mexicans. The questionnaire asked household diet questions only. Urban areas have more choices of and access to junk foods and hence, a higher possibility of consuming such foods outside of homes. Hence, it is possible that the availability of junk foods might neutralize the effects of time preferences.

Women are less likely than men to quit smoking at all discount rate levels which is in accordance with current literature on gender differences in smoking cessation efforts (Pirie, Murray et al. 1991; Osler, Prescott et al. 1999; Grogan, Fry et al. 2009) which indicates that women who smoke are less likely to quit due to fears of weight gain and other adverse effects on their appearances. This seems to be the case for even women who are more future-oriented. It may also be the case that smoking cessation programs may be more oriented towards helping men as gender norms in Mexico tend to favor men over women. However, we cannot investigate either of these lines of reasoning with the available data. Results in the case of current smokers runs contrary to our hypothesis. We find that lower discounters are more likely to be current smokers. Even if include ex-smokers, we get similar results. This may be due to the fact that smoking is an addictive behavior stemming from prolonged chemical dependency on nicotine which may be harder to change even among people who value their health and keep otherwise healthy habits (Cutler and Glaeser 2005; Cutler and Lleras-Muney 2010).

3.6.2 Model Specifications and Measurement Methods

Our analysis uses data collected during 2005-06. During that period gross domestic savings as a percentage of GDP in Mexico was around 23% (World Bank data) and those rates have remained between 22-24% during the past decade, indicating that it is a relatively stable measure. Hence, we used the planning time horizon used for savings decision as a stable proxy measure. Our hypothesis 1.b that time discounting measured using different proxies and measurement methods would produce similar results did not hold in many instances. While time discounting measured using hypothetical gambles produced significant results as discussed earlier, the alternate predictor, planning time horizon, did not produce any significant results and the models did not converge in many cases. While these results counter our hypothesis, they are in line with literature where studies that use a broad savings or investing measure as a proxy for time preferences have found no significant relationships between discounting and health behaviors (Frederick, Loewenstein et al. 2002; Borghans and Golsteyn 2006). Our results indicate that different measurement methods do not produce identical results. However, it is encouraging to note that the magnitudes of the results were similar although they differed in statistical significance.

Proclivity to save may be more of a function of having enough disposable income, being financially educated and savvy and having access to reliable savings instruments, rather than that of time preferences and hence, may be a more noisy measure of time preference compared to the calculated discounting using gambles. On the other hand, gambles questions have their own drawback which we discuss in the next subsection. Moreover, both of these measures operate in the financial decision making domain and financial decisions may not automatically correlated well with decision making in health domain and both our measures might be equally ill-equipped in this regard.

3.6.3 Limitations

Our study is cross sectional (as the preference measures are available only in the second wave of the data) and hence, it is not possible to infer causality. The data used in this study are limited to Mexicans. There are no other comparable minority groups within this dataset that are relevant to the population mix in the United States. Also, there are no other comparable studies among other minority groups in the U.S. in order to be able to compare results of this study with other racial/ethnic groups. This lack of direct comparison groups or other comparable studies limits the generalizability of this study to the other minority groups in the U.S. Still, these analyses contribute to furthering our understanding of time preferences among a developing country population which is also very relevant to United States due to geographic proximity and consistent migration.

While the instrumental variable approach worked for most of the analyses, we can also see from table 3.2.1 that regular OLS or probit models were more appropriate in certain cases. Instrumental variable approach helps with reverse causality as well as with correcting errors in the measurement of the primary regressor. While the current data with hypothetical choice based preference measures collected at a population level are a considerable advance in the measurement of time discounting, there are several drawbacks. There are only 5 choice questions with short term (1 month) delay and with 1,000 pesos initial reward and a 2,000 pesos final reward. The first question asked shows a positive reward, which might bias respondents towards expecting a higher reward and hence a higher discount rate. Many surveys tend to mix the positive and negative rewards in a 'titration' procedure to alleviate this 'anchoring bias'. However, anchoring bias is further exacerbated in this questionnaire as all the subsequent questions are asked in the order of increasing rewards resulting in increased discount rates. This ordering of questions tend to make respondents expect a higher reward with each question. Hence, the chosen discount rates may be higher than the true discount rates. As there are only 5 questions, these data are less granular for more nuanced analysis of discount rates leading us to rely on model estimates based on five available discount rates.

The hypothetical choice questions produce discount rates that not equally spaced (i.e. 0%, 5%, 15%, 35%, 75% and 100%) which results in constructing a discount rate variable that is a 'quasi-interval' variable. For statistical analysis, we are forced to treat this as a continuous variable as no statistical procedures are available to conduct IV analysis with such an endogenous variable and a continuous instrument (probability of investing in savings schemes). Thus, we may be missing some true variability in discount rates as we smooth it as a continuous variable, and thereby potentially masking the true functional form of the discounting function.

The monetary rewards in the choice questions are hypothetical and there is some evidence in literature that hypothetical rewards yield lower discount rates although the debate is ongoing. Hence, we should be careful in not over interpreting the magnitude of results.

Our study takes into consideration risk profiles of people. However, uncertainty associated with healthy behaviors might act as barriers for some people who might tend to prefer certain gains over uncertain ones. Nevertheless, sensitivity analyses using long-term discount rates produced comparable results improving confidence in our results.

3.6.4 Broader Implications for Policy

The strong relationships between lower discount rates and better health behaviors indicates that lowering time preferences might lead to better health behaviors, controlling for other factors. Higher time preferences (as seen in first stage instrumental variable regressions) are associated with older age and lower levels of educations, especially education levels less than high school. Hence, we reiterate the current knowledge that improving education levels might be effective in improving health behaviors. Also, younger ages are associated with lower discount rates. While aging cannot be stopped, the effects of contributive factors including individual shocks such as unemployment or sudden illness can be lessened by having supportive social structures. At the time of the survey there was no universal health insurance coverage or unemployment benefits for people in informal labor sector in Mexico. However, it needs to be seen whether the newly adapted universal health insurance system in Mexico might alleviate such shocks to some extent. Smoking cessation programs in Mexico tend to be expensive and only about 10% of the population has the information on how to access those programs (Heredia-Pi, Servan-Mori et al. 2012; Servan-Mori, Heredia-Pi et al. 2012). Programs catering to women and hard-to-reach rural populations are essential in improving smoking cessation rates which are high even among people with low discount rates.

CHAPTER 4. TIME-INCONSISTENT DISCOUNTING AND HEALTH BEHAVIORS

This chapter empirically tests whether time-inconsistent preferences which account for 'procrastination' or 'present bias' explain healthy behaviors better than the models that are naïve to the problem. This chapter also examines whether policy interventions such as 'Oportunidades' alleviate health behaviors among people who have time-inconsistent preferences.

The standard economic model of discounted utility used in the study of health behaviors (as described in chapter 3) assumes that the preferences are time-consistent i.e. short term and long term discount rates are the same. This time consistency is possible with an exponential form of discounting. However, our experiences as well as empirical data does not support time-consistent decision making. People are found to have lower discount rates for long time horizons and larger discount rates for short time horizons(Thaler 1981; Benzion, Rapoport et al. 1989; Chapman 1996). Such inconsistencies are explained by hyperbolic discounting models, which model a discounting as a declining function over time or by quasi-hyperbolic models that explicitly account for 'present bias' or 'procrastination' in the immediate time period (Loewenstein and Prelec 1992; Laibson 1997; O'Donoghue and Rabin 1999; O'Donoghue and Rabin 2000; Scharff 2009).

While most of the empirical evidence for time-inconsistent preferences is from experiments conducted on small samples in lab settings or from the anomalies in observed behaviors (Loewenstein and Prelec 1992), in this chapter we explore whether there is evidence for such inconsistent discounting at a population level using a hyperbolic or a quasi-hyperbolic model. Then, we will also compare the discounting models in terms of their explanation of observed health behaviors. Further, we will explore whether such taking into account suboptimal behaviors resulting from such inconsistencies explains some of the successes of the Mexican social welfare program, Oportunidades (a conditional cash transfer program). This program provides short term cash incentives to means-tested households conditional upon them following certain health and education related outcomes and is regarded as very successful by external evaluators including the World Bank. If health behaviors are influenced by higher short-term discount rates, then a program that forces people to follow healthy behaviors by asking them to tie short term behaviors to short term rewards might alleviate suboptimal decisions resulting from such higher short term discount rates. Understanding whether the program has differential effects among such high discounters would potentially lend strength to arguing for targeted program expansions.

4.1 Research Questions and Hypotheses

Research Question 2.A.: *Can we detect time-inconsistency in time preferences with regard to health behaviors?*

Hypothesis 2.a.: Time discounting conforms to a hyperbolic or a quasi-hyperbolic functional form indicating time-inconsistent discounting.

Rationale: A hyperbolic or quasi-hyperbolic form would indicate that discount rates are higher for immediate outcomes and are lower for future outcomes. These functional forms which are noticed in laboratory experiments indicate that present utilities are heavily discounted compared to future utilities.

Research Question 2.B.: *How does time-inconsistent discounting influence healthy behaviors?*

Hypothesis 2.b: People who exhibit *time-inconsistent discounting* (i.e. higher short term discount rates compared to long-term discount rate) are *less* likely to follow optimal healthy behaviors compared to people who have *discount rates that are time-consistent*, all else being equal.

Rationale: Higher short term discount rates indicate that present utilities are heavily discounted compared to future utilities and hence, value from healthy behaviors appear smaller in the short term when such behaviors have to be followed. This results in procrastinating to follow healthy behaviors.

Research Question 2.C.: *Does 'Oportunidades' participation improve health behaviors among people who have time-consistent discounting?*

Hypothesis 2.c.1: Participants in 'Oportunidades' who have *time-inconsistent discounting* are associated with better health behaviors compared to non-participants with any type (time consistent or time-inconsistent) discounting, all else being equal.

Rationale: Oportunidades provides a short term incentive to follow healthier choices including choice of diet and preventive care. People with time-inconsistent discounting have difficulties with their time preferences over short time horizons (and have long term preferences similar to that of population averages) and hence, may benefit more if they are given a short term incentive that will help them with aligning their short term preferences and lowering short term discount rates.

4.2 Conceptual Model

Exponential time discounting assumes that a person evaluates new alternatives by integrating them into existing plans for investment (leading to a dynamically consistent set of preferences). If an individual is indifferent between two health outcomes $h'$and h'' at periods t' and t'', then she remains indifferent when the periods are incremented by a constant term k (van der Pol and Cairns 2011),

$$h'_{t'} \sim h''_{t''} \quad iff \quad h'_{t'+k} \sim h''_{t''+k}\,, \quad h' \prec h'', t' < t'' \; and \; k > 0 \text{ ----------------(4.1)}$$

This argument implies that the choice is consistent irrespective of whether t' *and* $t''$are one-week from today or 10-years from today as long as it is sometime in future (i.e. $k>0$). While this seems like a reasonable assumption, empirical data suggests that most of us do not possess well-formed plans for future consumption and may not be able to project utilities realistically into future and hence, many field and experimental studies reject exponential discounting (Frederick, Loewenstein et al. 2002). Further, empirical research indicates that most of us discount near future more heavily and distant future less heavily, which leads to potentially inconsistent preferences over time (Ainslie 1992; Ainslie and Haslam 1992). To address this problem of discounting near-future periods differently than distant-future periods, it is suggested in the literature to use a hyperbolic or quasi-hyperbolic functional form for discounting (Laibson 1997; Laibson, Repetto et al. 1998; O'Donoghue and Rabin 2000; Angeletos, Laibson et al. 2001)with the latter being preferred by economists (van der Pol and Cairns 2011) and the former by psychologists. The quasi-hyperbolic form advocated by Laibson (Laibson 1997) incorporates a bias for the present (or an immediacy effect) but maintains a constant discount rate for future time periods similar to an exponential form, whereas the hyperbolic form accounts for declining discount rates over time without explicitly modeling the immediate present.

The general three-parameter discounting model proposed by Benhabib, Bisin and Schotter (Benhabib, Bisin et al. 2010) allows us to test the exponential, hyperbolic and quasi-hyperbolic models. This model is applicable when we allow for choices between smaller sooner rewards today and larger later rewards at a later time t. This model values a reward y at a time t as yD(y, t) where D(y, t) is the discount function. The formulation is:

$$yD(y,t) = \begin{cases} y & if\ t = 0 \\ y\beta(1-(1-\theta)rt)^{\frac{1}{1-\theta}} & if\ t > 0 \end{cases} \text{-------------------------(4.2)}$$

The three factors, r, β and θ represent the discount rate (r), present-bias (β) and the hyperbolicity (θ) of the discount function. When θ = β =1, this equation reduces to exponential discounting. When θ=2 and β =1, it reduces to true hyperbolic form. When θ=2 and β is free, it reduces to quasi-hyperbolic discounting[18]. When θ >2, the function becomes a hyper-hyperbolic function (i.e. the discount rates fall sharper than in a hyperbolic function). We do not test the last formulation as we do not have sufficient data point to estimate that formulation. We will

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[18]The quasi-hyperbolic form advocated by David Laibson incorporates a bias for the present (β) but maintains a constant discount rate for future time periods similar to an exponential form. If β=1, the model reduces to the standard DU model. Presence of a β≠1 implies the presence of present bias where a person with such preferences would put off an onerous activity more than she would like.

constrain θ to values < 2 and test exponential, hyperbolic and quasi-hyperbolic functional forms of discounting. Recalling from chapter 3, healthy behaviors are written as:

$$HB=f\,(D, X, Y, \varepsilon) = f(g(X, \eta), X, Y, \varepsilon) \text{ ----- } (4.3)$$

In the above equation, HB represents health behaviors, D is the time discounting, X are the factors that affect both health behaviors and time discounting, Y are the factors that influence health behaviors only and ε, η are the random error terms. D (or time discounting) is construed as one consistent and all-encompassing measure of discounting over a lifetime. Now, behavioral economics indicates that a hyperbolic or quasi-hyperbolic functional form of discounting would explain people's choices better compared to exponential discounting, when they are faced with choosing smaller sooner or larger later rewards. Hence, we will utilize the generalized form of discounting (equation 4.2). We utilize 10 combinations of y (larger later rewards) and t from the Mexican Family Life Survey i.e. 1000, 1100, 1200, 1500 and 2000 pesos in a month; and 10,000, 12,000, 15,000, 20,000 and 40,000 pesos in 3 years.

From chapter 3 and as expressed in equation 4.3 above, we find that the discount function D is influenced by a number of demographic variables such as age, education, current health, income etc. (see chapter 4). In other words, individual differences in discount rates are explained by those demographic variables. Applying those results, we can write the discount rate (r) and present bias (β) as functions of those demographic variables. In other words:

$$r = r_0 + \sum r_i X_i \quad \text{and } \beta = \beta_0 + \sum \beta_i X_i \text{ ------------------}(4.4)$$

Comparing the different discount functions in terms of how well they explain actual health behaviors would indicate which functional form would explain heterogeneity of health behaviors. [The functional form of discounting may be influenced by a number of psychological factors such as anticipatory utility (Loewenstein 1987), preferences for sequences of outcomes (Loewenstein 1993; Chapman 2005) or visceral influences (Loewenstein 1988). While we do not explore these factors, here we would acknowledge that the above influences may differ between people, leading to different discount functions.]

Further, if having a higher discount rate for immediate present precludes one from starting a health behavior then a having a commitment contract to commit to the health behavior ex-ante (either voluntarily or involuntarily) would improve welfare. In other words, much like how Odysseus tied himself to the mast to avoid the temptation of sirens' song(Ashraf, Karlan et al. 2006), one who ties themselves to a commitment to follow a health behavior might just overcome their high short term discount rate. This rationale has been applied to many problems that arise due to time-inconsistent discounting including savings decisions, retirement planning, deadlines and gym membership ((Laibson, Repetto et al. 1998; O'Donoghue and Rabin 1999; Bernheim, Skinner et al. 2001; Diamond and Köszegi 2003; Richard H. Thaler and Shlomo Benartzi 2004; Ashraf, Karlan et al. 2006; DellaVigna and Malmendier 2006). Based on these studies and based on the possibility of time-inconsistent preferences dictating health behaviors, we will examine an existing social program in Mexico to find out whether it helps overcome such preferences.

