Impatience, Incentives, and Obesity*

Charles Courtemanche† Patrick McAlvanah‡

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Abstract

This paper hypothesizes that the interaction of changing economic incentives with hyperbolic discounting can help explain the increasing mean and variance of the body mass index (BMI) distribution. We present a model predicting that impatient individuals should both weigh more than patient individuals and experience sharper increases in weight in response to falling food prices. We then test these predictions using individual-level data from the National Longitudinal Survey of Youth matched with local food prices from the Council for Community and Economic Research. Both the beta and delta components of a quasi-hyperbolic discount function predict BMI and obesity even after controlling for demographic, human capital, occupational, and financial characteristics as well as risk preference. Obesity is therefore partly attributable to rational intertemporal tradeoffs but also partly to time inconsistency. We then show that the interaction of present bias with local food price predicts BMI, with falling food prices leading to the largest weight gains among those exhibiting the greatest present bias. These results provide insight into why, in an environment of cheaper and more readily available food, increases in BMI appear to be concentrated amongst the right tail of the distribution rather than spread throughout the entire distribution.

Keywords: Obesity, weight, body mass index, time inconsistent, time inconsistency, hyperbolic discounting, present bias, self control, discount factor, discount rate, time preference, food prices

JEL Classification: I10, D9

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†Corresponding author. Department of Economics, Bryan School of Business and Economics, University of North Carolina at Greensboro. Box 26170, University of North Carolina at Greensboro, Greensboro, NC 27402. National Bureau of Economic Research, Cambridge, MA. Email: cjcourte@uncg.edu.

‡Federal Trade Commission, 600 Pennsylvania Avenue NW, Mail Drop NJ 4136, Washington DC. Email: pmcalvanah@ftc.gov. The views expressed in this article are those of the author and do not necessarily reflect those of the Federal Trade Commission.

1 Introduction

The US obesity rate has skyrocketed in recent decades, rising from 13% in 1960 to 34% in 2006 (Flegal et al., 1998; National Center of Health Statistics, 2008). Obesity, defined as a body mass index (BMI) of at least 30, is both a public health and public finance concern.[1] Adverse health conditions attributed to obesity, which include heart disease, diabetes, high blood pressure, and stroke, lead to an estimated 112,000 deaths per year (Strum, 2002; Flegal et al., 2005). Treating obesity-related conditions costs an estimated $117 billion annually, with about half of these expenditures financed by Medicare and Medicaid (US Department of Health and Human Services, 2001; Finkelstein et al., 2003).

A growing literature argues that changes in economic incentives have decreased the opportunity cost of eating and raised the opportunity cost of exercise, leading to an increase in population weight. Factors lowering the monetary or time costs of food consumption include falling real food prices (Lakdawalla and Philipson, 2002; Philipson and Posner, 2003; Chou et al., 2004; Lakdawalla et al., 2005; Goldman et al., 2010), increased restaurant density (Chou et al., 2004; Rashad et al., 2006; Dunn, 2008; Currie et al., 2010; Anderson and Matsa, forthcoming), and reduced preparation time for food consumed at home (Cutler et al., 2003). Reduced on-the-job-physical activity (Lakdawalla and Philipson, 2002 and 2005; Philipson and Posner, 2003), urban sprawl (Ewing et al., 2003; Frank et al., 2004; Eid et al., 2008, Zhao and Kaestner, 2010) and historically cheap gasoline (Courtemanche, forthcoming) are factors influencing the opportunity cost of physical activity.[2] Less is known, however, about the role of underlying preferences. This paper provides a theoretical and empirical investigation of the interplay between hyperbolic discounting, economic incentives, and BMI. We show that measures of both long-run patience and present bias predict BMI, and that individuals exhibiting

[1] BMI = weight in kilograms divided by height in meters squared.

[2] Other economic factors linked to obesity include cigarette prices (Chou et al., 2004; Gruber and Frakes, 2006; Chou et al., 2006; Rashad et al., 2006; Baum, 2009; Nonnemaker et al., 2009; Courtemanche, 2009), Walmart Supercenters (Courtemanche, 2011), work hours (Courtemanche, 2009), health insurance coverage (Bhattacharya et al. 2010), the minimum wage (Meltzer and Chen, 2010), and the unemployment rate (Ruhm, 2000 and 2005).

the greatest degree of present bias gain the most weight when food prices fall. The interaction between impulsivity and incentives provides a possible explanation for why, as shown in Figure 1, the rise in population weight in recent decades has been concentrated amongst the right tail of the BMI distribution rather than spread evenly throughout the distribution.

Some prior research examines the link between time preference and BMI.[3] Komlos et al. (2004) hypothesize that people may have become less patient over time, contributing to the rise in obesity. They support this theory by illustrating a time-series relationship between obesity and both the savings rate and debt-to-income ratio in the US, and also by demonstrating that countries with low savings rates have higher obesity rates. Smith et al. (2005) proxy for time preferences with savings behavior and find some evidence of a connection to BMI using data from the National Longitudinal Survey of Youth (NLSY). Zhang and Rashad (2007) estimate a link between time preference and BMI in two datasets, the small Roper Center Obesity survey and the larger Behavioral Risk Factor Surveillance System. Their proxies for time preference are self-reported willpower in the former and desire but no effort to lose weight in the latter. Chabris et al. (2008) find a relationship between impatience and BMI using a more direct measure of time preference, the discount rate computed from answers to questions on intertemporal trade-offs administered in a laboratory setting to 126 subjects from the Boston area. Ikeda et al. (2010) utilize direct time preference measures in a large Japanese survey and demonstrate that greater patience is negatively associated with BMI.

Even if time preference and BMI are related, if people have not become less patient over time, then time preferences alone cannot explain trends in BMI. Borghans and Golsteyn (2006) consider a number of proxies for time preference available in a Dutch dataset and find that the extent to which time preference and BMI are related depends heavily on the choice of proxy. They examine trends in some of their proxies and find no evidence that the rate of time preference has changed over time. In a meta-analysis of experimental and field studies on time preferences published from 1978-2002, Percoco and Nijkamp (2009) find no

[3] A related literature examines the link between risk preference and BMI; see, for instance, Anderson and Mellor (2008).

evidence of changing time preferences over the sample period. Simpson and Vuchinich (2000) demonstrate a high test-retest reliability for time preferences measured in lab experiments, and Meier and Sprenger (2010) find a similar high degree of stability for time preferences in a longitudinal field experiment. In both of these studies, the within-person stability of time preference was similar to those of personality traits, suggesting that time preference is also a relatively fixed factor over an individual's lifetime.

We build on the obesity literature in three ways. First, we utilize a large national dataset, the 2006 NLSY, which includes not only questions on body weight and hypothetical intertemporal trade-offs but also a rich array of other individual information. These data allow us to push further than prior research toward establishing that the estimated association between time preference and BMI is a ceteris paribus relationship rather than a spurious correlation. We do this both by controlling for potential confounders and conducting falsification tests. Building up from a simple regression to a model that includes demographic characteristics, IQ, education, income, net worth, work hours, and risk preference demonstrates that greater impatience consistently increases BMI and that the coefficient estimate is stable across specifications. Female obesity is more significantly related to present-bias and male obesity is more related to time-consistent impatience. The effects are strongest for whites, and are accompanied by related effects on the probabilities of being obese and severely obese. Falsification tests find no evidence of a link between time preference and either height or health conditions that are less directly tied to eating and exercise.

Second, we examine, both theoretically and empirically, whether impatience and incentives interact in determining BMI. Even if underlying rates of time preference have not changed over time, impatience can still help to explain changes in the BMI distribution if patient and impatient people respond differently to changing economic incentives. Individuals who are highly concerned about future health might never develop unhealthy eating habits regardless of how cheap and available food becomes, whereas those who are less interested in the future might be more responsive. We find evidence to support this hypothesis by matching the

NLSY to local food price data from the Council for Community and Economic Research (C2ER). The interaction between impatience and incentives might help to explain why the BMI distribution has become more spread out over time (as shown in Figure 1), as opposed to merely shifting to the right.