The conditional cash transfer program in Mexico, 'Oportunidades' (previously known as PROGRESA), provides short-term cash transfer to families with school-age children (based on geography and means-testing). This program aims to improve investment into human capital among poor families by providing incentives to improve education, nutrition and health outcomes among children and pregnant women, while improving overall family nutrition. The cash transfer is conditional upon school attendance, regular visits to primary care providers and upon eating balanced healthy meals. The actual cash transfers are made to the women in the households as women are generally in charge of children and household diets. This method also aims to change household decision dynamics by empowering women to be decision makers for education and health related decisions.

This program was started in 1997 and by 2005 (survey period), one in five Mexicans were covered by this program. Beneficiaries are identified using periodic socioeconomic and demographic survey. Rural beneficiaries are enrolled in their villages or homes, whereas urban beneficiaries have to visit appointed government facilities to do so. External evaluations have found the program to reduce anemia by half in first 10 years of the program; low height prevalence was reduced by a third; morbidity (general sickness) among children was lower than non-participant households; and overweight and obesity are lower in women participants compared to national average. There was also lower levels of tobacco and alcohol use and junk food consumption among teens whose households were long term beneficiaries (Fernald, Gertler et al. 2009).

While primary motive of the program is to improve human capital investments in health and education by circumventing the need for child labor or for eating cheap unhealthy foods, it can also be construed as hindering such short sited decisions. Suppose that short term costs are C and long term benefits are B. Then, having a high discount rate in short term might make one evaluate $C > B$, leading to sub optimal behaviors. However, a conditional cash which would be lost if the behavior is not followed would lead one to reassess costs and benefits. If the cash is sufficient enough to reverse the above evaluation, then it works as a commitment contract, leading one to a better healthy behavior. If 'Oportunidades' works in this way, then we can expect to see people who have hyperbolic or quasi-hyperbolic behaviors and who are participants in this program to have better health behaviors compared to people who have same discounting, are eligible but are non-participants in the program. [Note that non-participation might be due to not qualifying or due to a conscious decision for some reason to not participate. The take-up rate for this program is about 97% in rural areas and 60% in urban areas. The latter lower take-up rate is attributed to the requirement of going to a program office during an enrollment period to register whereas in rural areas the program was made easily accessible and was heavily promoted.]

4.3 Study Design

4.3.1 Data

Please refer to Chapter 3.3.1 for a detailed account of the data and the analytical sample.

4.3.2 Variables

Hypothesis 2.a.: Time discounting conforms to a hyperbolic or quasi-hyperbolic functional form - Choice (0 or 1) is the dependent variable for testing the hypothesis 2.a. If the immediate reward is chosen, choice is coded as 1 and choice=0 if the later reward is chosen. We include initial reward, delayed reward and time delay as independent variables (see equation 4.5 below). Then, we include demographic variables (age, sex, location (urban, semi-urban or rural), education, asset index, current health status, and current employment status) which might influence discount functions as other RHS variables (see equations 4.4 and 4.5). We will omit some of the other variables that influence discount rates such as risk preferences, life events such as migration or shocks to health, employment, wealth or family circumstances. This is due to the fact that including all these variables would render the model untestable due to data limitations (further discussed in results chapter). However, omitting these might bias the estimated discount rates.

Hypothesis 2.b.: People who exhibit time-inconsistent discounting are less likely to follow optimal health behaviors compared to people who have time-consistent discounting -

The dependent variables for testing the hypothesis 2.b. are health behaviors – diet, physical activity and smoking – which are described in chapter 3. The independent variable is a dichotomous measure of time-inconsistent discounting. Using the best discounting model (resulting from analysis for testing hypothesis 2.a), we estimate the long and short term discount rates at an individual level. Then, if the short-term discount rate is larger than the long-term discount rate we code the time-inconsistency to be 1; else it is 0 (following Ikeda et al. (Ikeda, Kang et al. 2010)). Other RHS variables include age, sex, location (urban, semi-urban or rural), marital status, education, annual income, current health status, risk preference (see Appendix B) and current employment status, life change events such as permanent migration, and shocks including loss of employment, accidents, serious health issues/ diseases/ hospitalization of family members, death in the family and losses due to natural disasters in the past 4-5 years (see chapter 3 for details).

Hypothesis 2.c. – The dependent variable for testing hypothesis 2.c. (where we aim to test the effects of participation in 'Oportunidades' for people with time-inconsistent preferences) is the household diet (number of times fruits and vegetables consumed per week and number of times soda/chips/cookies consumed per week). We only test the dietary behaviors as those are the only health behaviors that are directly affected by participation in 'Oportunidades' and which are relevant to our study aims. [We do not test for use of preventive services as the questions on outpatient services utilization do not clearly indicate the reasons for such visits.] The main independent variables are a binary indicator variable for time-inconsistency (as described above) and a binary indicator variable indicating participation in ‘Oportunidades’. We also include a term corresponding to the interaction of these independent variables. Other RHS variables include age, sex, location (urban, semi-urban or rural), marital status, education, annual income, current health status, risk preference (see Appendix B) and current employment status, life change events such as permanent migration, and shocks including loss of employment, accidents, serious health issues/ diseases/ hospitalization of family members, death in the family and losses due to natural disasters in the past 4-5 years (see chapter 3 for details).

We do not include factors such as health beliefs or access measures here, which might bias results. [See chapter 3 for detailed explanation.]

4.4 Methods

4.4.1 Measurement Model

Let HB be the health behavior, D be the discount rate with D_e, D_h and D_q indicating exponential, hyperbolic and quasi-hyperbolic discount functions. To test the hypothesis 2.a, we estimate the discount rates as follows. In our survey, respondents make up to 10 choices between smaller immediate rewards (x) now or larger later rewards (y) with a delay (t). The initial reward x is either 1,000 pesos or 10,000 pesos. Corresponding to the immediate reward choice of 1,000 pesos, later reward (y) varies between 1000, 1100, 1200, 1500 or 2000 pesos with a delay of one month; for the immediate reward of 10,000 pesos, later reward varies between 10,000, 12,000, 15,000, 20,000 or 40,000 pesos with a delay of three years. Based on the survey questionnaire design (as described in appendix A), each respondent can make up to 10 choices.

Then, we code a binary choice variable 'choice' as follows based on answers to the above choices: if y, the later reward, is chosen, then choice = 0 and choice = 1 if immediate reward x is chosen. Following the formulation used by Benhabib et al (Benhabib, Bisin et al. 2010) and by Tanaka and Camerer (Tanaka, Camerer et al. 2010), we write the probability of choosing immediate reward x (or probability of choice being 1) over delayed reward y in a time period t as Pr(x>(y,t)). Then, using equation 4.2, for t > 0, we can use a logistic function to describe this probabilistic relation as:

$$P\big(x > (y,t)\big) = \frac{1}{1+\exp(-\mu\left(x-y\beta(1-(1-\theta)rt)^{\frac{1}{1-\theta}}\right))} \text{ ------ (4.5)}$$

Here, μ is the sensitivity parameter or a measure of noise in the responses. As described earlier in the conceptual model section, the above function is a general form. By constraining β=1 and as θ approaches one in the limit, the discounting reduces to exponential discounting function ($D_e = e^{-rt}$) in the limit. When β=1 and θ =2, it reduces to true hyperbolic discounting ($D_h = 1/(1+rt)$). When θ=1 and β is free, it reduces to quasi-hyperbolic discounting ($D_q = \beta e^{-rt}$). Further, to test the influence of demographic variables on discount rate (r) and on present-bias (β), we will re-estimate the above models by substituting r and β from equation 2.4. Based on the above estimation of discount rate and present-bias at a population level, we will estimate individual level discount functions D_{ie}, D_{ih} and D_{iq}. Then, we can write the health behaviors as,

$$HB_i = \tau_{0i} + \tau_{1i} D_{ie} + \tau_{3i} X_i + \tau_{4i} Y_i + \xi_i \text{ ---- } (4.6.a.)$$

$$HB_i = \tau_{0i} + \tau_{1i} D_{ih} + \tau_{3i} X_i + \tau_{4i} Y_i + \xi_i \text{ ---- } (4.6.b.)$$

$$HB_i = \tau_{0i} + \tau_{1i} D_{iq} + \tau_{3i} X_i + \tau_{4i} Y_i + \xi_i \text{ ---- } (4.6.c.)$$

where X and Y are demographic variables as described in section 3. We will compare these models to find out the best discounting model that best explains observed health behaviors.

Further, using the best discounting model, we estimate long and short term discount rates. We construct an indicator H for having time-inconsistent discounting if short term discount rates are larger than long term discount rates and include the discount rate r, calculated based on the preferred model. The estimation equation to test hypothesis 2.b. can be written as:

$$HB_i = \gamma_{0i} + \gamma_{1i} H_i + \gamma_{2i} r_i + \gamma_{3i} X_i + \gamma_{4i} Y_i + \varepsilon_i \text{ ---- } (4.7).$$

Lastly, to test the hypothesis 2.c., the estimation equation can be written as:

$$HB_i = \mu_{0i} + \mu_{1i} P_i + \mu_{2i} H_i + \mu_{3i} r_i + \mu_{4i} X_i + \mu_{5i} Y_i + \varphi_i (PH)_i + \varepsilon_i \text{ ------}(4.8)$$

Here P represent program participation (P=1 for CCT participants and P=0 for CCT non-participants); H=1 represents time-inconsistent discounting, r is the discount rate; and X, Y are demographic variables as described in chapter 4. Here, φ represents the combined effect of program participation and time-inconsistent discounting on healthy behaviors.

4.4.2 Descriptive Statistics

Table 4.1 below shows the distribution of population by the delayed rewards they chose for both short and long term rewards with delays of one month and 3 years respectively. Further, people who fall on or above the diagonal of the table (i.e. in the shaded area of the table) have lower short term discount rates compared to long term discount rates. In other words, the population that falls into the shaded area have time consistent preferences and the rest have time inconsistent preferences with higher short term discount rates.

First, this tables shows that a clear majority of the population falls into the highest discounting category for both short and long term discounting which is in agreement with results from chapter 4. While the implicit discount rates for short and long term are very different in terms of their magnitude, the percentage of people in each discounting category is comparable. Secondly, as short term discount rates increase (as indicated by choosing larger delayed rewards down the columns) people are more likely to be time-inconsistent discounters. Finally, as both long term and short term discount rates increase (as we move down and to the right from the top left hand side of the table), people seem to exhibit exponential discounting.

While having large discount rates in the short term is not favorable to following healthy behaviors (as discussed in chapter 3), being a time-consistent discounter might still be beneficial. This is because if one has consistent preferences, then if the person is persuaded to follow health behaviors he or she might be more likely to continue with those behaviors. On the other hand, if the person has a larger short term discount rate and also has inconsistent preferences, they might plan on following health behaviors if persuaded but due to inconsistent preferences might not follow through with their plans. Hence, we will further explore how these two dimensions of time preferences influence health behaviors in section 4.5.2.

Note that historically time discounting has been assumed to show declining rates over time with the decline being either exponential or hyperbolic or quasi-hyperbolic. The exponential discounting is termed time-consistent as we described earlier in section 4.2. However, it is possible that people might have higher long term discount rates and lower short term discount rates which implies increasing impatience which is the opposite of traditional declining discount rates. While some lab experiments have detected such behaviors (Attema, Bleichrodt et al. 2010) it is still a emerging debate on whether such preferences are truly reflective of time preferences or whether they are more indicative of a risk averse attitude towards potential suboptimal returns from long term investments. Hence, we use the more accepted definition of time-inconsistent preferences as described earlier. [While there are a small percentage of about 300 people who fall into this 'increasing impatience' category, they are distributed equally among the shaded cells.]

Table 4.1 Percentage by Delayed Reward Choices for delay of 1 month and 3 years

Long term reward (pesos) / Short term reward (pesos)	10,000	12,000	15,000	20,000	40,000	Total
1,000	**291**	150	96	96	313	946
1,100	112	**1,164**	347	266	521	2,410
1,200	60	280	**693**	434	444	1,911
1,500	43	145	429	**957**	961	2,535
2,000	111	214	373	637	**10,476**	11,811
Total	617	1,953	1,938	2,390	12,715	19,613

Population level characteristics are shown in table 4.2.1 with univariate means and bivariate associations over hyperbolic discounting.

Table 4.2.1 Descriptive Statistics by Time Inconsistent Preference Indicator

	Pop. Means/ Percentage	Hyperbolic	Non-Hyperbolic
Physical Activity			
Regular Exercise (yes/no)	14%	11%	17%
Minutes exercised per week	96	93	98
Diet			
Veg/Fruits (times per week)	30	30	31
Cookie/Chips/Soda (times per week)	6	7	6
Smoking			
Current Smoker (yes/no)	8%	8%	10%
Quit smoking (yes/no)	34%	36%	31%
Age (years)	41	43	34
Sex			
Male	44%	43%	45%
Female	56%	57%	55%
Marital Status			
Single	23%	0%	58%
Divorced/Widowed	11%	12%	5%
Married	66%	87%	36%
Location			
Urban	38%	36%	41%
Semi Urban	22%	24%	22%
Rural	40%	40%	37%
Education			
No Education	11%	12%	8%
Primary or Less	41%	45%	30%
Secondary	25%	25%	27%
High School	13%	10%	10%
College	10%	7%	7%
Graduate	<1%	<1%	<1%
Health Status			
Very Good	7%	6%	9%
Good	49%	46%	50%
Normal	40%	44%	37%
Bad	4%	4%	3%
Very Bad	<1%	<1%	<1%
Asset Index	5	5	5
Currently Employed?	50%	50%	53%
Risk Categories			
Risk Neutral	9%	6%	9%

	Pop. Means/ Percentage	Hyperbolic	Non-Hyperbolic
Risk Taker (Lowest)	2%	2%	2%
Risk Taker(Low)	8%	9%	9%
Risk Taker(Fair)	43%	44%	41%
Risk Taker (High)	5%	5%	6%
Risk Taker(Highest)	32%	33%	32%
Permanent Migration?	9%	10%	9%
Shocks			
Serious Accidents?	8%	9%	9%
Serious Health Problems in Last 4 Years?	13%	14%	12%
Death in the family in the last 5 Years?	9%	8%	10%
Major Disease/Accident/Hospitalization in the last 5 Years?	11%	11%	13%
Unemployment in the past 5 Years?	7%	7%	9%
Faced natural disasters in 5 Years?	<1%	<1%	<1%
N	10,257	5,990	4,267

Univariate average sample characteristics of 'Oportunidades' eligible respondents and bivariate statistics by program participation status are presented in table 4.2.2. About 7% of the sample are current beneficiaries of Oportunidades. This number looks lower compared to national averages (of one in six) because our sample includes adults aged 18 or older only and national samples include children who make up the majority of the program beneficiaries. Program participants have lower vegetable/fruit consumption as well as lower junk food consumption. This might be because people choose to be in the program as they need additional income but they might just be able to stretch their income only slightly for fresh foods which are costlier than packaged goods. Lower junk food consumption may be related to the fact that most of the participants are rural or semi-urban (small town) residents where junk food prevalence is lower compared to urban areas. Most participants are female as the program targets women, specifically pregnant or lactating mothers and household food decision makers. The majority of the participants have lower education levels, lower employment and more likely to be married. In terms of assets, there seems to be no difference (and we do not have income data for the whole sample). Note that in terms of sample size, our participant sample is small (n=409) compared to eligible non-participants (n=5,462) which is our control group.

Table 4.2.2 Descriptive Statistics: 'Oportunidades' eligible population

	Pop. Means/ Per.	Oportunidades	
		Participants	**Non-Participants**
Program Participation		7%	93%
Outcome Variables			
Diet			
Veg/Fruits (times per week)	30	29	31
Cookie/Chips/Soda (days consumed per week)	6	6	7
Control Variables			
Age (years)	40	42	36
Sex			
Male	44%	24%	56%
Female	56%	76%	44%
Marital Status			
Single	24%	19%	36%
Divorced/Widowed	10%	10%	6%
Married	66%	71%	58%
Location			
Urban	38%	6%	40%
Semi Urban	23%	15%	24%
Rural	39%	79%	36%
Education			
No Education	11%	23%	8%
Primary or Less	39%	45%	34%
Secondary	26%	18%	27%
High School	14%	12%	17%
College	11%	2%	13%
Graduate	<1%	0%	<1%
Health Status			
Very Good	8%	4%	9%
Good	48%	41%	51%
Normal	41%	48%	36%
Bad	4%	6%	3%
Very Bad	<1%	<1%	<1%

	Pop. Means/ Per.	Oportunidades	
		Participants	Non-Participants
Asset Index	5	5	5
Currently Employed?	51%	28%	59%
Risk Categories			
Risk Neutral	7%	11%	7%
Risk Taker (Lowest)	2%	2%	2%
Risk Taker(Low)	9%	11%	10%
Risk Taker(Fair)	43%	40%	43%
Risk Taker (High)	6%	5%	5%
Risk Taker(Highest)	33%	32%	34%
Permanent Migration?	10%	5%	10%
Shocks			
Serious Accidents?	9%	5%	9%
Serious Health Problems in Last 4 Years?	13%	13%	11%
Death in the family in the last 5 Years?	9%	7%	9%
Major Disease/Accident/Hospitalization in the last 5 Years?	12%	15%	12%
Unemployment in the past 5 Years?	7%	8%	7%
Faced natural disasters in 5 Years?	<1%	<1%	<1%
N	10,257	409	5,462

4.4.3 Statistical Methods

All analyses are conducted using Stata 12. The analytical sample includes 179,070 observations on approximately 17,900 individual adults (age>=18 years). Here each individual has multiple observations (1-10 per individual) as they make up to 10 choices as described earlier. The variables used in the analyses are checked for missing values in order to rule to out any systematic patterns of missing data. As the data on most of the variables included in the regression analyses are missing for only a small number of cases and are determined to be missing completely at random, these data are not imputed and the regression analyses use the default option of list-wise deletion of incomplete cases. The variables are also tested for multi-collinearity to ensure that the model is parsimonious. We employ a cluster level correction for standard errors to adjust for with-in subject correlations.

To test hypothesis 2.a., we fit the logistic function (equation 4.5) by using non-linear regression procedure to estimate exponential, hyperbolic and quasi-hyperbolic discount functions (equation 4.5). Then, we repeat the same by including demographic variables which influence the discount rate r and present-bias β. We test the model fit by comparing adjusted R^2, AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) of these models. We conduct several sensitivity analyses in order to test for the robustness of the model. First, we conduct the same analysis among people who have the highest rates of discounting only as they are the population that seem to have worse health behaviors (as concluded in chapter 3) and hence of specific interest. Next, we impute the choice variable as follows to increase the sample size per individual. The survey questionnaire asks the respondents a set of questions with smaller sooner and larger later rewards; as soon as the respondent switches from choosing the smaller sooner reward to wait for a larger reward, the questionnaire moves on to next section rather than going through all the rest of the larger reward choices. As described earlier, we code this as ‘choice=0’ and rest of the skipped reward rows as ‘choice=.’ as those questions are not asked. This original formulation results in 10 or less choices per individual. Now, we recode the rows where ‘choice=.’ to ‘choice=0’. This is justified by assuming that people who, for example decide to wait for 1,500 pesos would also wait for 2,000 pesos if it were offered. Doing so would increase the sample size and also sample size at an individual level to 10 rows per individual.

Next, to test hypothesis 2.b., we use logistic regression for dichotomous outcome measures (physical activity (yes/no), current or ex-smoker (yes/no) and quit smoking (y/n)) and OLS for continuous outcome measures (minutes of physical activity, number of times vegetable/fruits consumed per week and number of times chips/soda/cookies are consumed per week). To test hypothesis 2.c., we use OLS regression as the outcome diet measures are continuous.

4.5 Results

4.5.1 Results for Hypothesis 2.a.

We are unable to estimate the quasi-hyperbolic model due to having only 10 or fewer observations per individual, which makes model convergence problematic. While the models converge when the convergence criterion is relaxed (to converge at 0.1 as opposed to the default value of 10^{-5}), the results are sensitive to initial values of beta; slightly different initial values of beta yield very different parameter estimates. This might be due to the inherent problem with non-linear regression where different initial values might converge at different local minima of the non-linear curve leading to widely different estimates. We were unable to find initial values of beta which are less than 1[19] that would yield consistent estimates. Keeping beta as a free parameter yields results that are unreliable with no standard error estimates. Hence, we report estimates from exponential and hyperbolic discounting models only (table 4.3.1 – models 1 & 2). Next, we show the results of model comparisons where we allow the discount rate r to depend upon demographic variables (table 4.3.1 – models 3 & 4). Note that we use a subset of

[19] Values of β are estimated in literature to be between 0.2 - 0.8 (Frederick, S., G. Loewenstein, et al. (2002). "Time Discounting and Time Preference: A Critical Review." Journal of Economic Literature **40**(2): 351-401.

demographic variables from chapter 3 which are statistically and conceptually significant; this is because including all the demographic variables results in model non-convergence.

Selecting the Best Model

The R^2 which is typically interpreted as the proportion of variance explained the model is commonly used as an indicator of a statistical model's goodness-of-fit. Hence, most of the previous literature utilizes it for discounting model selection with the premise that model that produces the highest value of R^2 fits the data best (Bickel and Marsch 2001; Odum, Madden et al. 2002; Komlos 2004; Smith, Bogin et al. 2005; Epstein, Salvy et al. 2010; Tanaka, Camerer et al. 2010; van der Pol and Cairns 2011). This approach is, however, problematic when applied to results from non-linear regressions albeit unacknowledged by many previous studies cited above. This is because, by definition[20] R^2 for a linear regression cannot be negative as SSE for the mean represents the maximum SSE for the model. However, for nonlinear models it is not necessarily the case and negative R^2 values are possible for such models (Motulsky and Christopoulos 2003; Johnson and Bickel 2008). Hence, it has been argued that when applied to non-linear regression R^2 does not provide any clear meaning. Nonetheless, we report R^2 for readers' reference. We also report root mean squared error (RMSE) which has been used to compare models (Kirby and Santiesteban 2003). Here, however, the RMSE is not helpful in discerning the better model as the RMSE value for all the models is the same (0.310) in our analysis.

The AIC (Akaike Information Criterion) or BIC (Bayesian Information Criterion) are other model fit statistics that are used to compare non-nested models resulting from non-linear

[20] $R^2 = 1 - (\frac{SSEmodel}{SSEmean})$, where SSE is the sum of squares errors

regressions[21] (Johnson and Bickel 2008; StataCorp 2009). AIC[22] does not depend upon the sample size, but on the number of parameters estimated (which is same in all the models). BIC depends on the sample size as well as on the number of parameters estimated. While AIC and BIC do not claim to indicate the 'true model', they are used to rank-order the candidate models. The model with the least AIC (or BIC) is first selected and a difference in AICs of the other candidate models and the model with minimum AIC (AIC_{min}) are calculated as: $\Delta_i = AIC_i - AIC_{min}$, where AIC_i is the AIC of the ith model. Then, if $\Delta_i <= 2$, the ith model has substantial support in the data; if $2 < \Delta_i < 7$, then the ith model has weak support in the data and if $\Delta_i > 10$, then that model has essentially no support in the data (Burnham and Anderson 2004). BIC is used in a similar fashion (Raftery 1995). However, increasing the number of explanatory variables reduces AIC and BIC (as it increases the log-likelihood). Hence, we compare models without and with demographic explanatory variables separately. The absolute values of AIC are large which is due to the nature of scaling in the data used, which results in a large log-likelihood number. With the absolute numbers being large, a difference of 2 or 10 might seem trivial. But large AIC values contain large scaling constants, while the differences in AIC would get rid of the scaling constant. Hence, only the difference in AIC is interpretable (Johnson and Bickel 2008) and hence, we use that differences to compare models. Similar explanation applies also to BIC.

Between the first 2 models in table 4.2.1, the exponential model (model 1) has the lower AIC, which indicates that it is the best fit model among the models tested here. However, the difference between the exponential model's AIC and that of the hyperbolic model (model 2) is 1

[21]These are commonly used in Statistics, Biostatistics and Psychology; it is used in some of the discounting model comparison

[22] AIC = -2LL+2k, where LL = log-likelihood and k is the number of parameters estimated.

and hence, we can say that hyperbolic model also has substantial support in the data. Comparing BICs yields the same conclusion. Between the models 3 & 4 in table 2, the difference in AIC's is 4 where exponential model (model 3) has the lower AIC. Then, by applying above criteria, we can conclude that hyperbolic model (model 4) has 'weak' support in the data. Again, BIC comparison supports the same conclusion. We can also see that being female, being better educated and being employed are all associated with lower discount rates in both models, which is in agreement with the results from chapter 3. Including demographic variables results in smaller corresponding discount rates for both exponential and hyperbolic models. This is consistent with the expectation that the demographic variables explain some of the variability in choice of a discount rate, while making conceptual sense. Hence, the models 3 & 4 which include demographic variables are preferred. However, even in that case, we cannot conclusively choose between the exponential and hyperbolic models. While exponential model (model 3) has lower AIC and BIC numbers, the hyperbolic model (model 4) has weak support in the data and cannot be rejected. Hence, we cannot reject the null hypothesis that both models are supported by data.

Table 4.3.1 – Comparison of Discounting Models

	Model 1 (Exponential)	Model 2 (Hyperbolic)	Model 3 (Exponential)	Model 4 (Hyperbolic)
Constant	0.379***	0.379***	0.379***	0.379***
	(0.001)	(0.001)	(0.001)	(0.001)
Noise μ ($*10^{-6}$)	0.000***	0.000***	0.000***	0.000***
	($1.04*10^{-6}$)	($1.04*10^{-6}$)	($1.06*10^{-6}$)	($1.06*10^{-6}$)
Discount Rate r	0.216***	0.304***	0.202***	0.283***
	(0.003)	(0.006)	(0.033)	(0.060)
Female			-0.003	-0.003
			(0.009)	(0.017)
Education			-0.028***	-0.051***
			(0.004)	(0.007)

Location			-0.004	-0.008
			(0.005)	(0.009)
Health Status			0.007	0.013
			(0.006)	(0.011)
Employed			-0.030***	-0.053**
			(0.009)	(0.017)
Asset Index			0.013**	0.023**
			(0.004)	(0.008)
R-Squared	0.016	0.016	0.017	0.017
Root MSE	0.3	0.321	0.320	0.320
BIC	84031	84033	81746	81750
AIC	84002	84003	84657	84661
N	149,248	149,248	145,945	145,945

*** p<0.05, ** p<0.01, *** p<0.001**

Sensitivity Analyses

We conduct several sensitivity analyses in order to test for the robustness of the above conclusion. First, we conduct the same analysis among people who have the highest rates of discounting only as they are the population that seem to have worse health behaviors (as concluded in chapter 3) and hence of specific interest. The results are presented in table 3 (models 5 & 6). The AIC and BIC values between the models differ by 6 with exponential model having the lower values. This indicates that while exponential model is the better model, there is weak support for hyperbolic model, a conclusion which is in accordance with earlier conclusions, even among people with highest discounting rates in this sample.

Next, we impute the choice variable to increase sample size as described in statistical methods section. Results of this estimation of exponential and hyperbolic models with demographic variables is shown in table 3 (models 7 & 8). Comparing these models as before, shows that the AIC values differ by 13 points and BIC values by 12 points with exponential model having the smaller ICs. These results indicate that the hyperbolic model does not have support when the data are imputed as described here and that exponential model is preferable with this data. This result in contrast to previous results points to exponential model as the better choice, which only makes the above conclusion mode confusing. However, this result is not completely surprising as the imputation hinges on the assumption that people make rational choices of larger later rewards when the amounts are larger than the amounts described here. The imputed data with potential to make infinite number of such imputations confirms the hints in literature that at very large choice sets where the choices are given in a monotonically increasing fashion, the discounting rates tend to be larger and conform to exponential modeling (Frederick, Loewenstein et al. 2002). However, this conclusion does not help in adding conclusive evidence on deciding on a better model, as we expected from this analysis.

Table 4.3.2 – Sensitivity Analysis: Discounting Models

	Highest Discounting Category Only		**Imputed Choice**	
	Model 5 (Exponential)	**Model 6 (Hyperbolic)**	**Exponential**	**Hyperbolic**
Constant	0.290***	0.290***	0.232***	0.232***
	(0.001)	(0.001)	(0.002)	(0.002)
Noise μ (*10)	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Discount Rate r	0.197***	0.267***	0.211***	0.303***
	(0.018)	(0.033)	(0.024)	(0.047)
Female	-0.004	-0.007	-0.018**	-0.036**
	(0.005)	(0.009)	(0.007)	(0.013)
Education	-0.002	-0.004	-0.009***	-0.019***
	(0.002)	(0.004)	(0.003)	(0.005)
Location	0.000	0.001	0.000	0.000
	(0.002)	(0.005)	(0.003)	(0.007)
Health Status	-0.001	-0.002	-0.007	-0.015
	(0.003)	(0.006)	(0.004)	(0.009)
Employed	-0.002	-0.004	-0.015*	-0.028*
	(0.005)	(0.009)	(0.007)	(0.013)
Asset Index	0.005*	0.009*	0.014***	0.026***
	(0.003)	(0.005)	(0.003)	(0.006)

Adj. R-Squared	0.272	0.275	0.067	0.067
RMSE	0.334	0.334	0.426	0.426
BIC	12605	12611	197588	197601
AIC	12534	12540	197498	197510
N	19,464	19,464	174,810	174,810

*** p<0.05, ** p<0.01, *** p<0.001**

Based on the above analysis, we conclude that while exponential model has better support in the data, hyperbolic model cannot be ruled out. Hence, we cannot affirm the hypothesis 2.a, nor can we refute it. Hence, we conclude that while the data supports time-consistent time discounting, there is also a weak support for time-inconsistent discounting.

4.5.2 Results for Hypothesis 2.b.

Based on the above analysis, we conclude that while exponential model has better support in the data, the hyperbolic model cannot be ruled out. So going forward, we utilize components from both models to test hypothesis 2.b. The discount rates are calculated using the exponential model (model 3); to accommodate for the hyperbolic discounting, we include an indicator variable (as discussed in the variables section). The mean short-term (monthly) discount rate is 35% and mean long-term discount rate is 2%. About 58% of the sample are hyperbolic discounters (with short-term discount rate > long-term discount rates). The results from the regression analysis of health behaviors are shown in table 4.4.

As discount rates increase, the odds of being physical active decrease slightly (OR=0.99, p<0.01) and hyperbolic discounters have lower odds of having regular physical activity (OR=0.9) as expected. Women have lower odd of exercising, and so are people living in rural and semi-urban areas. Higher levels of education are associated with increased odds for exercising. Among people who exercise, the minutes of exercise decreases as discount rates increase (a 4 minute decrease per day for 10% increase in discount rate). The number of minutes of physical activity decrease is larger in hyperbolic discounters compared to people with time-consistent preferences. All these results are statistically significant at 5% (except being a hyperbolic discounter), though the magnitudes are smaller.