Finally, we provide a preliminary attempt to disentangle whether the observed relationship between time preference and BMI represents rational intertemporal substitution or self-control problems, a distinction that has critical implications for policy. If people make eating and exercise decisions via time-inconsistent preferences, then lower food prices could actually decrease welfare, providing a justification for policies designed to alter these decisions (Cutler et al., 2003). If instead individuals make these decisions by rationally trading off current and future consumption in a way that maximizes lifetime expected utility, then policies that alter eating and exercise could be socially wasteful even if they reduce population weight. We fit the NLSY's intertemporal tradeoffs using the quasi-hyperbolic ($\beta\delta$) specification, decomposing time preferences into a present-biased, time-inconsistent component and a time-consistent component. BMI is consistently associated with present-biased time-inconsistent discounting, suggesting that the observed effect on BMI represents self-control problems rather than rational intertemporal substitution.

2 Theoretical Model

We present a simple theoretical model to highlight the interaction of impatience and incentives in weight accumulation. We demonstrate that more impatient individuals should display a greater response to decreasing food prices than patient individuals. We consider a modified version of the Philipson and Posner (2003) and Lakdawalla and Philipson (2009) model of food choice and weight accumulation. Our novel extension is to model weight gain as non-instantaneous; instead, food intake increases weight after a time lag. Modeling food intake as conferring immediate hedonic benefits but delayed health costs implies that a consumer's optimal weight choice is a function of time preferences as well as utility preferences.

Utility U depends on Weight (W), food intake (f), and other consumption goods (c). Assume there exists an ideal weight W^*, and utility is decreasing from deviations in either direction from this ideal weight. This implies that $\frac{\partial U}{\partial W}(W^*) = 0$ with $\frac{\partial^2 U}{\partial W^2} < 0$. Food and consumption goods provide instantaneous utility, $\frac{\partial U}{\partial f}, \frac{\partial U}{\partial c} > 0$ with $\frac{\partial^2 U}{\partial f^2}, \frac{\partial^2 U}{\partial c^2} < 0$. Let subscripts denote time periods. Assume that food increases weight in the *subsequent* period, so that future weight is an increasing function of current weight and current food intake $W_{t+1} = g(W_t, f_t)$, with $\frac{\partial g}{\partial W_t}, \frac{\partial g}{\partial f_t} > 0$. Note that assuming that food increases weight instantaneously as well as in the future period would not change our key comparative static result that more impatient individuals place less emphasis on future weight gain, and hence a greater sensitivity to declining food prices.

Consider an infinitely lived consumer in discrete time with additively separable and stationary utility. Normalize the price of consumption to 1 and let p denote the relative price of food. A consumer begins with initial wealth I_0, which he can save at market interest rate r. Let δ denote the per-period discount factor, with $0 < \delta < 1$. A consumer chooses food f and other consumption c to maximize:

$$\max_{f,c} \sum_{t=0}^{\infty} \delta^t U_t(W_t, f_t, c_t) \quad \text{s.t.} \quad \frac{\sum p f_t}{(1+r)^t} + \frac{\sum c_t}{(1+r)^t} = I_0 \tag{1}$$

Letting V denote the value function yields the following Bellman equation:

$$\begin{aligned} V(W_t, I_t) &= \max_{f_t, c_t} \{U_t(W_t, f_t, c_t) + \delta V[W_{t+1}, I_{t+1}]\} \qquad (2) \\ \text{s. t.} &: \; W_{t+1} = g(W_t, f_t) \\ I_{t+1} &= (I_t - p_t f_t - c_t)(1+r). \end{aligned}$$

The first-order conditions are thus:

$$\frac{\partial V}{\partial f_t} = \frac{\partial U_t}{\partial f_t} + \delta \frac{\partial V}{\partial W_{t+1}} \frac{\partial W_{t+1}}{\partial f_t} - \delta \frac{\partial V}{\partial I_{t+1}} \frac{\partial I_{t+1}}{\partial f_t} = 0 \tag{3}$$

$$\frac{\partial V}{\partial c_t} = \frac{\partial U_t}{\partial c_t} - \delta \frac{\partial V}{\partial I_{t+1}} \frac{\partial I_{t+1}}{\partial c_t} = 0 \tag{4}$$

which implies that at the optimum:

$$\frac{\partial U_t}{\partial f_t} + \delta \frac{\partial V}{\partial W_{t+1}} \frac{\partial W_{t+1}}{\partial f_t} = p_t \frac{\partial U_t}{\partial c_t}. \tag{5}$$

Note that if a person is underweight, $\frac{\partial V}{\partial W_{t+1}}$ may be positive, which could happen at sufficiently high food prices. However, individuals in our modern U.S. sample are presumably either at or above their ideal weight and therefore $\frac{\partial V}{\partial W_{t+1}} < 0$. Our comparative static results focus on the cases in which $\frac{\partial V}{\partial W_{t+1}} < 0$. Equation (5) implies that a consumer should eat food until its benefits and weight costs are equalized with the per-dollar utility of other consumption goods. Food yields immediate benefits $\frac{\partial U_t}{\partial f_t}$, with explicit financial cost p and implicit weight cost $\frac{\partial V}{\partial W_{t+1}}$; however, the weight cost of food occurs in the future and is therefore discounted by δ.

We now consider the relationship between patience, food consumption, and weight. Our first result is that more patient individuals consume less food and will have a lower weight. That is, for a given p, if $\frac{\partial V}{\partial W_{t+1}} < 0$, then as $\delta \to 1$, f_t declines. Greater patience has two effects. First, in equation (5), as δ approaches 1, the negative $\frac{\partial V}{\partial W_{t+1}}$ term carries a greater impact. To maintain equality with the $p_t \frac{\partial U_t}{\partial c_t}$ term requires more patient individuals to increase $\frac{\partial U_t}{\partial f_t}$, i.e. to reduce food consumption f_t. Since the weight-gain cost occurs in the future, impatient individuals discount this cost and effectively face a lower total price of food than do more patient individuals. Further, as patience increases the present value of all future consumption increases, necessitating a reduction in present food consumption in favor of greater future wealth.

Our second result reveals the interaction between time preferences and food prices. We demonstrate that more patient individuals should display a smaller response to changes in food prices. If $\frac{\partial V}{\partial W_{t+1}} < 0$, then as $\delta \to 1$, $\frac{\partial f}{\partial p}$ increases and becomes less negative. Consider a decrease in food price p. The left-hand side of equation (5) must decrease to preserve equality, so the individual should eat more food in response to falling food prices and $\frac{\partial U_t}{\partial f_t}$ will decline. As the individual increases food consumption, he also incurs future weight gains through the negative $\frac{\partial V}{\partial W_{t+1}}$ term, further helping to decrease the left-hand side term. However, the negative weight-gain effects $\delta \frac{\partial V}{\partial W_{t+1}}$ are more pronounced for more patient individuals than for impatient individuals. As such, more patient individuals will purchase less additional food after a decrease in food prices than will impatient individuals, $\frac{\partial^2 f}{\partial p \partial \delta} > 0$. The greater emphasis on future weight effects causes patient individuals to display a dampened increase in food consumption in response to cheaper food compared to impatient individuals; alternatively, more impatient individuals should be more responsive to changes in food prices. Our data analysis tests these theoretical predictions.

3 Data

We test these theoretical predictions using data from the NLSY, a panel from the US Bureau of Labor Statistics that follows 12,686 individuals annually from 1979 to 1994 and then biennially through 2008.[4] We restrict our analysis to the 2006 wave, as in that year the survey included questions on hypothetical intertemporal trade-offs that allow for the construction of our time preference measures. In 2006 only 6,592 individuals remained in the panel, and we restrict the analysis sample to the 5,982 individuals without missing information. The respondents were between 14 and 22 years old at the start of the panel, so the age range in our sample is 41 to 49.

Our main dependent variable is BMI, which we compute from self-reported weight and

[4]The 12,686 respondents consist of a random sample of 6,111 plus supplemental samples of 5,295 minority and economically disadvantaged youths and 1,280 military youths. We employ the NLSY's sampling weights throughout the analysis.

height. We use weight from 2006 and height from 1985; the respondents were not asked about height after 1985 as they were all adults by then. Following Cawley (1999) and others, we adjust for measurement error in self-reported weight and height by exploiting the fact that another national dataset, the National Health and Nutrition Examination Survey (NHANES), includes both actual and self-reported measures. Using 41 to 49 year olds from the 2005-2006 NHANES, we predict actual weight and height as a quadratic function of self-reported weight and height for each sex and race (white, black, or another race) subgroup. We then adjust NLSY weights and heights accordingly and use the adjusted values to compute BMI. The correlation between actual and self-reported BMI is very high, and the results are similar if we do not employ the correction. We also use BMI to construct indicator variables for whether or not the respondent is overweight ($25 \leq BMI < 30$), Class I obese ($30 \leq BMI < 35$), or severely obese ($BMI \geq 35$), with the omitted category reflecting $BMI < 25$.

Our independent variables of interest are time preference measures computed from two questions on hypothetical intertemporal trade-offs available in the 2006 NLSY survey. The first question is,

> "Suppose you have won a prize of $1000, which you can claim immediately. However you have the alternative of waiting one year to claim the prize. If you do wait, you will receive more than $1000. What is the smallest amount of money in addition to the $1000 you would have to receive one year from now to convince you to wait rather than claim the prize now?"

We compute respondents' discount factors – which we name "Discount Factor 1" ($DF1$) – from their answers ($amount1$) as follows:

$$DF1 = \frac{1000}{1000 + amount1}. \tag{6}$$

The second question is,

"Suppose you have won a prize of \$1000, which you can claim immediately. However, you can choose to wait one month to claim the prize. If you do wait, you will receive more than \$1000. What is the smallest amount of money in addition to the \$1000 you would have to receive one month from now to convince you to wait rather than claim the prize now?"

We use these answers ($amount2$) to compute annualized (via simple multiplication) discount factors – named "Discount Factor 2" ($DF2$) – through the following formula:

$$DF2 = \frac{1}{12/\frac{1000}{1000+amount2} - 11}. \tag{7}$$

We exploit the fact that the NLSY contains two intertemporal discounting questions, one over a monthly interval and the other over an annual interval, to compute a measure of present-bias. A time-consistent individual should have the same (annualized) discount factor over the monthly interval as the annual interval. By contrast, a present-biased individual will display decreasing impatience and have a greater discount factor for the annual delay than the monthly delay. We jointly fit an individual's responses to both intertemporal questions using the quasi-hyperbolic discounting specification, whereby individuals discount outcomes τ periods away at $\beta\delta^{\tau}$. The parameter δ reflects an individual's "long-run" level of patience, whereas β reflects any disproportionate weight given to the immediate present at the expense of all future periods (Phelps and Pollak, 1968; Laibson, 1997). If $\beta = 1$, then quasi-hyperbolic discounting reduces to traditional, time-consistent discounting, whereas $\beta < 1$ reflects potentially time-inconsistent impulsivity and present-bias.

Assuming annual periods, an individuals' joint responses to these two questions imply that

$$\begin{aligned} \beta\delta^{\frac{1}{12}} &= \frac{1000}{1000 + amount2} \\ \beta\delta &= \frac{1000}{1000 + amount1} \end{aligned}$$

yielding $\delta = (\frac{1000+amount2}{1000+amount1})^{\frac{12}{11}}$ and $\beta = \frac{1000}{\delta(1000+amount1)}$. To assess the relative contribution of impulsivity versus impatience towards obesity, our main regressions include both β and δ as regressors. As robustness checks, we explore the sensitivity of the results to the use of Discount Factor 1 or Discount Factor 2 as our measure of time preference. In unreported regressions, we also verified that the conclusions reached are similar using discount rates instead of factors.

Some economists object that hypothetical questions, such as the ones above, provide no incentive for respondents to carefully assess the intertemporal trade-off and thus may not be representative of individuals' true preferences. However, at least in the domain of time preferences, several studies have demonstrated no difference in responses between real and hypothetical decisions (Johnson and Bickel, 2002; Madden et al., 2003). Of studies demonstrating a difference between real versus hypothetical time discounting decisions, Kirby and Marakovic (1995) found that subjects discounted real amounts more impatiently, whereas Coller and Williams (1999) found that respondents discounted real amounts more patiently. Taken together, these studies suggest that there is no systematic bias between the temporal discounting of real versus hypothetical amounts.

Note that the above discount factor computations implicitly assume linear utility. We also utilize the answer to a 2006 NLSY question on risk preference as a control in order to address the possible concern that time and risk preference are correlated. This question is:

> "Suppose you have been given an item that is either worth nothing or worth \$10,000. Tomorrow you will learn what it is worth. There is a 50-50 chance it will be worth \$10,000 and a 50-50 chance it will be worth nothing. You can wait to find out how much the item is worth, or you can sell it before its value is determined. What is the lowest price that would lead you to sell the item now rather than waiting to see what it is worth?"

We also construct a set of control variables using the NLSY's information on age, race, gender, marital status, education, occupation, work hours, income, and net worth. As dependent variables in falsification tests, we utilize binary variables reflecting whether the respondents have arthritis, asthma, anemia, chronic kidney or bladder problems, chronic stomach problems, frequent colds, or frequent headaches.

We match these individual-level data to local price information from the second quarter of 2006 taken from the C2ER's American Chamber of Commerce Researchers Association Cost of Living Index (ACCRA COLI). The second quarter 2006 ACCRA COLI computes prices for a wide range of grocery, energy, transportation, housing, health care, and other items in 311 local markets throughout the US. Most of these local markets are single cities, but some are multiple cities (i.e. Bloomington-Normal, IL) while others are entire counties (i.e. Dare County, NC). We use the county identifiers from the restricted version of the NLSY to match each respondent to the closest ACCRA COLI market. This leads to measurement error in the price variables that increases with distance from the nearest ACCRA COLI market. To mitigate potential attenuation bias, in the regressions that include prices we drop the 892 respondents living in counties greater than 50 miles from the closest ACCRA COLI area, reducing the sample size to 5090. The conclusions reached are similar using 30, 40, 60, and 70 mile distance cutoffs. Our food price variable is the average price of the 19 reported food items, weighted by their share as given by the ACCRA COLI. Table 1 lists these items while giving their average prices and weights. We also construct a non-food price variable by taking the weighted averages of the price indices for housing, utilities, transportation, health care, and miscellaneous goods and services.

Tables 2 and 3 report the names, descriptions, means, and standard deviations of the variables used in the empirical analysis. The average BMI is 28.2; 38% of the sample is overweight but not obese, 20% is class I obese, and 12% is severely obese. The mean discount factor is 0.6 using the annual delay question and 0.4 using the monthly delay question, corresponding to a 66% and 150% annual interest rate. Though this degree of financial impatience may appear implausibly high, note that the NLSY questions explicitly establish receiving money immediately as the status quo. A robust finding is that preferences are sticky towards a status quo option, and measuring patience via this willingness to delay methodology yields greater elicited impatience than methods which do not impose an immediate intertemporal reference point (Loewenstein, 1988; Shelley, 1993; McAlvanah, 2010). The average respondent is more patient over longer delays, supportive of hyperbolic discounting or diminishing impatience. The quasi-hyperbolic specification implies that the average individual discounts any future outcome with β equal to 0.80, and subsequent periods with discount factor of 0.75, or about 33% per year. The inclusion of β implies a more patient level of annual discounting than the prior specifications. 85% of individuals have $\beta < 1$, indicating that the vast majority of respondents are present-biased. Seven percent of respondents are exactly time-consistent with $\beta = 1$, whereas eight percent of respondents are hyperopic and future-biased with $\beta > 1$.