Results on diet measures are mixed. Vegetable and fruit consumption decreases as discount rates increase but hyperbolic discounters have slightly more fruits and vegetable intake which is contrary to hypothesis. These results for vegetable/fruit consumption are not statistically significant. Again contrary to hypothesis, junk food consumption is slightly lower with higher discount rates. Magnitude of this is very small but it is statistically significant. On the other hand, hyperbolic discounters have more junk food consumption but it is not statistically significant. Households where women make food-related decisions consume more vegetable and fruits. Interestingly, as education levels increase junk food consumption decreases, with the exception of people with high school education who consume more junk food compared to people with no education. This might be related to increased incomes associated with higher education levels which might make one have access to extra income to purchase fashionable junk foods in Mexico. Then again as education above high school might make people more aware of consequences of eating such foods as well as make them put above the threshold to be able to comfortably afford fresh foods which tend to be expensive (in terms of pesos/calorie) in Mexico similar to the U.S. This is also substantiated by the above analysis where results show that education is positively correlated with more fruits/vegetables consumption as expected.

As discount rates increase people are less likely to quit smoking (OR=0.99, $p<0.05$) and but there is not an effect on being a current smoker (OR=1.00). Results for hyperbolic discounting are also small and not statistically significant.

Table 4.4 – Regression Results: Discount rates and Hyperbolic Discounting on Health Behaviors

Regression Results: Discounting Rate & Hyperbolic Discounting on Health Behaviors						
	Exercise (Y/N)	**Exercise (mins/day)**	**Veg/Fruits (week)**	**Junk (week)**	**Current Smoker**	**Quit Smoking**
	OR/SE	Coeff./SE	Coeff./SE	Coeff./SE	OR/SE	OR/SE
Short-term discount rate	0.995*	-0.365**	-0.010	-0.010**	1.003*	0.992*
	(0.002)	(0.138)	(0.009)	(0.003)	(0.002)	(0.003)
Hyperbolic Discounter	0.896	-0.073	0.530	0.198	0.810	1.031
	(0.083)	(8.319)	(0.517)	(0.198)	(0.091)	(0.179)
Age	1.006	-0.527	0.056**	-0.031***	0.993	1.021**
	(0.003)	(0.293)	(0.019)	(0.007)	(0.004)	(0.007)
Female	0.754**	-3.026	4.918***	0.056	0.243***	1.29
	(0.081)	(9.886)	(1.311)	(0.447)	(0.035)	(0.291)
Education (ref: no education)						
Primary or less	3.660***	-32.428	1.489*	0.675*	0.767	1.979*
	(0.956)	(30.206)	(0.715)	(0.276)	(0.141)	(0.614)
Secondary	7.506***	8.774	1.926*	0.927**	0.946	1.757
	(2.059)	(24.993)	(0.854)	(0.329)	(0.200)	(0.609)
High school	9.185***	4.127	3.058**	1.386***	1.098	1.792
	(2.624)	(25.479)	(1.016)	(0.411)	(0.258)	(0.696)
College	11.871***	2.962	6.783***	0.864	0.732	1.637
	(3.404)	(26.202)	(1.224)	(0.476)	(0.190)	(0.686)
Graduate	23.174***	-30.773	1.473	0.541	0.83	0.882
	(12.152)	(25.989)	(11.095)	(1.387)	(0.562)	(1.030)
Location (ref: rural)						
Semi-urban	0.719**	-1.918	-0.109	-0.502*	0.676**	0.68
	(0.077)	(8.977)	(0.585)	(0.233)	(0.089)	(0.161)
Urban	0.525***	-1.975	-2.960***	-0.469*	0.520***	0.89
	(0.059)	(9.154)	(0.534)	(0.207)	(0.067)	(0.182)
Health Status (ref: very good)						
Good	1.208	28.520*	-0.849	0.272	0.716	1.06
	(0.217)	(11.108)	(1.004)	(0.417)	(0.135)	(0.329)
Normal	1.419	39.291***	-1.207	-0.286	0.831	1.183
	(0.262)	(11.812)	(1.004)	(0.417)	(0.160)	(0.379)
Bad	0.93	35.834	-4.099**	-0.25	0.559	2.836*
	(0.287)	(22.612)	(1.360)	(0.543)	(0.200)	(1.386)
Very bad			-6.997	2.21	0.641	4.37
			(4.732)	(2.148)	(0.685)	(5.585)
Employed	0.904	19.748	1.121*	0.189	1.481**	0.78

	(0.094)	(10.527)	(0.528)	(0.209)	(0.221)	(0.162)
Asset Index	0.995	6.809*	-0.585*	-0.262**	1.141*	0.814*
	(0.049)	(3.122)	(0.242)	(0.097)	(0.071)	(0.078)
Married	1.053	7.321	2.151**	0.244	1.043	0.955
	(0.151)	(13.453)	(0.693)	(0.266)	(0.193)	(0.272)
Risk taking level (ref: neutral)						
Lowest	0.713	9.316	-1.544	-0.122	0.804	3.423*
	(0.254)	(16.236)	(1.638)	(0.691)	(0.320)	(2.048)
Low	1.07	17.164	-0.595	-0.16	1.129	1.792
	(0.228)	(15.304)	(0.980)	(0.402)	(0.280)	(0.800)
Fair	0.851	19.382	-0.483	0.274	0.863	1.544
	(0.153)	(11.658)	(0.770)	(0.338)	(0.181)	(0.627)
High	1.035	19.291	-0.143	0.299	0.822	2.493
	(0.250)	(15.008)	(1.192)	(0.487)	(0.242)	(1.227)
Highest	1.201	18.225	-1.031	0.467	0.775	1.793
	(0.217)	(11.047)	(0.794)	(0.345)	(0.167)	(0.739)
Had accident?	1.333*	16.666	2.317*	0.032	1.382*	1.609*
	(0.178)	(12.135)	(0.922)	(0.360)	(0.203)	(0.335)
Permanent migration	1.026	-24.975**	-1.167	-0.081	1.053	1.714*
	(0.140)	(9.346)	(0.771)	(0.322)	(0.170)	(0.414)
Death in family	1.052	5.141	0.115	0.34	1.169	0.963
	(0.162)	(16.771)	(0.812)	(0.313)	(0.216)	(0.279)
Illness	1.134	-10.16	0.044	-0.431	0.963	1.226
	(0.147)	(10.550)	(0.704)	(0.278)	(0.160)	(0.291)
Recent job loss	1.292	6.999	-0.53	0.088	1.407*	0.823
	(0.191)	(10.631)	(0.861)	(0.339)	(0.245)	(0.222)
Natural disasters	0.922	-35.152*	0.151	1.355	2.481*	0.549
	(0.484)	(13.973)	(2.790)	(1.010)	(1.148)	(0.423)
Constant	0.031***	19.18	25.636***	8.335***	0.140**	0.32
	(0.018)	(42.215)	(2.763)	(1.090)	(0.095)	(0.296)
N	6,489	764	3,018	3,018	6,489	833

*** p<0.05, ** p<0.01, *** p<0.001**

4.5.3 Results for Hypothesis 2.c.

The results from the regression analysis of diet measures are shown in table 4.5 and the marginal means over the interactions are shown in table 4.6. From table 4.5, we can see that the interaction of hyperbolic discounting and program participation is not statistically significant, still, people who participate in 'Oportunidades' and who are hyperbolic discounters eat slightly more fruits and vegetables (b=1.3) and less junk food (b=-1.7) compared to people who are non-participants and non-hyperbolic discounters.

Table 4.5 – Regression Results: Oportunidades Participation & Hyperbolic Discounting on Diet

Regression Results: Oportunidades Participation & Hyperbolic Discounting on Diet		
	Veg/Fruits (/week)	**Junk (/week)**
	Coeff./SE	Coeff./SE
Oportunidades Participation	0.865	-0.645
	(1.148)	(0.437)
Hyperbolic Discounter	3.969	-1.726*
	(2.177)	(0.855)
Interaction of Oportunidades*Hyperbolic Discounting	1.288	-0.703
	(1.422)	(0.586)
Short-term discount rate	0.007	-0.007
	(0.002)	(0.006)
Age	0.039	-0.034**
	(0.031)	(0.012)
Female	5.183*	-0.095
	(2.619)	(0.811)
Education (ref: no education)		
Primary or less	3.383**	0.954*
	(1.110)	(0.439)
Secondary	4.581**	1.160*
	(1.447)	(0.586)
High school	3.693*	1.535*
	(1.762)	(0.718)
College	8.365***	0.900
	(2.019)	(0.886)
Location (ref: rural)		
Semi-urban	0.581	-0.040
	(1.086)	(0.442)
Urban	-2.719**	0.087
	(1.019)	(0.411)
Health Status (ref: very good)		
Good	0.291	0.755
	(1.582)	(0.731)
Normal	0.216	0.575
	(0.611)	(0.736)
Bad	-4.104	-0.968
	(2.300)	(0.921)
Very bad	2.038	-0.167
	(4.331)	(2.803)
Employed	2.012*	0.40
	(1.023)	(0.411)
Asset Index	-0.468*	-0.275
	(0.401)	(0.157)
Married	-0.067	0.189
	(1.726)	(0.677)
Risk taking level (ref: neutral)		
Lowest	1.754	1.343

	(3.435)	(1.391)
Low	1.093	1.186
	(1.696)	(0.661)
Fair	-0.080	1.182*
	(1.290)	(0.533)
High	2.186	1.548
	(2.374)	(0.890)
Highest	-0.911	0.897
	(1.324)	(0.549)
Had accident?	2.022	-0.284
	(1.669)	(0.645)
Permanent migration	-1.294	0.174
	(1.226)	(0.561)
Death in family	1.402	0.793
	(1.548)	(0.620)
Illness	-0.591	-0.670
	(1.155)	(0.504)
Recent job loss	-0.698	-0.390
	(1.617)	(0.605)
Natural disasters	2.630	2.113
	(3.866)	(1.093)
Constant	22.491***	7.582***
	(4.835)	(1.795)
N	851	851

*** p<0.05, ** p<0.01, *** p<0.001**

From table 4.6, we can see that 'Oportunidades' participation increases vegetable/fruit consumption and decreases junk food consumption. However, these differences are very small and not statistically significant. When we compare the interaction terms, we see that program participation is associated with more fruits/vegetable consumption and less junk food consumption among hyperbolic discounters, which is as expected by hypothesis 2.c. However, the differences are very small and not statistically significant.

Table 4.6 – Marginal Means: Regression of Oportunidades Participation & Hyperbolic Discounting on Diet

	Veg/Fruits (per week)		Junk Food (per week)	
	Margin	Std. Err.	Margin	Std. Err.
Oportunidades				
0	30.501	0.424	6.532	0.173
1	31.663	0.898	6.098	0.385
Hyperbolic Discounting				
0	30.527	0.909	6.707	0.343
1	30.776	0.419	6.376	0.174
Interaction Oport*Hyp				
0 0	29.832	1.022	7.031	0.386
0 1	30.697	0.475	6.387	0.195
1 0	33.528	1.933	5.305	0.759
1 1	31.120	0.985	6.328	0.429

4.6 Discussion

4.6.1. Hyperbolic Discounting and Health Behaviors

We are unable to assess present bias due to lack of sufficient data points at an individual level. We find some support in data for both exponential and hyperbolic models. While we cannot reject the hypothesis that exponential model is inferior to hyperbolic model in terms of explaining observed discount rates, we cannot confirm that hyperbolic models fare better. Hence, this part of the study is inconclusive. This might be due to the fact that we do not have sufficiently granular data to fit either models. Nevertheless, the non-linear regression results for these models are robust to most of the sensitivity analyses which makes us more confident about the above conclusion. Non-linear regression is one of the most flexible methods that can be used to compare model fits of models based on different non-linear functional forms. Hence, the use of non-linear regression in the context of health behaviors would add to the literature by being one of the few studies using the method and possibly leading the way for further studies.

While theoretical premise of quasi-hyperbolic and hyperbolic models have gained traction over the past decade, there are only a handful of studies that confirm theory in population level field studies. Most of the theory is developed by simulation studies that are based on small sample base cases (such as 30-50 observed data points from students or volunteers). One of the larger field study of discount rates of Vietnamese farmers by Tanaka, Camerer and Nguyen (Tanaka, Camerer et al. 2010) is a rare anomaly. This study still includes only about 600 individuals. Because of this sample size, the study is able to collect about 75 data points per individual, thereby, estimating stable models. (They find evidence for quasi-hyperbolic discounting.) This study is based on an extensive field experiment rather than on a sample survey which is the basis for our study. The field experiment model is definitely a huge improvement over simulation or small sample lab studies, but still limited to a few villages rather than a nationally representative sample. Collecting such granular data is required for stable model estimation, but it is harder and expensive to do via sample surveys. Future studies could potentially employ a hybrid approach, where a national sample survey could be used as a basis to select representative manageable samples for whom the field experiment can be administered. Then, combining survey data and field experiments, we can potentially conduct more realistic simulations to study discounting behaviors at a population level.

The results for physical activity measures indicate hyperbolic discounters showing worse behaviors, but these results are not statistically significant. While we do need better measures for discounting as discussed above, the weak results indicate that hyperbolic discounting behavior might make people postpone or not start exercising. Further, with higher discount rates, they are at a relatively high disadvantage for starting or maintaining such behaviors.

We do not find support for a statistically significant relationship between diet measures and hyperbolic discounting. As discussed in chapter 4, diet questionnaire has detailed questions on fruits and vegetable consumption and less number of questions on junk food consumption. This might result in people (irrespective of discounting profiles) answering positively to healthy food consumption as that is the socially desired behavior which is also reinforced by the survey instrument itself. This social desirability bias might be at play with reporting junk food consumption. We know is that at a population level people tend to project healthier eating behaviors. Although we do not have any specific evidence pertaining to Mexico, it is not completely unreasonable to expect such bias in Mexico also. However, we do not have any support in literature about whether hyperbolic discounters report it any differently than others, but we can expect them to behave in a manner similar to others in the absence of specific contradicting evidence. This bias along with smaller sample sizes for smoking measures might be the cause of non-significant results on smoking behaviors. While smoking studies in literature show that hyperbolic discounters have worse smoking behaviors, these studies are extremely small sample studies (n~30) and do not measure discounting with gamble-type questions; many of them use a single question to measure discounting but have more detailed measures for smoking (Frederick, Loewenstein et al. 2002; Odum, Madden et al. 2002; Johnson and Bickel 2008). Our survey instrument has information on years of smoking and number of cigarettes, but the sample size for those questions is small to be able to estimate any of the above models. Hence, such comparison should be done with caution and further studies should include detailed questions on smoking behaviors for a larger sample.

4.6.2. Hyperbolic Discounting and Oportunidades

Our results for participation in Oportunidades indicates that the program has some benefits among hyperbolic discounters as hypothesized. However, again, small sample sizes of program participants could be one of the reasons for the results to be non-significant. While many external evaluations have sung praises of the program among all participants, it is encouraging to know that program participation decreases junk food consumption, specifically among hyperbolic discounters. This result if substantiated with further studies, could inform designing programs for people who might not be part of Oportunidades currently.

4.6.3 Limitations

The above method of calculating present bias has all the inherent deficiencies associated with hypothetical gambles method (Frederick, Loewenstein et al. 2002) some which were described in chapter 4. As described earlier, not having many more data points make the measurement of discount rates less accurate or rough, while it is still an improvement over the implicit discount rates measured in chapter 4. The questionnaire asks questions in a sequence of monotonically increasing rewards and delays. The questions for 1-month delay are asked before the questions for the 3-year delay. A rational respondent would be reasonably expected to recognize this pattern and potentially decide to wait longer when it comes to second set of questions with a 3-year delay. This behavior would result in estimating low long term discount rates and hence, lower estimates for hyperbolic discounting. If this is the case, we might be underestimating the hyperbolic discounters which might potentially lead to insignificant results. To avoid this, future surveys should utilize a ‘titration’ procedure, which would mix and match time delays and rewards and ask questions by avoiding particular patterns of increasing or decreasing delays or rewards. Such titration procedures would also help in recognizing inconsistent responses. However, this type of procedure would be successful with more questions as smaller set of questions might still be guessable. Hence, future surveys should be built on a careful trade-off for survey costs in terms of money and time, as well as accuracy of data collected and they should consider adapting hybrid approaches as discussed earlier.