4 Empirical Analysis

4.1 Discount Factor and BMI, Overweight, and Obesity

We begin the empirical analysis by estimating the association between time preferences and BMI. Our main regression equation is

$$BMI_i = \alpha_0 + \alpha_1\beta_i + \alpha_2\delta_i + \boldsymbol{\alpha}_3\mathbf{DEMO}_i + \boldsymbol{\alpha}_4\mathbf{HC}_i + \boldsymbol{\alpha}_5\mathbf{LABOR}_i + \boldsymbol{\alpha}_6\mathbf{FIN}_i + \alpha_7 RISK_i + \varepsilon_i \quad (8)$$

where i indexes individuals. The main parameters of interest are β and δ, the computed measures of present-bias and long-run patience, respectively. **DEMO** is a set of demographic controls including age and indicators for gender, race, and marital status. **HC** is a set of variables reflecting endowment of and investment in human capital; these include IQ (as measured by score on the Armed Forces Qualifying Test) and dummies for educational attainment. **LABOR** is a set of controls for labor market activity, comprised of work hours and indicators for whether an individual's employment is blue-collar, white-collar, or service industry, relative to the omitted category of unemployment. **FIN** consists of the financial controls income and net worth, along with the square of income since prior research has documented an inverted U-shaped relationship between income and BMI (Lakdawalla and Philipson, 2002). Finally, $RISK$ is the measure of risk preference. We include the sets of control variables in an effort to isolate the ceteris paribus relationship between time preference and BMI. If levels of patience and BMI both differ systematically on the basis of age, gender, race, marital status, intelligence, education, income, net worth, time spent working, or risk preference, failing to adequately control for these variables may bias the estimators of α_1 or α_2. Our model contains a more detailed set of covariates than prior studies examining the relationship between computed measures of time preference and BMI. Borghans and Golsteyn (2006) control for only age and sex; Chabris et al. (2008) control for only age, sex, education, and depression symptoms; and Ikeda et al. control for only age, gender, college degree, work hours, smoking, and risk preference.[5] We begin with a simple regression of BMI on discount factor and then gradually add the sets of controls to build up to the full model (6). As robustness checks, we also estimate (6) replacing β and δ with the simple patience measures of $DF1$ with $DF2$.

Table 4 reports the results, starting in column (1) with a regression with no control variables and gradually building up to the full model in column (6) in order to evaluate the robustness of the estimates. Both present-bias β and long-run patience δ are statistically significant and negatively associated with BMI in all six specifications, suggesting that impulsivity and time-consistent impatience are separately and significantly associated with BMI. Including the demographic and human capital controls in columns (2) and (3) attenuates the coefficient estimate for β somewhat, but across columns (3) to (6) the estimate stabilizes at -0.86 to -1 units. These estimates imply that a one standard deviation increase in β (decrease in impulsivity) of 0.2 lowers weight by 0.17 to 0.2 BMI units, or 1.11 to 1.29 pounds at the sample mean height of 67.3 inches. The coefficient estimate for δ is stable across specifications and ranges from -0.48 to -0.63. A standard deviation increase in δ (increase in long-run

[5] We do not control for smoking in any of our specifications as smoking is related to time preference (Chabris et al., 2008) and also influences BMI (e.g. Chou et al., 2004), creating the possibility for an over-controlling problem. Less obvious over-controlling problems could also exist for some of the variables we do include, such as education, work hours, income, and net worth. This highlights the importance of presenting results from a number of specifications with different combinations of control variables to ensure the estimates are stable.

patience) of 0.33 therefore decreases weight by 0.16 to 0.21 BMI units, or 1.02 to 1.34 pounds at the sample mean height. Though we are of course unable to control for every potential confounding factor, the fact that the conclusions reached are not sensitive to the choice of covariates increases our confidence that our results reflect ceteris paribus relationships between β and δ and BMI rather than spurious relationships driven by omitted variable bias.

Columns (7) and (8) of Table 4 report the results using discount factors computed from the annual and monthly delay questions, respectively, instead of the β-δ approach. Discount factor is highly significant in both regressions, with greater patience again indicating lower BMI. A standard deviation increase in discount factor decreases BMI by 0.25 units using $DF1$ and 0.27 units using $DF2$.

The results for the control variables are generally consistent with prior research. Being male, black, or married, not having a college degree, having a lower net worth, and working longer hours is associated with an increased BMI. Additional income is associated with a decrease in BMI but at a diminishing rate. Individuals working at relatively physically demanding blue collar and service jobs have lower BMIs than those working in white collar jobs or not working (the omitted category), though the differences are either statistically insignificant or marginally significant. Age, IQ, and risk preference are not statistically associated with BMI conditional on time preference and the other regressors. The lack of an effect for age likely reflects the limited age range in the sample.

Table 5 displays the coefficient estimates for β and δ, splitting the sample by gender and race and using the full set of control variables. Table 5 also presents the results using a univariate measure of time preference, annual discount factor $DF1$, as a robustness check. Using $DF1$ as the simple measure of time preference reveals that the effect of discount factor on BMI is strong and significant for men, and still negative but smaller and insignificant for women. However, decomposing time preferences reveals an interesting dichotomy between males and females. For females, the coefficient on β is negative and statistically significant whereas δ is not significant; the reverse pattern holds for males. This suggests that the relationship between intertemporal preferences and BMI is driven by impulsivity and present bias and females, but time-consistent impatience for males. When stratifying by race, discount factor's impact is strong and significant for whites but small and insignificant for non-whites. Decomposing time preferences into β and δ reveals that both β and δ are negative and significant for whites but insignificant for non-whites, though this is presumably attributable to the smaller non-white sample size.

We next estimate the association between discount factor and probability of being overweight, Class I obese, or severely obese using an ordered probit model. Since an increase in BMI is not harmful to health throughout the entire distribution and actually improves health at the far left tail, it is important to verify that weight gain caused by impatience is accompanied by increased odds of becoming overweight or obese. We estimate

$$\begin{aligned} P(CATEGORY_i &= j) = \Phi(\alpha_j - (\gamma_0 + \gamma_1\beta_i + \gamma_2\delta_i + \gamma_3\mathbf{DEMO}_i + \gamma_4\mathbf{HC}_i + \gamma_5\mathbf{LABOR}_i \\ &+\gamma_6\mathbf{FIN}_i + \gamma_7 RISK_i + \mu_i)) \end{aligned} \tag{9}$$

where

$$CATEGORY = \left\{ \begin{array}{c} 0 \text{ if } BMI < 25 \\ 1 \text{ if } 25 \leq BMI < 30 \\ 2 \text{ if } 30 \leq BMI < 35 \\ 3 \text{ if } BMI \geq 35 \end{array} \right\}$$

and Φ is the cumulative distribution function for the standard normal distribution. Table 6 reports the estimates for γ_1 and γ_2 as well as the marginal effects on the probabilities of being overweight, obese, or severely obese. β and δ are each statistically significant at the 10% level with negative coefficient estimates, indicating that greater patience is associated with a lower BMI category. The marginal effect of present bias β on P(Overweight) is insignificant, though the marginal effects on P(Class I Obese) and P(Severely Obese), however, are -0.026 and -0.031. These effects are sizeable, representing 13% and 25% of the sample Class I obesity and severe obesity rates. Similar results hold using $DF1$ as a robustness check. An increase in annual discount factor lowers BMI category at the 5% significance level, and significantly reduces the probabilities Class I Obese and Severely Obese.

We close this section with a series of falsification tests. First, we re-estimate (8) using height in inches instead of BMI as the dependent variable. Since it is implausible that impatience affects BMI by making people shorter rather than increasing their weight, such a finding would call into question the validity of the identification strategy. We then utilize as dependent variables chronic health conditions that are less directly the result of intertemporal choices than BMI. These conditions include arthritis or rheumatism; asthma; kidney or bladder problems; stomach, liver, intestinal, or gall bladder problems; anemia; frequent colds, sinus problems, hay fever, or allergies; and frequent or severe headaches, dizziness, or fainting spells. We also consider a dependent variable representing the total number of these conditions reported. These health problems are less clearly tied to eating and exercise than obesity, so any meaningful "effect" of discount factor likely reflects a mis-specified model rather than a causal effect. We estimate linear models for height, probit models for the individual health conditions, and a Poisson model for the total number of conditions. Table 7 reports the marginal effects. Neither β nor δ is ever significant at the 5% level and is only significant at the 10% level in one of the nine regressions. In unreported regressions, identical results hold using $DF1$ as the measure of impatience. These results increase our confidence that the findings for BMI are not the artifact of omitted variables correlated with patience and either health or stature. The falsification tests also help alleviate concerns about reverse causality, as having a high BMI might decrease an individual's life expectancy and thereby cause her to optimize over a shorter time horizon. If this were the case, the measured discount factor should be correlated with all health problems regardless of whether they are the direct result of behaviors.