Not having the measure for income is another limitation as this data are missing systematically for women and rural residents. While asset index is a reasonable measure, it measures rural assets better than assets of urban dwellers who may rent a house but may have a better income. This results in not capturing income effects in the regressions, which is highly influential in determining discount rates as well as in determining health behaviors such as smoking or junk food consumption.

4.6.5 Broader Implications for Policy

Short term commitment devices such as the Oportunidades program are expected to help people overcome present bias or hyperbolic discounting. While such options are utilized to address savings problems around the world (Ashraf, Karlan et al. 2006), similar programs to address health behaviors are not common. Our study indicates that same paradigm might be at play when it comes to the success of Oportunidades. While many of the beneficiaries of Oportunidades benefit due to increased cash flow as well from the premise of commitments that go along with it, we explore the same question to understand whether the success of the program is because it holds people back from making unfortunate decisions. Such decision can stem from a monetary necessities or ignorance, but also from impulses to take shortcuts. It is the latter mechanism that we explore in this study and find some evidence for it. Such decision making paths lead to worse health behaviors among all people. While we need to refine our measurement of discounting and expand to include more Oportunidades participants and their program related outcomes, we find some evidence that Oportunidades helps in alleviating worse health behaviors. Further, we can conclude that having access to ‘Oportunidades’ type of programs might benefit people who fall out of the eligibility criteria but have similar decision making short comes.

Further, such programs might work not only in Mexico, but also in the United States. New York City under Mayor Bloomberg ran a program that was based on Oportunidades, called ‘Opportunity NYC’. While this pilot program from 2007-2010 produced moderate results by increasing dental checkup rates and savings, it had no effects on preventive care visits as those were already high in the Bronx neighborhood that is usually overloaded with social programs. But it is notable that such program produce positive outcomes in the U.S. also. While it may not be feasible to expand Oportunidades to all Mexicans or ‘Opportunity NYC’ to all of the United States, it might be beneficial to target programs to the most vulnerable. Further, considering the preponderance of free-market philosophy around the world, social entrepreneurs should take note to develop such products for the general public. Whether such programs are offered by governments for the most vulnerable for free or whether they are market-based services offered by the private sector, our study indicates that a large portion of the population that has time-inconsistent behaviors and suboptimal health behaviors would benefit from participating in such programs.

CHAPTER 5. REFERENCE DEPENDENCE, LOSS-GAIN ASYMMETRY AND HEALTH BEHAVIORS

In the previous chapters, we explore how time preferences influence healthy behaviors in terms of the magnitude (chapter 3) and the functional form (chapter 4) of time discounting. Time discounting as described by the traditional DU model provides a useful framework for analyzing how future utilities are weighted with respect to current utility. In order to explain time-inconsistent preferences resulting from higher short-term discounting compared to lower long-term discounting, alternate functional forms of the discount function such as hyperbolic discounting are adapted. These models predict utility in future periods as being discounted by a discount function that is either time-consistent (exponential) or time-inconsistent (hyperbolic). The common theme here is that these models describe the role of the weights (i.e. discount function) attached to the utility function in shaping future utility streams [please refer to the discount function D in equation 3.1: $U_T = \sum_{\tau=t+1}^{T} D_\tau \,.\, u(h_\tau, Z_\tau)$]. However, these changes to discounting function alone might not sufficiently explain differences in actual health behaviors. It is reasonable to postulate that the utility function itself might be influenced by factors other than investment and consumption which in turn might further explain heterogeneity in health behaviors. Hence, in this chapter we will combine several theories that enrich or modify the utility function to further understand decision making processes with regard to health behaviors.

Specifically, in this chapter we explore the postulation from Prospect Theory (Kahneman and Tversky 1979; Kahneman, Knetsch et al. 1991) that the marginal utility of a health behavior depends on the relative gain (or loss) from a reference point. We also investigate whether one's future expectations of health in comparison with that of his/her peers act as potential a reference point from which such utilities are assessed and whether hyperbolic discounting (i.e. having higher short term discount rate compared to long term discount rates) exacerbates the behavioral implications of the differences between losses and gains.

Finding the evidence for the postulation above would increase our confidence in advocating for health behavior interventions that take into account the role of peer influences, which can be designed and delivered in terms of loss-gain frames. Understanding the evaluation of behaviors in comparison to peers would help in targeting the groups of people who would benefit the most from such interventions.

5.1 Research Questions and Hypotheses

In this chapter, we will test the following hypotheses in order to examine the research question – "what constitutes the reference point from which losses and gains from health behaviors are assessed?" and examine whether social comparisons of health, hyperbolic discounting and their interaction would influence expected future health behaviors.

Research Question 3.A: Do social comparisons of health act as a reference point from which losses and gains from future health behaviors are assessed?

Hypothesis 3.a.1.: People whose perceived health status is worse than that of their peers are *less* likely to follow unhealthy behaviors in the future compared to people whose perceived health status is better compared to their peers, all else being equal.

Rationale – Suppose that a moderately overweight individual has peers who are without any glaring current health issues, but with sedentary life styles. Then, even if this overweight individual is aware of potential future health issues due to obesity, she may ignore them as long as she considers herself in comparable or better health than her peers. In other words, she does not have much to gain in terms of what is acceptable as good health; on the other hand, adapting better healthy behaviors would be a ‘loss’ in the short term due to the time required to be spent on physical activities or due to eating less desirable (albeit healthy) foods. On the other hand, if she considers her health to be inferior to those of her peers, she may be motivated to ‘gain’ better health by adapting healthier behaviors.

Research Question 3.B: Does hyperbolic discounting change behaviors differently in the loss domain compared to gain domain as assessed from the reference point of peer comparisons of health?

Hypothesis 3.b.1.: Compared to non-hyperbolic discounters, hyperbolic discounters whose perceived health status is worse than that of their peers are *less* likely to follow unhealthy behaviors, all else being equal.

Hypothesis 3.b.2.: Compared to non-hyperbolic discounters, hyperbolic discounters whose perceived health status is better than that of their peers are *more* likely to follow unhealthy behaviors, all else being equal.

Rationale – Hyperbolic discounting interferes with how future utility is assessed in loss domain compared to gain domain.

5.2 Conceptual Model

Prospect theory and its later modifications (Kahneman and Tversky 1979; Kahneman, Knetsch et al. 1991; Loewenstein and Prelec 1992) postulate that the utility function might be sensitive to whether the utility is construed as a loss or a gain in the future. This concept is used extensively to address message framing on health behavior intentions for a variety of health behaviors including cancer screening, physical activity and diet (Van Assema, Martens et al. 2001; Jones, Sinclair et al. 2003; Rothman, Bartels et al. 2006). Further, messages with gain frames are more likely to influence preventive behaviors such as skin cancer prevention, smoking cessation and physical activity as found in a meta-analysis of message framing (Gallagher and Updegraff 2012). However, analysis using loss-gain framing to understand actual health behaviors (rather than to message framing to influence health behaviors) is still an area for further exploration. Application of loss-gain framing to actual behaviors specifically to investment and savings behaviors including 401(k) and other retirement savings confirms that people are more sensitive to loss than to gains (Madrian and Shea 2001; Richard H. Thaler and Shlomo Benartzi 2004). Particularly, this theory was utilized by Thaler and Benartzi to the equity premium puzzle (where stocks have outperformed bonds over the last century by a surprisingly large margin as shown by empirical data) and their analysis has paved way to new insights into investment decision making. Their analysis which that incorporates a loss-gain paradigm explains this observed behavior by attributing it to the distaste of investors for short term losses. Insights from such analysis have resulted in adopting policies where savings is made the default option (Richard H. Thaler and Shlomo Benartzi 2004). Hence, such analysis applied to health behaviors themselves might help in informing policy and in developing innovative interventions.

Further, reference dependence paradigm derived from Prospect theory (Tversky and Kahneman 1991; Kőszegi and Rabin 2006; Kőszegi and Rabin 2007) considers the utility derived from a choice as consumption and reference utilities. This paradigm is used to analyze a number of real-life situations ranging from retirement planning to political choices (Tanaka, Camerer et al. 2010). While original Prospect theory advocates using the status quo as the reference point, it also alludes that expectations and experiences may shape the reference point from which losses and gains are assessed. However, it does not elaborate nor provide guidance on how to find such a reference point. Kőszegi and Rabin formalize the idea of the reference point by formulating a model of reference dependence where expectations about future, past experiences and social comparison act as reference point in the utility function (Kőszegi and Rabin 2006).

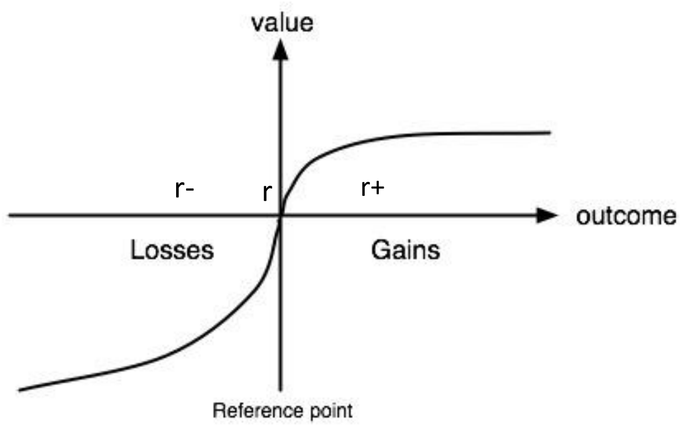
We have seen in earlier chapters that healthy behaviors are determined by the available consumption bundles (in terms of wealth, access or knowledge), as well as the investment aspect as described by Grossman model of Health Capital (Grossman 1972). Here, the model assumes that health behavior decisions are made in isolation which is impossible in practice. Charles Manski's influential article on social interactions (Manski 2000) recognizes three channels through which individual decisions are affected by social interactions – i) constraints in shared resources (e.g.: availability of only so many treadmills in a local gym) ii) expectations based on peer interactions or comparisons with peers (e.g.: discussion of pleasures from smoking or illness from smoking might modify behaviors) iii) actual preference modification by peers (e.g.: eating more in the company of friends and family). Literature related to health behaviors indicates that health behaviors follow these social interaction patterns - obesity is known to spread in social networks; adolescents who smoke are influenced by their peers to do so (Powell, Tauras et al. 2005; Christakis and Fowler 2007; Trogdon, Nonnemaker et al. 2008). It is also well known that obesity and sedentary life style trends are endemic at the national level with several states showing worse health behavior patterns than others. While there are many contributing factors such as advertising, sedentary jobs or easy access to cheaper foods, there seems to be some merit to the argument that we look to our peers as models in terms of setting expectations for our own future. (Note that much of the current literature on peer effects is concentrated on the effects of peers on habit formation among adolescents.) Such social comparison combined with how one expects to fare in future could be a potential reference point from which utilities are assessed.

From Prospect theory and reference dependence as described above, we postulate further that the investment and consumption utilities derived from health behaviors (while being discounted as discussed earlier) might be modified by utilities derived from social comparison with peers, or utility derived from the expectation of future or both. Combining the above paradigms, we can write the utility derived from a healthy behavior as a discrete sum of utilities from consumption (C), investment (I) and reference dependence (r) as follows:

$$U(I, C, r) = u(I) + u(C) + u(r \mid I, C) \quad \text{----} \ (5.1)$$

The last term above represents utility from a reference bundle given the consumption and investment levels. It is referred to as the 'gain-loss' utility (Kőszegi and Rabin 2006) and is assumed to satisfy the properties of Prospect theory's value function – an 'S' shaped function with the reference point being the point of inflection; gains are on the right side of the reference point (r) and losses are on the left (figure 5.1). The three main properties of this function are (Kahneman, Knetsch et al. 1991) – i) reference point - how the outcomes are evaluated depend upon how much the outcomes depart from the reference point and in which direction; ii) loss aversion – the function is steeper in the loss domain implying a loss is valued more than the same (absolute) magnitude of gain; and iii) diminishing sensitivity – marginal values of both losses and gains decrease with their size. The function is an asymmetric S-shaped function, concave above the reference point and convex below. From here it is evident that finding what would constitute the reference point is key to analyzing behaviors as losses or gains.

Figure 5.1: Value function - Adapted from Kahneman & Tversky (Kahneman and Tversky 1979)



In this chapter, we will combine the theoretical paradigms from Grossman model, Prospect theory and from Manski's theory of social interactions to explore how health behaviors are valued by individuals over time. Current interactions with peers (specifically comparisons of health) would influence investments into health which will translate to future health behaviors. Suppose that an individual is used to unhealthy habits (overeating, not exercising or not getting recommended preventive tests), but thinks that her health is better than her peers. Assume that such social comparison is her reference point from which she assesses her utilities; then her current health is already in the top right quadrant in the above figure (point r_+). Then, investing in health producing activities would move her to the right of point r_+. As she perceives her health to be already better than her reference point, the gains are smaller and hence, she will be better off if she invests her resources in an activity that produces a larger marginal gain. On the other hand, if she perceives her health to be worse than her peers (point r_- in the above figure), then investing in healthy activities move her towards her reference point r. This move towards r involves higher marginal gains compared to moving to the right of r_+. [In both cases, risk attitudes of the persons determine the level of uncertainty that they are willing to associate with the results of their actions.]

As we mentioned above, Prospect theory posits that the value function is asymmetrical with respect to the reference point and gains of equal size are valued less than losses of the same size due to the asymmetric S-shape of the value function (Kahneman, Knetsch et al. 1991). Applying this paradigm, the marginal gain from a health behavior is less for the people who consider themselves to be above their social reference point compared to the people who are below their reference point. For a person whose health is in the loss domain (lower left quadrant), a healthy behavior may result in a movement up the curve towards r; but as long as that movement is in the loss domain, the absolute change in utility is valued more compared to the same absolute change in the gain domain. Hence, one whose reference point is to the left of r is more likely to pursue health behaviors.

Hyperbolic Discounting –In chapter 3, we concluded that having a higher time discount rate is associated with worse health behaviors. In chapter 4, we further analyzed time discounting and conclude that while higher discount rates are associated with worse health behaviors, people who have high short term discount rates compared to long-term discount rates (i.e. hyperbolic discounters) have even worse health behaviors compared to people whose time discounting over long and short time horizons are the same (i.e. exponential discounters).

Hyperbolic discounting implies that choices would be time-inconsistent. In other words, a choice that appears to be have a high value in the future due to low discount rates, does not appear equally attractive in the short term due to higher discount rate for the short term. This discrepancy in valuation implies that future health behaviors might look more attractive than current health behaviors. Hence, we expect hyperbolic discounters to attach higher value to future healthy behaviors and in turn, forecast following healthy behaviors to a larger extent.

While we acknowledge the influence of all the variables discussed in earlier chapters, we expect hyperbolic discounting to cloud judgments further in the 'loss-gain' model as losses are discounted more than gains according to Prospect theory. If we expect people to follow better health behaviors in the loss-domain to prevent their losses (as reasoned above), we can expect hyperbolic discounters to project having even better future behaviors than non-hyperbolic discounters as the difference between short and long term discount rates are larger for them than for the non-hyperbolic discounters.

Similarly, in the gain domain, we expect people to follow healthy behaviors to a lesser extent as they have less to gain from such behaviors. Here, we can expect hyperbolic discounters to attach even lesser value to such future behaviors as the difference between present and future values are larger for them and they have even less to gain. Hence, we expect them to project worse future health behaviors than non-hyperbolic discounters.