4.2 Interaction of Discount Factor and Food Prices

We next test the second prediction of the theoretical model and examine heterogeneity in the effect of local food prices on BMI on the bases of impulsivity β and long-run patience δ. Food prices are perhaps the most obvious economic incentive related to body weight, and the decline in real food prices in recent decades is generally regarded as a contributing factor to the rise in obesity (Lakdawalla and Philipson, 2002 and 2005; Philipson and Posner, 2003; Chou et al., 2004; Goldman et al., 2010). Changing economic incentives such as falling food prices may explain the increase in the mean of the BMI distribution, but do not explain why the variance of the distribution has also increased. We hypothesize that changing incentives have interacted with individuals' levels of patience to both shift the BMI distribution to the right and thicken its right tail. Testing for effects of the interactions of β and δ with food prices provides a preliminary test of this theory.

The regression equation is similar to (8) but adds local food prices ($PFOOD$), non-food prices (PNF), and the interaction of food prices with discount factor:

$$\begin{aligned} BMI_{ic} &= \alpha_0 + \alpha_1\beta_{ic} + \alpha_2\delta_{ic} + \boldsymbol{\alpha}_3\mathbf{DEMO}_{ic} + \boldsymbol{\alpha}_4\mathbf{HC}_{ic} + \boldsymbol{\alpha}_5\mathbf{LABOR}_{ic} + \boldsymbol{\alpha}_6\mathbf{FIN}_{ic} + \alpha_7 RISK_{ic} \\ &\quad + \alpha_8 PFOOD_c + \alpha_9(\beta_i * PFOOD_c) + \alpha_{10}(\delta_i * PFOOD_c) + \alpha_{11}PNF_c + \varepsilon_i \qquad (10) \end{aligned}$$

where c indexes counties.[6] Controlling for non-food prices helps ensure that the estimated effects of food prices are not simply capturing a more general price effect. The endogeneity of food prices is a natural concern. However, note that the regressors of interest in equation (10) are the interactions of food price with β and δ, not food price itself. Even if the coefficient estimator for food price is biased by unobservable market-level factors affecting both food prices and weight, the estimator for the interaction term would only be biased if the effect of these unobservables differs systematically for people with different levels of patience and impulsivity. It is not obvious why this would be the case. Further, the natural direction of

[6] In unreported regressions, we verified that the standard errors remain virtually identically clustering by county.

the bias in the estimator for food price is upward, as areas with high demand for food might have both higher food prices and higher body weights. However, we will still estimate an inverse relationship between food prices and BMI, so endogeneity bias is not preventing us from obtaining the signs predicted by economic theory.[7]

Table 8 displays the results in a similar format as Table 4, starting with a model with no controls and gradually building up to the full specification in column (6). Columns (7) and (8) again experiment with the alternative discount factor measures. Table 9 contains some additional robustness checks. One potential concern is that the food basket used to compute market prices contains both healthy and unhealthy items, whereas the rise in obesity may be the result of cheaper junk food rather than lower across-the-board food prices. The first two columns of Table 9 therefore experiment with dropping the (arguably) healthier items from the food basket in an attempt to isolate the price of unhealthy food. The first column excludes the fruits and vegetables (lettuce, bananas, potatoes, peas, peaches, and corn). The second column also excludes the meats (steak, beef, chicken, sausage, eggs, tuna, and chicken frozen dinner), leaving only white bread, cereal, potato chips, and the three restaurant meals.[8] The third through fifth columns of Table 9 use 2-, 4-, and 6-year lags of food prices rather than contemporaneous prices to mitigate potential concerns about reverse causality [NOT YET DONE]. Finally, the last column of Table 9 adds interactions of food prices with all the other covariates in the model, addressing the possible concern that estimated heterogeneity by time preference might actually reflect heterogeneity by characteristics that are correlated with time preference, such as income and education.

The coefficient estimate for food price is negative across all 11 specifications in Tables

[7]In unreported regressions, we also attempted a panel data specification using the variation in city food prices over time. Due to the limited sample size, the fixed effects specification did not permit meaningful precision.

[8]In an unreported regression we included separate variables for the prices of fruits/vegetables, meats, and other (unhealthy) foods, along with interactions of these three food prices with β and δ. The coefficient estimates for price and the interactions were both much larger for "other" foods than for fruits/vegetables and meats, suggesting that consumers' BMIs – and the BMIs of impatient consumers in particular – are most responsive to the prices of unhealthy foods. However, multicollinearity among the price variables prevented any of the price variables or interaction terms from being statistically significanct. We therefore consider these findings speculative and do not present them in the paper.

8 and 9 and significant in 9. The interaction term $\beta * PFOOD$ is significant at the 5% level in all regressions and positively associated with BMI, supporting the prediction that greater impulsivity (lower β) strengthens individuals' response to food prices. The coefficient estimates for the interaction term are all within a standard error of each other, ranging from 3.07 to 4.39. The interaction term $\delta * PFOOD$ is also positively associated with BMI in all specifications, with coefficient estimates ranging from 1.23 to 1.52. However, $\delta * PFOOD$ is only significant at the 10% level in one regressions, with the p-values in the others ranging from 0.11 to 0.19. The evidence regarding the interaction of long-run patience and food prices is therefore less conclusive than that for the interaction of impulsivity and food prices. In the specifications using discount factors instead of β and δ (columns (7) and (8) of Table 8), the interaction terms are both significant at the 5% level and suggest that greater impatience (lower $DF1$ and $DF2$) strengthens the food price effect.

Figure 2 uses the estimates from the full model from column (6) of Table 8 to show how the marginal effect of food price on BMI changes from the 1st to 99th percentiles of the impulsivity distribution. This range spans a large present bias of $\beta = 0.33$ to a slight future bias of $\beta = 1.11$. The solid line shows the marginal effect, while the dashed lines represent the endpoints of the 95% confidence interval. A \$1 increase in food price (30% of the sample mean) decreases the BMIs of the most impulsive individuals by about 3 units, or over 19 pounds at the sample mean height. This effect weakens as β increases, gradually approaching zero. The confidence intervals show that the food price effect is statistically significant up to approximately the 23rd percentile of $\beta = 0.62$. The entire statistically detectable effect of food prices on BMI is therefore concentrated among the most impulsive individuals.

Figures 3-5 illustrate how this heterogeneity in the food price effect can affect the variance of the BMI distribution. We perform a median split, defining individuals with a "high present bias" as those with $\beta \leq 0.845$ and those with a "low present bias, time consistent preferences, or future bias" as those with $\beta > 0.845$. We use the regression results from column (6) of Table 8 to plot the predicted BMI distributions for the two groups at the sample mean food price of \$3.35, as well as at \$0.40 above and below the mean. We choose \$0.40 above and below the mean because, according to Consumer Price Index (CPI) data from the Bureau of Labor Statistics, the real price of food at home fell by 12% during the 50 years preceding the survey year 2006, and 12% of our sample mean food price is \$0.40.[9] Figure 3 therefore represents the predicted BMI distributions at 1956 food prices, Figure 4 shows the distributions at 2006 prices, and Figure 5 presents the distributions if the price of the food basket falls by another \$0.40 in the future. Figure 3 shows that at 1956 food prices the predicted BMI distributions of the two groups are nearly on top of each other. As food prices fall to 2006 levels in Figure 4, a difference between the two distributions emerges and more impulsive have higher predicted BMIs than less impulsive ones. Figure 5 projects that if real food prices fall further in the future the gap between the two groups will widen even further.

5 Conclusion

This study investigates the connection between time preference, food prices, and BMI. We present a theoretical model predicting that greater impatience should both increase BMI and that impatient people should be more responsive to falling food prices. We then test these predictions using the 2006 NLSY matched with local price data from C2ER. Time preference is significantly associated with BMI and the probabilities of being overweight and obese. The effect of time preference on BMI is attributable to both present-biased, time-inconsistent preferences as well as time-consistent impatience, suggesting that both rational intertemporal substitution and impulsive behavior contribute to obesity. The interaction of time preferences and food prices reveals that present-biased individuals are more responsive to food prices, whereas no such effect exists for time-consistent long-run impatience. This suggests that present-biased and impulsive individuals are predominantly responsive to food prices, whereas patient individuals are responsive to both food prices and health effects. Our

[9] After adjusting for changes in the overall CPI, the CPI for food at home dropped from 219.4 to 193.1 between 1956 and 2006, a decline of 12%.

results potentially help to explain the rightward shift in the BMI distribution in recent decades as well as the most dramatic increase in the right tail. Future research should investigate whether other economic incentives besides food prices might also interact with individuals' rates of time preference in determining weight. Additional research should continue to focus on the influence of self-control problems on weight and the corresponding policy implications.

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Table 1 – ACCRA COLI Food Items (2006)

Item	Average Price	Weight
24 oz white bread	1.175	0.0861
18 oz box of corn flakes; Kellogg's or Post	2.987	0.0399
Head of iceberg lettuce	1.219	0.0267
1 lb bananas	0.518	0.0555
10 lb sack potatoes	3.753	0.0264
15 oz can sweet peas; Del Monte or Green Giant	0.826	0.0110
29 oz halves or slices peaches; Hunts, Del Monte, or Libby's	1.805	0.0127
16 oz whole kernel frozen corn	1.240	0.0110
1 lb t-bone steak	8.383	0.0354
1 lb ground beef	2.539	0.0354
1 lb whole uncut chicken	1.057	0.0440
1 lb package sausage; Jimmy Dean or Owen	3.183	0.0454
Dozen large eggs; grade A or AA	1.150	0.0100
6 oz chunk of light tuna; Starkist or Chicken of the Sea	0.746	0.0378
8 to 10 oz frozen chicken entree; Healthy Choice or Lean Cuisine	2.538	0.0876
12 oz plain regular potato chips	2.419	0.0730
1/4 lb patty with cheese; McDonald's	2.549	0.1133
11" to 12" thin crust cheese pizza; Pizza Hut or Pizza Inn	10.250	0.1133
Thigh and drumstick of chicken; Kentucky Fried Chicken or Church's	2.863	0.1133

Table 2 – Summary Statistics for Body Weight and Time Preference Variables

Variable Name	Description	Mean (Std.Dev.)
BMI	Body mass index (kg/m^2)	28.26 (5.76)
Overweight	Binary variable equal to 1 if 25≤BMI<30	0.38 (0.48)
Obese (class I)	1 if 30≤BMI<35	0.20 (0.40)
Severely obese	1 if BMI≥35	0.12 (0.32)
Beta	Computed using the quasi-hyperbolic discounting specification	0.80 (0.20)
Delta	Computed using the quasi-hyperbolic discounting specification	0.75 (0.33)
Discount factor 1	Computed from amount needed to wait a year to receive $1000	0.59 (0.25)
Discount factor 2	Computed from amount needed to wait a month to receive $1000	0.39 (0.30)

Note: Obeservations are weighted using the NLSY sampling weights.

Table 3 – Summary Statistics for Other Variables

Variable Name	Description	Mean (Std.Dev.)
Age	Age in years	44.87 (2.230)
Female	1 if female	0.48 (0.50)
Race: black	1 if race is black	0.13 (0.34)
Race: other	1 if race is neither black nor white	0.03 (0.16)
Married	1 if married	0.64 (0.48)
AFQT	Percentile score on armed forces qualifying test in 1985	48.97 (28.54)
High school	1 if highest grade completed=12	0.41 (0.49)
Some college	1 if 13≤highest grade completed≤15	0.24 (0.42)
College	1 if highest grade completed=16	0.28 (0.45)
White collar	1 if current occupation is white collar	0.52 (0.50)
Blue collar	1 if current occupation is blue collar	0.20 (0.40)
Service	1 if current occupation is service	0.09 (0.28)
Hours worked	Average hours worked per week in the preceding year	35.92 (19.40)
Income	Total household income (units of $10,000)	8.31 (8.41)
Net worth	Household assets minus liabilities in 2004 (units of $10,000)	25.09 (47.57)
Risk	Amount (in $1,000s) needed to forego a 50% chance of $10,000 or $0	4.79 (3.27)
Arthritis	1 if ever had arthritis or rheumatism	0.12 (0.32)
Asthma	1 if asthmatic	0.07 (0.25)
Kidney/bladder	1 if kidney or bladder problems	0.05 (0.21)
Stomach	1 if trouble with stomach, liver, intestines, or gall bladder	0.10 (0.30)
Anemia	1 if anemic	0.04 (0.21)
Colds	1 if frequent colds, sinus problems, hay fever, or allergies	0.26 (0.44)
Headaches	1 if frequent or severe headaches, dizziness, or fainting spells	0.11 (0.31)
Food price	Weighted average price of 19 food items	3.34 (0.29)
Non-food index	Weighted average price index of non-food price categories	105.43 (17.82)

See notes for Table 2.

Table 4 – Impatience, Time-Inconsistency, and BMI

Dependent Variable: BMI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta	−1.70 (0.44)***	−1.30 (0.45)***	−1.00 (0.46)**	−0.96 (0.45)**	−0.86 (0.45)*	−0.92 (0.46)**	–	–
Delta	−0.58 (0.26)**	−0.63 (0.26)**	−0.57 (0.26)**	−0.56 (0.25)**	−0.48 (0.25)*	−0.50 (0.25)**	–	–
Discount factor 1	–	–	–	–	–	–	−0.98 (0.35)***	–
Discount factor 2	–	–	–	–	–	–	–	−0.90 (0.29)***
Age	–	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.05 (0.04)	0.05 (0.04)	0.04 (0.04)
Female	–	−0.74 (0.17)***	−0.71 (0.17)***	−0.54 (0.19)***	−0.57 (0.19)***	−0.58 (0.19)***	−0.58 (0.19)***	−0.56 (0.19)***
Race: black	–	2.13 (0.19)***	1.99 (0.22)***	2.01 (0.22)***	1.95 (0.22)***	1.96 (0.22)***	1.96 (0.22)***	1.94 (0.22)***
Race: other	–	0.59 (0.44)	0.49 (0.45)	0.49 (0.45)	0.53 (0.44)	0.53 (0.44)	0.54 (0.44)	0.51 (0.44)
Married	–	0.07 (0.19)	0.19 (0.19)	0.16 (0.19)	0.74 (0.22)***	0.74 (0.22)***	0.73 (0.22)***	0.74 (0.22)***
AFQT	–	–	−0.001 (0.004)	−0.003 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)
High school	–	–	0.19 (0.38)	0.03 (0.04)	0.10 (0.38)	0.10 (0.37)	0.11 (0.38)	0.09 (0.38)
Some college	–	–	−0.08 (0.41)	−0.29 (0.42)	−0.13 (0.41)	−0.12 (0.41)	−0.12 (0.41)	−0.14 (0.41)
College	–	–	−1.11 (0.044)**	−1.40 (0.44)***	−0.90 (0.45)**	−0.89 (0.45)**	−0.88 (0.45)**	−0.91 (0.45)**
White collar	–	–	–	0.04 (0.28)	−0.01 (0.028)	−0.01 (0.28)	−0.01 (0.28)	−0.01 (0.28)
Blue collar	–	–	–	−0.32 (0.32)	−0.45 (0.32)	−0.45 (0.32)	−0.46 (0.32)	−0.44 (0.32)
Service	–	–	–	−0.37 (0.35)	−0.59 (0.35)*	−0.60 (0.35)*	−0.59 (0.35)*	−0.60 (0.35)*
Work hours	–	–	–	0.02 (0.01)***	0.03 (0.01)***	0.03 (0.01)***	0.03 (0.01)***	0.03 (0.01)***
Income	–	–	–	–	−0.13 (0.03)***	−0.13 (0.03)***	−0.13 (0.03)***	−0.13 (0.04)***
Income^2	–	–	–	–	0.002 (0.001)**	0.001 (0.001)**	0.001 (0.001)**	0.002 (0.001)**
Net worth	–	–	–	–	−0.006 (0.002)***	−0.006 (0.002)***	−0.006 (0.002)***	−0.006 (0.002)***
Risk	–	–	–	–	–	−0.03 (0.03)	−0.03 (0.03)	−0.03 (0.03)

Notes: $n = 5982$. Heteroskedasticity-robust standard errors in parentheses. *** statistically significant at 1% level; ** 5% level; * 10% level. Observations are weighted using the NLSY sampling weights.