Current Health Behaviors - In addition, current health behaviors have some influence on future health behavior expectations as they might develop as habits that continue into future. A sophisticated individual might recognize them as a problem (in case of unhealthy behaviors) and project future behaviors as 'aspirational' or 'desirable' behaviors. On the other hand, a naïve individual might continue with unhealthy lifestyles which might have become habits that are hard to break (such as smoking or overeating). So current health behaviors and a desire to change them would influence future health behavior expectations.

Other factors - In chapter 3, we discuss how a number of factors such as age, gender, current health status, education, employment, health shocks, risk attitudes etc. influence health behaviors and here we predict that the same factors influence future health behavior expectation in the same way [please see chapter 3 for detailed description of these factors].

5.3 Study Design

5.3.1 Data

Please refer to Chapter 3.2.1 for a detailed account of the data and the analytical sample.

5.3.2 Variables

Dependent Variable

The dependent variable, future health behavior, is a continuous variable derived from the survey question – "How probable it is that you will consume high amounts of fatty foods in the coming year?" The answer ranges from a probability of 0% to a 100%.

Independent Variables

Health status compared to others – The independent variable is the health status of the respondent in comparison to peers. This is measured based on answer to the question "If you compared your health to others of same age and gender, would you say your health is (..)?". The answers are chosen as one of the options - "much worse, worse, same, better and much better". Hence, the independent variable is measured as a five-level Likert-like ordinal scale.

Hyperbolic discounting – Hyperbolic discounting is a binary categorical variable. It constructed using the discount rates calculated in chapters 4 and 5. If the short term discount rate is larger than the long term discount rate then that individual is considered to be a hyperbolic discounter.

<u>Other RHS Variables</u>

Body Mass Index (BMI) – As the outcome is an eating behavior in the future, we can expect that people who have different current weights might decide to follow different health behaviors, we include BMI as a control variable.

Physical Activity – Physical activity is a dichotomous measure of regular physical activity based on the answer to a question on whether the individual gets a routine weekly exercise or not. Including this as a control would control for the current propensity for following healthy lifestyles which may influence dietary choices.

Other RHS variables include individuals' demographic variables – age, sex, location (urban, semi-urban or rural), marital status, education, annual income, current health status, risk preference (see Appendix B) and current employment status. In addition, life change events such as permanent migration, and shocks including loss of employment, accidents, serious health issues/ diseases/ hospitalization of family members, death in the family and losses due to natural disasters in the past 4-5 years.

<u>Omitted Variables</u>

The desire or self-motivation to change current health behaviors would influence how one compares himself to peers as well as what they would like to achieve in the future. People who are highly motivated to change current behaviors might be less influenced by peers' health and their motivation might be the reason for change in future. In that case, at any given comparison level, the future unhealthy behavior (outcome measure) might be underestimated.

Health behaviors of the peer groups is shown to have influence on one's own behaviors and those would influence one's perceptions of peer's health. However, we do not have any measures of these behaviors. If peers have good health behavior they might lead to perception of lower levels of self-health and also might make one follow peer behaviors, thereby, possibly underestimating the results. On the other hand, unhealthy behaviors might make one complacent about their own health. Further, such unhealthy habits might lead to further worse behaviors, leading to overestimated results.

5.4 Methods

5.4.1 Measurement Model

Let fHB be an indicator variable representing the probability of pursuing an unhealthy behavior in the future. Let S be a measure of social comparison of self-health with those of peers and H be an indicator for hyperbolic discounting (i.e. has higher short term discount rates compared to long term discount rates which are derived from Appendix A and are described in chapter 4). Then, we can write:

$$fHB_i = \kappa_{0i} + \kappa_{1i} S_i + \kappa_{3i} X_i + \kappa_{4i} Y_i + \varepsilon_i \text{ ---- } (5.2)$$

$fHB_i = \kappa_{0i} + \kappa_{1i} S_i + \kappa_{2i} H_i + \kappa_{3i} (S_i * H_i) + \kappa_{4i} X_i + \kappa_{5i} Y_i + \varepsilon_i$ ---- (5.3), where X and Y represent the matrix of control variables (see chapter 4). The suffix i represents the individual i.

5.4.2 Descriptive Statistics

Table 5.1 below describes the analytical sample (n=17,713). A clear majority of people (62%) rate their health to be the same as those of their peers. Almost a quarter of the sample (27%) rates theirs health to be better and a smaller percentage (4%) rate their health to be much better than that of their peers. Around 7% of the sample rate their health to be worse and less than 1% rate their health to be much worse than that of their peers.

On the average, people predict one in three chance of pursuing unhealthy eating in future (31%); these projected expectations of worse eating behavior increase as they compare themselves more and more favorably to their peers. Almost 80% of the population are hyperbolic discounters; among them 63% rate their health to be same as others, a quarter (26%) rate it to be better than peers. Not surprisingly, physically active individuals rate their health same or better than their peers.

People who are underweight or obese are slightly more likely to report their health to be worse than that of their peers; however, a clear majority of all BMI groups consider their health to be same or better than that of their peers. Further, a majority people who self-report their health to be good or very good consider their health to be worse than that of their peers.

Table 5.1. Descriptive Statistics by Reference Point (Health Comparison to Peers)

	Pop. Means / Per.	Means/Percent across Comparison of Health to Peers' Health				
		Much Worse	**Worse**	**Same**	**Better**	**Much Better**
Outcome Variable						
Unhealthy Behavior in Future						
How probable is that you will consume high amounts of fatty food in the next year	31%	21%	25%	32%	30%	36%
Regressors of Interest						
How is your health compared to your peers?						
Much Worse	0.21%					
Worse	7%					
Same	62%					
Better	27%					
Much Better	4%					
Hyperbolic Discounting?	80%	0.21%	7%	63%	26%	4%
Control Variables						
Age (years)	41	47	51	40	40	40
Sex						
Male	44%	0.1%	6%	62%	28%	5%
Female	56%	0.3%	8%	62%	26%	4%
Health Status						
Very Bad	0.3%	0%	2%	43%	35%	20%
Bad	4%	0%	2%	65%	29%	4%
Normal	40%	0.3%	10%	64%	23%	3%
Good	49%	1.3%	47%	37%	13%	2%
Very Good	7%	11%	55%	21%	14%	0 %
Location						
Urban	38%	0.2%	6%	57%	31%	6%
Semi Urban	22%	0.1%	7%	64%	25%	4%
Rural	40%	0.3%	8%	65%	24%	3%
Education						
No Education	11%	0.8%	15%	62%	19%	3%
Primary or Less	41%	0.2%	9%	64%	24%	3%
Secondary	25%	0.1%	4%	62%	29%	5%
High School	13%	0%	4%	61%	29%	6%
College	10%	0%	3%	54%	35%	7%
Graduate	0.4%	0.2%	6%	45%	33%	16%
Marital Status						
Single	23%	0.2%	4%	62%	28%	5%

	Pop. Means / Per.	Means/Percent across Comparison of Health to Peers' Health				
		Much Worse	Worse	Same	Better	Much Better
Divorced/Widowed	11%	0.3%	12%	58%	26%	4%
Married	66%	0.2%	7%	63%	26%	4%
Currently Employed?	50%	0.1%	5%	62%	28%	5%
Risk Categories						
Risk Neutral	9%	0.3%	6%	66%	23%	5%
Risk Taker (Lowest)	2%	0.5%	9%	60%	26%	4%
Risk Taker(Low)	8%	0.2%	8%	59%	27%	5%
Risk Taker(Fair)	43%	0.2%	7%	63%	26%	5%
Risk Taker (High)	5%	0.1%	7%	58%	30%	5%
Risk Taker(Highest)	32%	0.2%	7%	61%	28%	4%
Routine Physical Activity?	12%	0.1%	4%	50%	37%	8%
Body-Mass Index (BMI) Categories						
Underweight(BMI<18.5)	2%	0%	10%	59%	28%	4%
Normal Weight(18.5<=BMI<25)	29%	0.3%	7%	62%	26%	5%
Overweight(25<=BMI<30)	32%	0.1%	7%	61%	28%	4%
Obese (BMI>30)	37%	0.2%	8%	62%	26%	4%
Permanent Migration?	9%	0.5%	7%	58%	30%	4%
Shocks						
Serious Accidents?	8%	0.7%	13%	54%	29%	4%
Death in the family in the last 5 Years?	9%	0.5%	9%	58%	29%	4%
Major Disease/Accident/Hospitalization in the last 5 Years?	11%	0.4%	12%	54%	29%	5%
Unemployment in the past 5 Years?	7%	0.4%	8%	56%	32%	5%
Faced natural disasters in 5 Years?	1%	0%	17%	55%	23%	6%
N	17,713	37	1,242	10,971	4,692	771

5.4.3 Statistical Methods

All statistical analyses were conducted using Stata 12. The analytical sample included 17,713 adults who are 18 years or older and have positive discount rates. The variables used in the analyses are checked for missing values in order to rule to out any systematic patterns of missing data. As the data on most of the variables included in the regression analyses are missing for only a small number of cases and are determined to be missing completely at random, these data are not imputed and the regression analyses use the default option of list-wise deletion of incomplete cases. The variables are also tested for multi-collinearity to ensure that the model is parsimonious.

As the outcome measure is continuous, we will use OLS regressions with robust standard errors. First, we regress the outcome measure on the social comparison health status (equation 5.1 to test hypothesis 3.a.1) along with other control variables. Next, we regress the outcome measure on peer comparison, hyperbolic discounting and their interaction term (equation 5.2 to test hypothesis 3.b.1 & 3.b.2). These regression do not use survey weights as the weights are not available from the survey source. In both of these regression, 'health same as others' is the reference group for the peer comparison variable and being a non-hyperbolic discounter is the reference group for the discounting type. The reference group for their interaction is the people who are non-hyperbolic discounters who think that their health is same as their peers' health.

5.5 Results

5.5.1 Peer Comparison of Health Status

The results of the OLS regression (n=16,690) of health status compared to those of peers as the main regressor is reported in table 5.2. It shows that people who think their health is much worse than their peers have 11% ($p<0.001$) lower probability of eating excessive fatty foods in future compared to the reference group of people who think their health is same as peers' health; people who think their health is worse than peers' health have 3% ($p<0.05$) lower probability of the same. Both of these results are statistically significant. However, people who think their health is much better than those of their peers have a small (1%) probability of eating excessive fat compared to reference group, however, this is not statistically significant. Contrary to our hypothesis, people who think their health is better than peers' health show a small probability (2%; $p<0.001$) of eating excessive fatty foods. Women expect a 5% ($p<0.001$) lower probability of consuming fatty foods compared to men; compared to rural residents urban and semi-urban residents expect to a lower probability of eating fatty foods. People who exercise regularly also expect a 5% ($p<0.001$) lower probability of eating fatty foods.

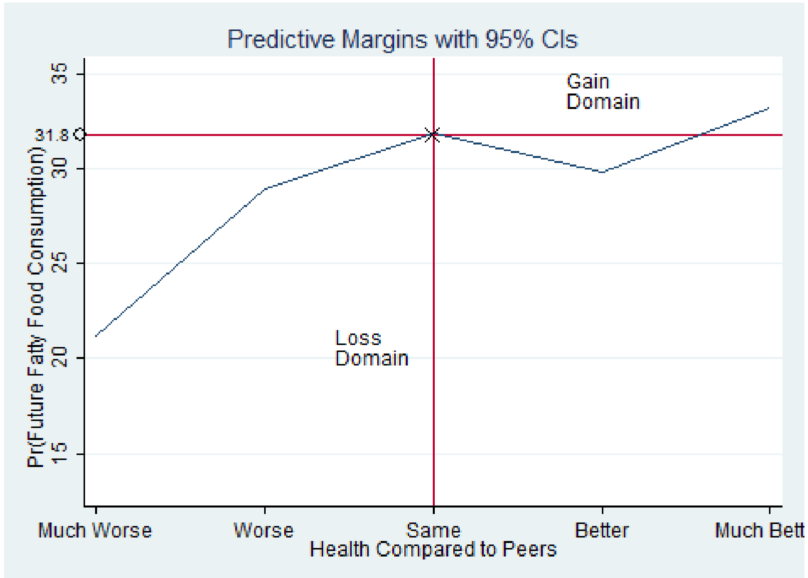
The graph of marginal predicted probabilities of future health behavior over health comparison statuses is presented in figure 5.2. Here we can see that as people move right in the loss domain towards thinking that their health is closer to those of their peers, they predict following worse behaviors as hypothesized. In the gain domain however, the results are not obvious. While there is a dip to the immediate right of the reference health state where people think their health is better than those of others, people seem to predict increasingly worse health behaviors as they compare themselves more and more favorably to others. Note that the predicted increases in the loss domain are higher compared to those in the gain domain as predicted by Prospect theory.

Table 5.2 OLS Regression of Probability of Eating Fatty Foods

Prob. of Eating Excessive Fatty Foods	**Coefficient**	**SE**
Health compared to others (ref: Same)		
Much Worse	-10.71*	4.25
Worse	-2.94***	0.81
Better	-2.05***	0.44
Much Better	1.31	1.04
Age	-0.27***	0.01
Female	-4.39***	0.44
Education (ref: no education)		
Primary or less	1.09	0.64
Secondary	2.48**	0.78
High school	1.47	0.87
College	0.12	0.93
Graduate	-1.62	3.16
Health Status (ref: normal)		
Very Bad	-1.5	3.70
Bad	-0.44	0.99
Good	-0.31	0.42
Normal	5.81***	0.85
Location (ref: rural)		
Semi-urban	-4.14***	0.50
Urban	-2.68***	0.45
Marital Status(ref: single)		
Divorced/widowed	0.6	0.79
Married	-0.08	0.51
Employed	0	0.43
Risk taking level (ref: neutral)		
Lowest	3.14*	1.37
Low	2.41**	0.88
Fair	2.02**	0.67
High	0.87	1.06
Highest	2.57***	0.69
BMI (ref: Normal)		
Underweight	-0.78	1.25
Overweight	2.17***	0.47
Obese	4.51***	0.47
Exercise (Y)	-4.59***	0.60
Had accident	-0.75	0.70
Permanent migration	0.7	0.69
Death in family	-1.03	0.68
Illness	-2.98***	0.60
Recent job loss	0.87	0.80
Natural disasters	0.07	2.03
Constant	42.54***	1.38
N	16,690	

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Figure 5.2 OLS Predicted Probability of Future Health Behaviors



Next, the results of OLS regression of predicted future health behaviors on the interaction of hyperbolic discounting and health comparison in table 5.3 (only the main effects and interaction terms are presented for brevity as other coefficients are similar in significance and magnitude to table 5.2).