Table 5 – Heterogeneity by Gender and Race

Dependent Variable: BMI

	Gender				Race			
	Women	Men	Women	Men	White	Non-White	White	Non-White
Beta	−1.24	−0.54	–	–	−1.10	0.26	–	–
	(0.61)**	(0.67)			(0.53)**	(0.72)		
Delta	−0.24	−0.81	–	–	−0.57	−0.24	–	–
	(0.37)	(0.35)**			(0.32)*	(0.35)		
Discount factor 1	–	–	−0.70	−1.31	–	–	−1.12	−0.20
			(0.50)	(0.49)***			(0.41)***	(0.55)
Demographics	YES	YES	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES	YES	YES	YES
Financial	YES	YES	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2989	2993	2989	2993	3894	2088	3894	2088

Notes: Heteroskedasticity-robust standard errors in parentheses. *** statistically significant at 1% level; ** 5% level; * 10% level. Observations are weighted using the NLSY sampling weights. "Demographic" controls include age, gender, race, and marital status. "Human capital" controls include AFQT score and the education dummies. "Labor" controls include work hours and white collar, blue collar, and service indicators. "Financial" controls income, income^2 and net worth.

Table 6 – Ordered Probit Results

Dependent Variable: BMI Category

Variable	Coefficient Estimate	Marginal Effects Overweight	Marginal Effects Obese (Class 1)	Marginal Effects Severely Obese	Coefficient Estimate	Marginal Effects Overweight	Marginal Effects Obese (Class 1)	Marginal Effects Severely Obese
Beta	−0.160 (0.086)*	0.0005 (0.001)	−0.026 (0.014)*	−0.031 (0.017)*	–	–	–	–
Delta	−0.080 (0.049)*	0.0003 (0.0005)	−0.013 (0.008)*	−0.015 (0.009)*	–	–	–	–
Discount factor	–	–	–	–	−0.171 (0.067)**	0.0006 (0.001)	−0.028 (0.011)**	−0.033 (0.013)**
Demographics	YES	YES	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES	YES	YES	YES
Financial	YES	YES	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES	YES	YES

$n = 5982$. See notes for Table 5.

Table 7 – Falsification Tests Using Various Health Conditions

Dependent Variables:

	Height	Arthritis	Asthma	Kidney/ Bladder	Stomach	Anemia	Colds	Headaches	Number of Conditions
Beta	−0.05 (0.20)	0.027 (0.024)	−0.015 (0.018)	0.013 (0.010)	−0.005 (0.022)	−0.004 (0.011)	0.004 (0.034)	−0.009 (0.022)	−0.001 (0.070)
Delta	−0.05 (0.11)	0.004 (0.014)	−0.007 (0.012)	0.007 (0.013)	−0.008 (0.013)	−0.003 (0.006)	−0.040 (0.021)*	−0.010 (0.013)	−0.056 (0.042)
Demographics	YES	YES	YES	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES	YES	YES	YES	YES
Financial	YES	YES	YES	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5982	5975	5971	5971	5970	5970	5973	5973	5952

Marginal effects reported in all regressions. See other notes for Table 5.

Table 8 – Interaction Effects of Food Prices with Time Preference

Dependent Variable: BMI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta	−14.55 (5.47)***	−14.70 (5.38)***	−14.13 (5.36)***	−14.41 (5.38)***	−13.80 (5.36)***	−13.76 (5.35)***	–	–
Delta	−4.77 (3.12)	−4.67 (3.13)	−5.10 (3.15)	−4.71 (3.14)	−5.27 (3.13)*	−5.19 (3.13)*	–	–
Discount factor 1	–	–	–	–	–	–	−11.01 (4.39)**	–
Discount factor 2	–	–	–	–	–	–	–	−7.10 (3.53)**
Food price	−3.87 (1.67)**	−4.05 (1.63)**	−4.22 (1.63)***	−4.22 (1.63)***	−4.31 (1.63)***	−4.26 (1.63)***	−1.96 (0.92)**	−0.83 (0.66)
Non-food index	−0.007 (0.008)	−0.007 (0.008)	−0.003 (0.008)	−0.002 (0.008)	0.006 (0.008)	0.006 (0.008)	0.005 (0.008)	0.005 (0.008)
Beta*food price	3.76 (1.62)**	3.93 (1.59)**	3.85 (1.58)**	3.95 (1.59)**	3.80 (1.59)**	3.77 (1.58)**	–	–
Delta*food price	1.28 (0.93)	1.23 (0.93)	1.37 (0.94)	1.26 (0.94)	1.46 (0.94)	1.43 (0.94)	–	–
Discount factor 1*food price	–	–	–	–	–	–	2.99 (1.30)**	–
Discount factor 2*food price	–	–	–	–	–	–	–	1.79 (1.04)*
Demographics	NO	YES	YES	YES	YES	YES	YES	YES
Human capital	NO	NO	YES	YES	YES	YES	YES	YES
Labor	NO	NO	NO	YES	YES	YES	YES	YES
Financial	NO	NO	NO	NO	YES	YES	YES	YES
Risk	NO	NO	NO	NO	YES	YES	YES	YES

$n = 5090$. See other notes for Table 5.

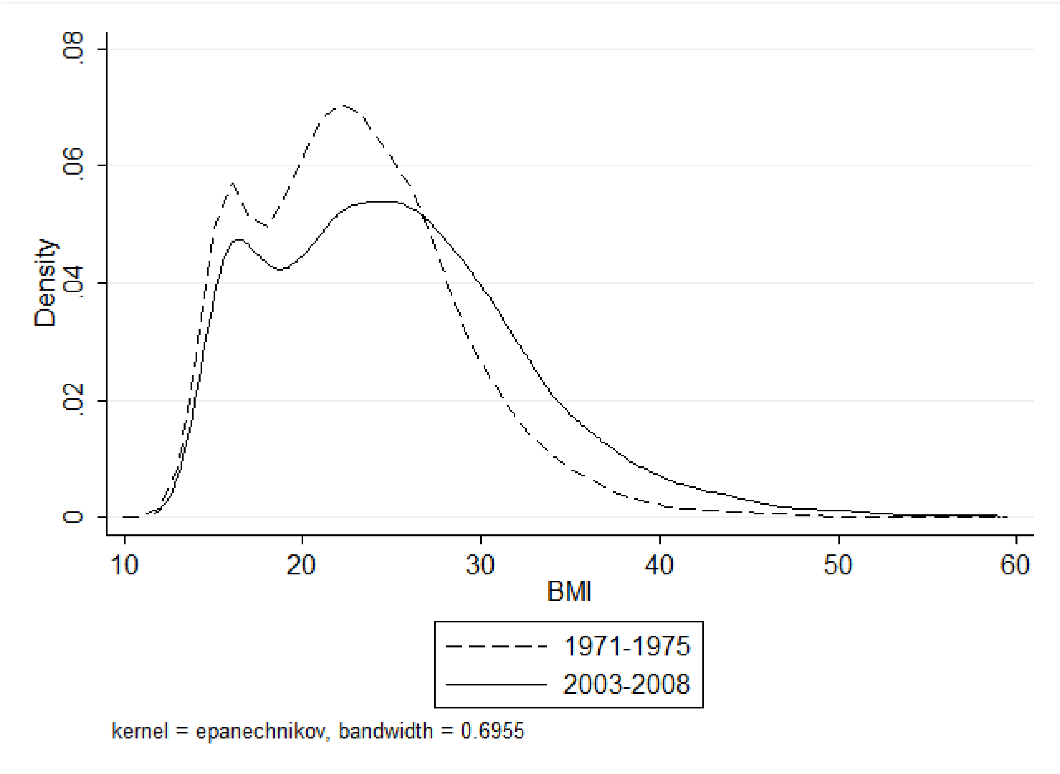
Table 9 – Interaction Effects: Additional Robustness Checks