Table 5.3 OLS Regression of Prob. Eating Fatty Foods with Interaction of Peer Comparison and Hyperbolic Discounting

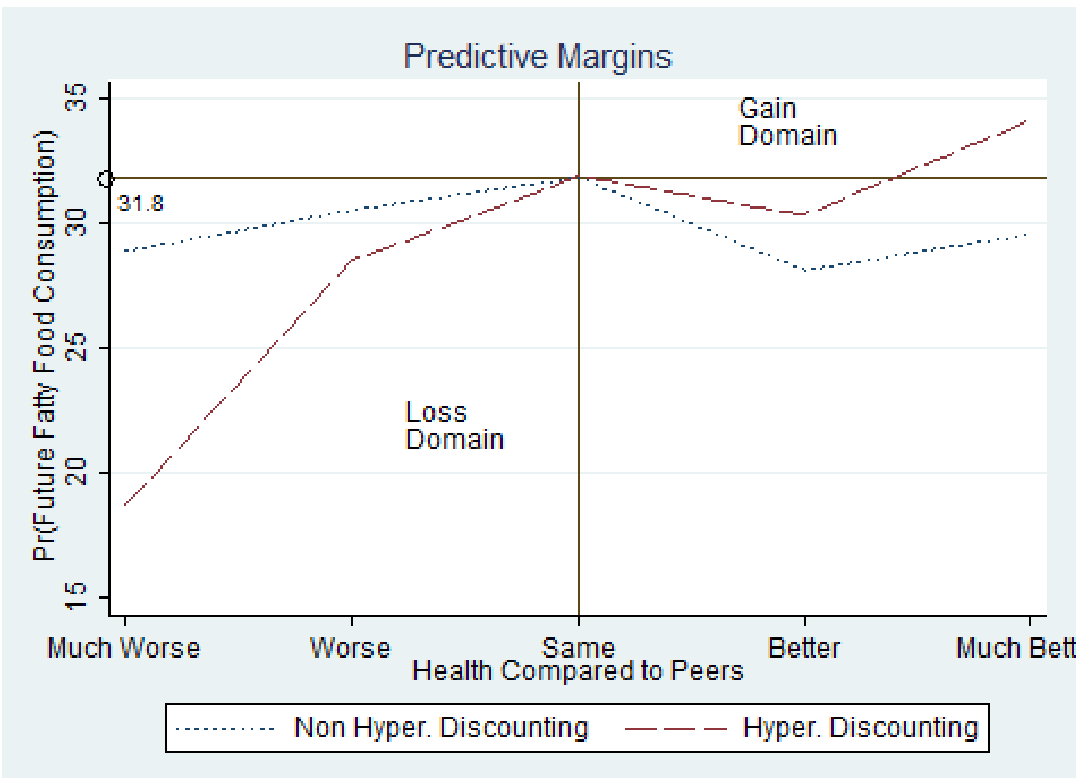
Prob. of Eating Excessive Fatty Foods		Coeff.	SE
Health compared to others (ref: Same)			
	Much Worse	-2.94	10.62
	Worse	-1.30	1.74
	Better	-3.70*	0.94
	Much Better	-2.27	2.26
Hyper. Discounting		0.28	0.61
Interaction Terms			
	Much Worse*Hyp	-10.23	11.49
	Worse*Hyp	-2.09	1.91
	Better*Hyp	2.12*	1.06

	Much Better*Hyp	4.51	2.53
N		16,690	

* p<0.05

While not all the interaction terms are statistically significant, the results are still interesting. The marginal probability plot to facilitate the interpretation of above results is presented below (figure 5.3).

Figure 5.3. OLS with Interaction: Marginal Predicted Probabilities



Here, in the loss domain, hyperbolic discounters tend to predict much better health behaviors in the future compared to non-hyperbolic discounters and the lines are steeper for hyperbolic discounters. In the gain domain, the reverse is true. Further, in the gain domain, non-hyperbolic discounters tend to predict better behaviors for themselves compared to their own in the loss domain which is contrary to hypothesis 3.1.a. The results indicate that the loss-gain asymmetry is especially pronounced among hyperbolic discounters.

5.6 Discussion

The results indicate that comparison with peers indeed acts as a point from which people tend to model their behaviors. As we find in the first regression, while people who are in the "loss" domain, tend to at least be aware that they would need to catch up with their peers by changing their behaviors, whereas people who rate their health to be better seem to appear indifferent or even negligent to the need to following healthy behaviors in future (which is essential for them to continue to be in a better health status). While peer comparison studies in literature that we have come across do not differentiate between these "loss-gain" domains and it remains true that most of the people think their health to be same as their peers, it is interesting to see such disparate behaviors at the ends of the comparison spectrum.

The results in the gain domain (among people who think their health to be better than their peers' heath) do not fully conform to our hypothesis. This might be because people who think their health is better may also be aware that their behaviors need to be kept up to be in the same health status. Or that they might just have started following healthy behaviors might make them feel superior to their peers while also being more conscious of the need to follow future healthy behaviors. The results are however as expected when people move further to the right and consider their health to be much better than their peers' health. In that case, they seem to be 'OK' with following less optimal behaviors.

We see from descriptive statistics that a majority of the sample are hyperbolic discounters who place a higher discount rate on their immediate present and a lower discount rate on their future. It implies that they will be predicting better behaviors in the future while probably postponing immediate their perusal. From the above results, we can see that these behaviors are further evident in the “loss-gain” domains. In the “loss” domain, as they are aware that their health is worse and they need to pursue better behaviors, they predict doing so with grander aspirations for the future compared to non-hyperbolic discounters in the same domain. While this is in line with their discounting profile, it is problematic as they could potentially be overestimating their future behaviors without realizing that as the time for action approaches they would continue to postpone following through those predictions. In the gain domain, same arguments are true, however the extent to which future unhealthy behaviors are predicted is smaller.

5.6.2 Limitations

There are several limitations to this study. There is only one predicted health behavior and people tend to predict in round numbers (i.e.30% or 50% rather than 67% or 28%). This tends to make the data distribution wide. While the kurtosis of the data is close to a normal distribution, the data is skewed slightly to right with most people predicting better health behaviors in future. This might reflect an overestimation of positive behavior due to social desirability bias in answering the question on future consumption of fatty foods.

While being optimistic and aspirational is commendable and nothing to sneer at, it will not tell us with confidence that those predicted behaviors will happen in future. The cross sectional nature of the data with the absence of a pattern of actual behaviors over a few time periods implores us to interpret these results with much caution.

The comparison of health with peers might be limited to external appearances (e.g.: waistline comparison) rather than to actual health itself. We can see from the descriptive statistics that people who are underweight or obese tend to rate their health worse than their peers' health. This might be indicative of the fact that physical appearance might be one of the factors based on which people tend to rate their health. If that is the case, our outcome (future eating behavior) can be expected to be more influenced by such comparison. If the comparison takes into account external appearances as well as intimate knowledge of peers' health issues, then its relationship to the future health behavior might be weak. As we do not have a clear indication how such comparison (or valuation) is formed, we will have to interpret the results conservatively.

In both loss and gain domains, being just aware of their health status might predict behaviors in future, but it does not guarantee that such behaviors are followed. Especially for hyperbolic discounters, the problems of following through with the plans may not ever materialize as they are prone to procrastinate. Whether people are aware of their actual behaviors and associated issues ('sophisticated') or ignorant of the impact of their behaviors ('naïve') would influence actual behavioral modifications. While we do not have data on whether people are aware of procrastination issues and whether they have plans to alleviate those tendencies, such data would facilitate in helping people by educating and providing commitment policies.

5.6.3 Broader Implications for Policy

Understanding whether people treat health behaviors as losses or gains can help in framing the policy responses. If people compare their health to those of their peers in order to follow healthy behaviors, it stands to reason that the policies or interventions should also address the problem from a social network or peer group perspective rather than targeting people with unhealthy behaviors in isolation. The peer group might comprise of friends, family, classmates or co-workers. While it may not be beneficial or practical to include all peers, the group intervention can happen in classrooms or at work places that could influence health behaviors.

Moreover, as comparison with peers has influence on future behaviors, we might use such social comparison to design the interventions in such way that social comparisons could motivate positive health behaviors. Further, these programs would be more effective if they target people who think their health is worse or better than those of their peers and also people who have higher short term discount rates.

Future research to elicit factors that influence such health comparisons is required to understand the relationship that is explored in this chapter. And, following people's actual behaviors overtime to understand how expectations translate into actual behaviors is essential in devising solutions. In reviewing the literature where loss-gain asymmetry is exploited to change behaviors either via message framing or via interventions, it is not clear whether such changes to policies would have a long-term impact on behaviors. For example, the changes to electricity bills to nudge energy savings behavior based on peer feedback or teacher performance incentives based on loss aversion paradigm have produced short-term effects (Fischer 2008; Levitt, List et al. 2012), but the long-term effectiveness of such policies when a potential 'regression to the mean' problem might undermine their spectacular short-term success. Hence, future research endeavors in this area must include an evaluation of long-term effectiveness of such policies.

CHAPTER 6. CONCLUSION

Time preferences have a long history of influencing various aspects of our decision making. Thinkers including Adam Smith, John Rae, William and Herbert Jevons, Eugen von Böhm-Bawerk, Irving Fisher and Paul Samuelson have recognized its importance and included it in models where decision making involved weighing choices that have consequences over time. With the formalization of its inclusion in DU models, time preferences have been an integral part of decision and policy analyses. And, hence it has been applied to decisions that affect health which naturally has consequences over one's lifetime. While measurement of time preferences is notoriously difficult, over the years it has evolved thorough field and experimental studies. While interest in measurement of time preferences and its influence on decision making has been mostly academic, there is an emerging interest in this topic in policy circles. As predicted by Adam Smith, myopic decisions made at individual level have created conditions that have dearly cost national economies including mortgage crisis and obesity epidemic. The calamitous nature of these problems have rekindled interest in scrutinizing all of the factors which cause such myopia and which are potentially amenable to policy interventions.

6.1 Implications

In this study, we examined how time preferences influence health behaviors at a population level in Mexico. Similar to the results from developed countries, results from Mexico indicate that even after controlling for endogeneity and various other factors, time discounting is an important determinant of health behaviors. Considering alternate functional forms of the discounting further helps in unravelling the immediate consequences of having high discount rates. Further, as preferences are formed by comparison to peers, we infer that it might be beneficial to address solutions at peer group levels. While education generally improved myopic behaviors, all education might not be as effective. Education specifically addressing to improve future orientation would be helpful in developing thinking and acting in ways where immediate gratification is not encouraged. Further, policy responses such as ‘Oportunidades’ might help by providing people who are myopic, a device that hinders suboptimal decisions by making incentives tied to behaviors that nudge towards delaying immediate gratification. However, policies such as ‘Oportunidades’ for all may not be optimal in terms of its cost effectiveness. In those cases, studies such as ours would help in targeting the most vulnerable who would benefit the most from such interventions. Further studies in this area could potentially encourage private sector to provide market based solutions that alleviate myopic decision making problems. Further, these types of studies can make consumers more sophisticated in understanding their shortcomings and to seek interventions to overcome such issues, thereby, creating market demand for such products.

Another important aspect to emerge from this study is that individuals’ rates of discounting vary widely and they affect their health behaviors. As we find more and more evidence for individual discount rates being different from what is applied in policy studies to analyze and rate policy options, it makes one question the current practices of using arbitrary market rates for discounting policy options and to wonder whether policy options if evaluated based on population’s true (or near true) preferences would result in different choices within the same budget constraints. In the public finance domain, there is emerging argument for using a ‘social rate of time preference’ in addition to a ‘social opportunity cost’ to come up with the right discount rate for policy analysis. While this argument looks convincing from a theoretical perspective, it is harder to implement none of the national surveys in developed or developing countries (including the United States and Mexico) measure time preferences in detail in a consistent manner and have no other mechanism to assess them. As we find more and more evidence in more than one decision making domain – be it retirement or health – that time preferences are indeed important, we can make the argument to spend the time and money required to collect such data at population levels, which is the first essential step to be taken if we were to incorporate ‘social rates of time preferences ‘in policy analysis.

6.2 Future Research Directions

There are several areas where this study can be enhanced by further research as noted in various chapters. In addition to those, there are several important future research opportunities which, if explored, would elucidate our understanding of time preferences and their impact on health behaviors and health.

6.2.1 Domain Independence of Time Preferences

One important consideration for the future studies is to understand whether time preferences vary across decision domains within individuals. In this study, we apply time preferences constructed using monetary rewards (i.e. time preferences in the monetary domain) to decisions in the health domain, with the implicit assumption that time preferences do not vary across money and health decision domains. This is in accordance with DU theory which uses a unitary discount rate for all types of consumption utilities (Frederick, Loewenstein et al. 2002). Current literature is not clear on whether time preferences are indeed specific to or invariant across decision domains. Some laboratory studies show that there are a number similarities in within-individual time preferences across money and health domains in terms of loss-gain asymmetry and hyperbolic forms and that average money and health domain discount rates do often match (Chapman and Elstein 1995; Chapman 1996). But these laboratory studies do not always agree with real behaviors that show considerable within-individual heterogeneity. For example, a smoker might have a diligent retirement savings portfolio. For the ease of policy analysis (such as cost effectiveness where same discount rates are applied for monetary costs and health benefits) and due to a lack of domain specific data, assumption of domain independence is common place even though it is regularly challenged on the basis of observed with-in individual heterogeneity. As a first step in understanding this issue, future studies should derive time preferences for both money and health domains separately and compare them within and across individuals. A promising nascent area of research in this regard is the multi-motive approach to understanding domain specific discount rates (Frederick, Loewenstein et al. 2002) where discount rates in different domains are built based on domain-specific influencers (such as utility from anticipation for eating ice cream or effects of habits in the case of addiction).

6.2.2 Time preferences over time

Time preferences at a point in time affect future decisions. But they are not time-invariant. For example, someone who is young and single might have a high discount rate now compared to 10 years later when he may be older and married. Life events change discount rates over time. While most of the literature holds discount rates as constant, we see from chapter 3 that many factors influence discount rates and those factors themselves are time-variant. To understand how time preference change over time, future studies and survey instruments should include longitudinal data collection on time preferences. Such data would facilitate our understanding of how time preferences vary across one's life span and how such temporal change affects decisions.

6.2.3 Population level data on time preferences

While we understand some of the shortcomings of the DU theory in terms of sub-optimally rational behaviors, such anomalies are usually studied with small sample select data, which makes health policy makers uncomfortable and incredulous on drawing any policy relevant conclusions. This is because when it comes to decisions that need to address the citizenry as a whole, it is hard to design or choose policy options based on what looks to be an outlier or an anomaly. Still, time and again, such outliers seem to be the 'true' influencers. In recent years, the 'opt-out/default' policies for organ donation or for retirement savings which originated as results of small scale lab studies in behavioral economics have received a lot of positive attention from policy makers and general public as these concepts have enjoyed reasonable success as social policies.   However, they may still be a stroke of luck as there are many other 'lab' studies that have had hard time catching on in terms of policy. Overall, many mainstream economists as well as policymakers remain skeptical of results from small-scale studies. Hence, it is imperative to continue studying this problem at a population level if we aim to influence policy. One way to do so is to incorporate time preference measurement in existing surveys. Specifically, in the United States even though there are many excellent national surveys, none of them collect detailed data on time preferences. Health and Retirement Survey (HRS) has 2 questions on time preferences that were asked in a few waves only and National Longitudinal Survey of the Youth (NLSY) included one question on planning for future. It will be beneficial to add these questions to longitudinal surveys such as HRS or NLSY which are nationally representative and include a variety of demographic groups that could potentially benefit from time preference related interventions for improving health behaviors and health.

6.2.4 Policy analysis based on behavioral economics perspective

In this study, we show that large-scale policy interventions such as 'Oportunidades' might help problems related to time-inconsistent preferences using a behavioral economics paradigm. Although analyzing this policy and its effectiveness in helping with such problems is not the inspiration or intention of this policy, such 'off-label' analysis shows that this policy helps people in making the right health behavior choices. To that end, it might be beneficial to apply new perspectives to design and analyze existing policies and experiment with small tweaks that might yield beneficial results to the most vulnerable.

6.3 Conclusion

Our daily decisions are fraught with chances to make mistakes stemming from tendencies for immediate gratification. Specifically, health behaviors which are vulnerable such tendencies result in large negative consequences at individual as well as at a national level. With detailed, longitudinal population level data, we can understand how time preferences are formed, how they changes over a life course, whether they are domain specific and whether they can be alleviated with interventions. Public sector policies can be enriched if they employ design elements that take into consideration some of the common decision making errors. Private sector should take note to provide market-based solutions to similar problems for the population sector that might not qualify for public sector interventions. Going forward, further research is warranted to build policy design and analysis frameworks that incorporate perspectives from behavioral economics to improve the impact and effectiveness of public policies and interventions as well to inform market-based solutions.

APPENDICES

Appendix A. Discount Rate Calculation

Table A.1: Discount Rate Questions

(SHORT TERM DISCOUNTING)		
PR03. Imagine now that you have won the lottery. You can choose to get paid:		
A. 1. 1,000 pesos today or 2. 1,000 pesos in a month Which one do you choose?	**A.** 1 → **PR03B**	2 → **PR03F**
B. 1. 1,000 pesos today or 2. 1,100 pesos in a month Which one do you choose?	**B.** 1 →**PR03C**	2 → **PR04**
C. 1. 1,000 pesos today or 2. 1,200 pesos in a month Which one do you choose?	**C.** 1 → **PR03D**	2 → **PR04**
D. 1. 1,000 pesos today or 2. 1,500 pesos in a month Which one do you choose?	**D.** 1 → **PR03E**	2 → **PR04**
E. 1. 1,000 pesos today or 2. 2,000 pesos in a month Which one do you choose?	**E.** 1 → **PR04**	2 → **PR04**
F. Why?	**F.**___→**PR03G**	
G. Now imagine you can choose between getting paid: 1. 1,200 pesos today or 2. 1,000 pesos in a month Which one you choose?	**G.** 1→ **PR04**	2→ **PR04**
(LONG-TERM DISCOUNTING)		
PR04. Imagine that you have won the lottery. You can choose to get paid:		
A. 1. 10,000 pesos today or 2. 10,000 pesos in three years Which one do you choose?	**A.** 1 → **PR04B**	2 → **PR04F**
B. 1. 10,000 pesos today or 2. 12,000 pesos in three years Which one do you choose?	**B.** 1 → **PR04C**	2 → **SECTION FH**
C. 1. 10,000 pesos today or 2. 15,000 pesos in three years Which one do you choose?	**C.** 1 → **PR04D**	2 → **SECTION FH**
D. 1. 10,000 pesos today or 2. 20,000 pesos in three years Which one do you choose?	**D.** 1 → **PR04E**	2 → **SECTION FH**
E. 1. 10,000 pesos today or 2. 40,000 pesos in three years Which one do you choose?	**E.** 1 → **SECTIÓN FH**	2 → **SECTION FH**
F. Why?	**F.** ____ → **PR04G**	
G. Now imagine you can choose between getting paid: 1. 12,000 pesos today or 2. 10,000 pesos in three years Which one do you choose?	**G.** 1→**SECTION FH**	2 → **SECTION FH**

Figure A.1: Flowchart –Discount Rates and Rate Categories

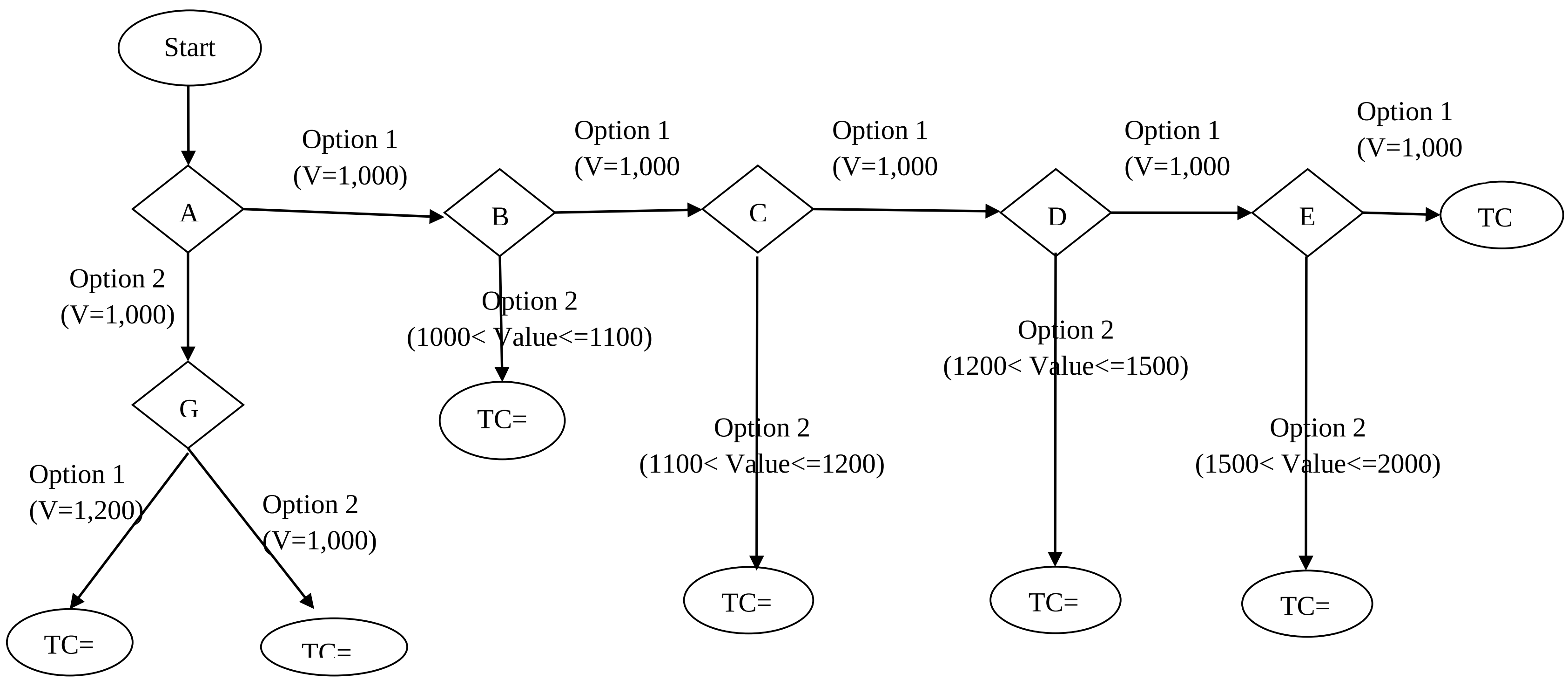


Table A.2: Calculation of Discount Rates

Question	**Option 1 Value**	**Action for Choice=1**	**Option 2 Value**	**Action for Choice = 2**	**Mid Value**	**Monthly discount rate**	**Category**	**Comments**
3A	1,000	B	1,000	G				
3B	1,000	C	1,100	done	1,050	5%	1	Mid value between 1,000 and 1,100
3C	1,000	D	1,200	done	1,150	15%	2	Mid value between 1,100 and 1,200
3D	1,000	E	1,500	done	1,350	35%	3	Mid value between 1200 and 1,500
3E	1,000		2,000	done	1,750	75%	4	Mid value between 1,500 and 2,000
3E	1,000	Done	2,000		2,000	100%	5	Value >= 2,000
3G	1,200		1,000	done	1,100	-8%	-1	Negative time preference
3G	1,200	Done	1,000			0%	0	Expected rational choice; assigned discount rate of 0 as this path is chosen from the first gamble, A.
Question	**Option 1 Value**	**Action for Choice=1**	**Option 2 Value**	**Action for Option 2**	**Mid Value**	**Annual discount rate(t=3yrs)**	**Category**	**Comments**
4A	10,000	B	10,000	G				
4B	10,000	C	12,000	done	11,000	3%	1	Mid value between 10,000 and 11,000
4C	10,000	D	15,000	done	13,500	11%	2	Mid value between 12,000 and 15,000
4D	10,000	E	20,000	done	17,500	21%	3	Mid value between 15,000 and 20,000
4E	10,000		40,000	done	30,000	44%	4	Mid value between 20,000 and 40,000
4E	10,000	Done	40,000		40,000	59%	5	Value >= 40,000
4G	12,000		10,000	done	11,000	-3%	-1	Negative time preference
4G	12,000	Done	10,000			0%	0	Expected rational choice; assigned discount rate of 0 as this path is chosen from the first gamble, A.

Discount rate = [(mid point value/choice 1 value)^period]-1 ;

Period = 1 month for question 3 and monthly discount rates are shown ; Period = 3 years for question 4 and annual rates are shown

Appendix B. Risk Preferences Calculations

Table B.1: Risk Preference Questions

RISK (SECCIÓN RG) : Now imagine a game of random chance. In a bag there is a blue chip and a yellow chip and an amount of money is written on each of them. (INTERVIEWER: SHOW THE SLIDES). If you stick your hand inside the bag and take out the yellow chip, we would pay you what is written on the yellow chip, if you take out the blue chip, we will pay what is written on the blue chip. Now you reach inside the bag, but you do not know yet what chip you will get.

RG02. Now imagine you can choose between the two bags shown on the slide: 1. In bag 1, if you get the blue chip **or** the yellow chip, you receive 1,000 pesos 2. In bag 2, if you get the blue chip you receive 500 pesos or 2,000 pesos if you get the yellow chip Which one of the bags do you choose? 8. DK (Don't Know)	1 → **RG05** 2 8 → **RG05**
RG03. Now imagine you can choose between the two bags shown on the slide: 1. In bag 1, if you get the blue chip you receive 500 pesos or 2,000 pesos if you get the yellow chip 2. In bag 2, if you get the blue chip you receive 300 pesos or 3,000 pesos if you get the yellow chip Which one of the bags do you choose? 8. DK	1 →**RG05** 2 8 → **RG05**
RG04. Now imagine you can choose between the two bags shown on the slide: 1. In bag 1, if you get the blue chip you receive 100 pesos or 4,000 pesos if you take out the yellow chip 2. In bag 2, if you get the blue chip you receive 100 pesos or 7,000 pesos if you take out the yellow chip Which one of the bags do you choose? 8. DK	1 →**RG08** 2 → **RG08** 8
RG05. Now imagine you can choose between the two bags shown on the slide: 1. In bag 1, if you get the blue chip you receive 1,000 pesos or 1,000 pesos if you get the yellow chip 2. In bag 2, if you get the blue chip you receive 800 pesos or 2,000 pesos if you get the yellow chip Which one of the bags do you choose? 8. DK	1 2 →**RG08** 8 → **RG08**

RG06. Now imagine you can choose between the two bags shown on the slide: 1. In bag 1, if you get the blue chip you receive 1,000 pesos or 1,000 pesos if you get the yellow chip 2. In bag 2, if you get the blue chip you receive 800 pesos or 4,000 pesos if you get the yellow chip Which one of the bags do you choose? 8. DK	 1 2 → **RG08** 8
RG07. (INTERVIEWER: show slide RG07 and read the quantities for each game of chance) Now imagine you can choose between the two bags shown on the slide: 1. In bag 1, if you get the blue chip you receive 1,000 pesos or 1,000 pesos if you get the yellow chip 2. In bag 2, if you get the blue chip you receive 800 pesos or 8,000 pesos if you get the yellow chip Which one do you choose? 8. DK	 1 2 8

Figure B.1: Flowchart – Risk Categories

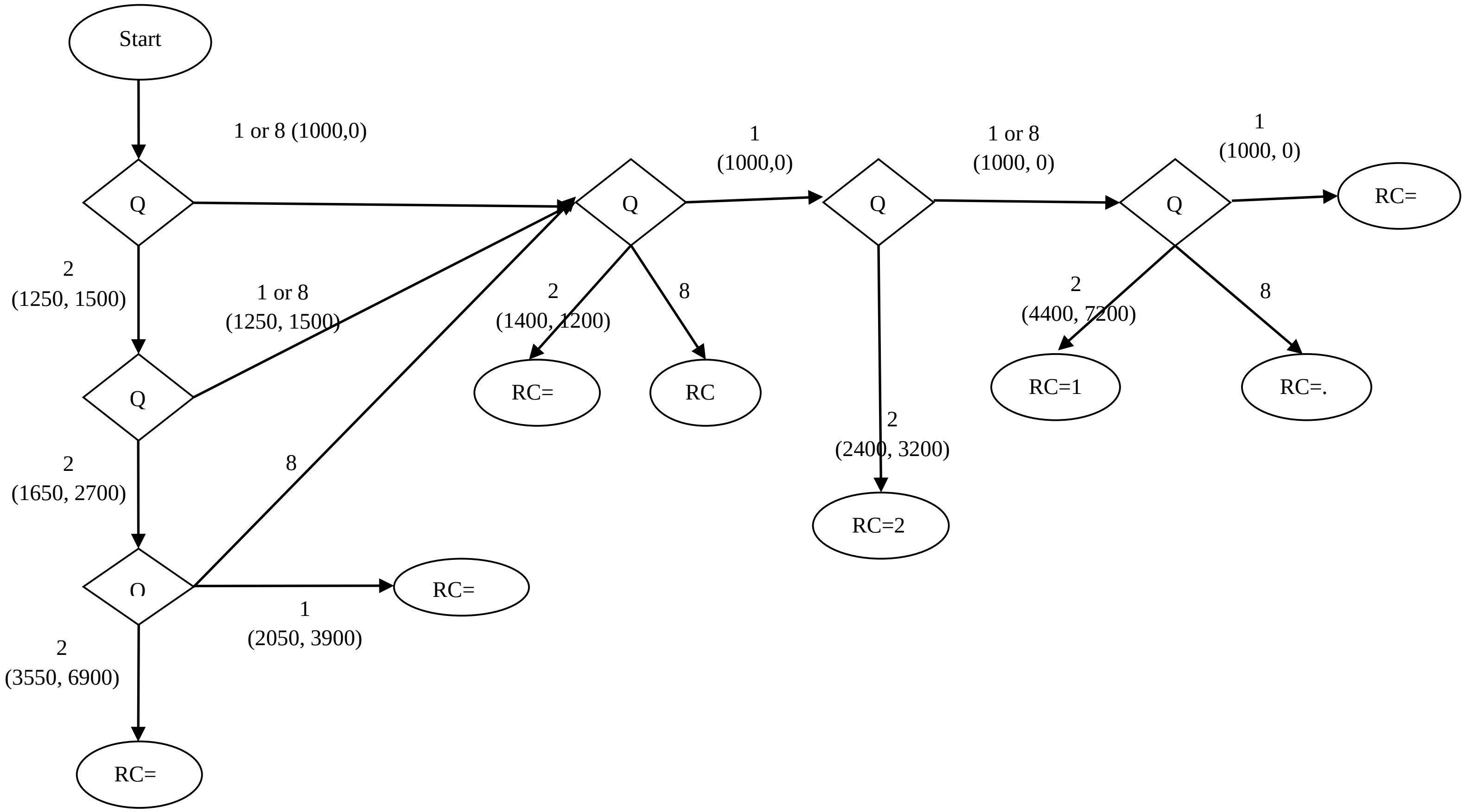


Table B.2: Risk Category Calculations

q	q-ans	blue	b_prob	yellow	y_prob	exp_ value	spread	action	Risk Category (1-6 lowest risk taker to the highest)	comments
2	1 or 8	1000	0.5	1000	0.5	1000	0	q5		
2	2	500	0.5	2000	0.5	1250	1500	q3		
3	1 or 8	500	0.5	2000	0.5	1250	1500	q5		
3	2	300	0.5	3000	0.5	1650	2700	q4		
4	1	100	0.5	4000	0.5	2050	3900	exit	4	
4	2	100	0.5	7000	0.5	3550	6900	exit	5	
4	8							q5		
5	1	1000	0.5	1000	0.5	1000	0	q6		
5	2	800	0.5	2000	0.5	1400	1200	exit	3	
	8 = Don't Know							exit	.	
6	1 or 8	1000	0.5	1000	0.5	1000	0	q7		
6	2	800	0.5	4000	0.5	2400	3200	exit	2	
7	1	1000	0.5	1000	0.5	1000	0	exit	0	Risk Neutral
7	2	800	0.5	8000	0.5	4400	7200	exit	1	This has the highest EV and spread, but to arrive here the participant has been choosing safe bets till this point
	8 = Don't Know							exit	.	

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