Dependent Variable: BMI

	Alternate food price measures					Interactions of Food
	13-item basket	6-item basket	2-year lag	4-year lag	6-year lag	Price and Controls
Beta	−14.18	−13.54				−15.82
	(5.55)**	(5.75)**				(5.71)***
Delta	−5.53	−6.14				−5.50
	(3.22)*	(3.50)*				(3.14)*
Food price	−4.08	−3.54				−8.02
	(1.54)***	(1.43)**				(6.43)
Non-food index	0.006	0.003				0.004
	(0.008)	(0.006)				(0.008)
Beta*food price	3.56	3.07				4.39
	(1.50)**	(1.42)**				(1.69)***
Delta*food price	1.40	1.42				1.52
	(0.88)	(0.87)*				(0.94)
Demographics	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES	YES
Financial	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES

$n = 5090$. See other notes for Table 5.

Figure 1 – Change in BMI Distribution from 1971-1975 to 2003-2008



The 1971-1975 distribution is estimated using the National Health and Nutrition Examination Survey (NHANES) I, while the 2003-2008 distribtution is estimated by pooling the 2003-2004, 2005-2006, and 2007-2008 NHANES. Between 1971-1975 and 2003-2008, the mean of the BMI distribution rose from 23.0 to 25.3 while the standard deviation increased from 5.9 to 7.4.

Figure 2 – Marginal Effect of Food Price on BMI Across Discount Factor Distribution

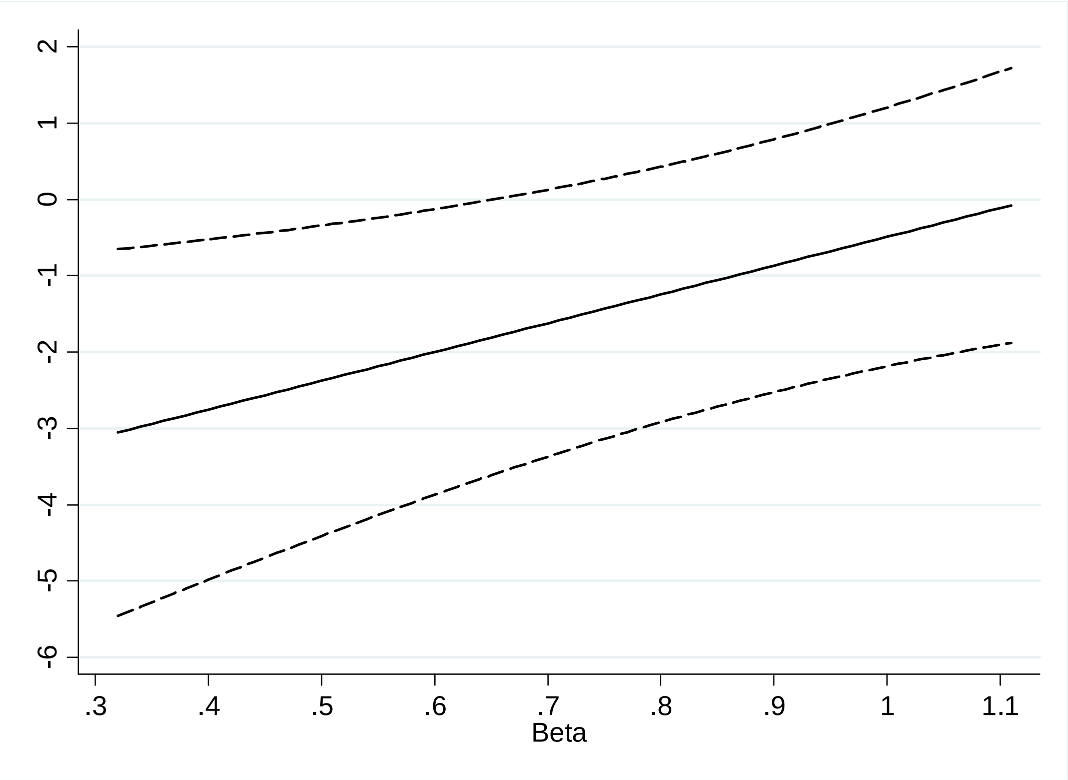


Figure 3 – BMI Distributions by Degree of Present Bias at Estimated 1956 Food Price=$3.75

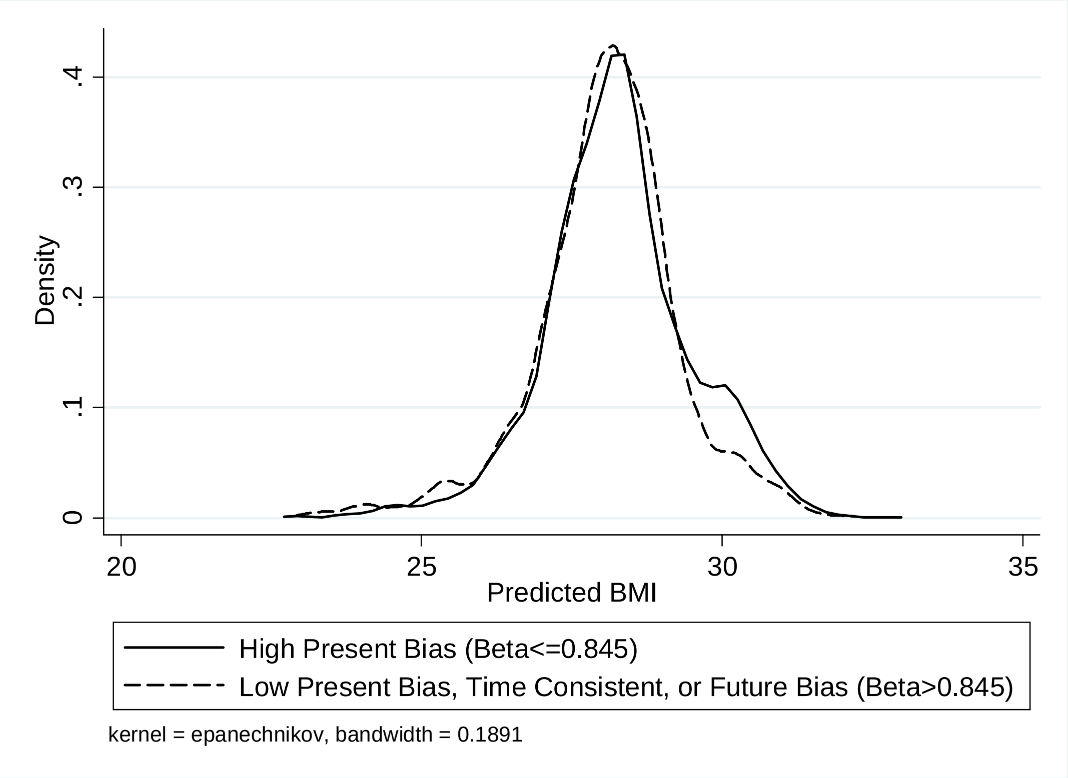


Figure 4 – BMI Distributions by Degree of Present Bias at 2006 Food Price=$3.35

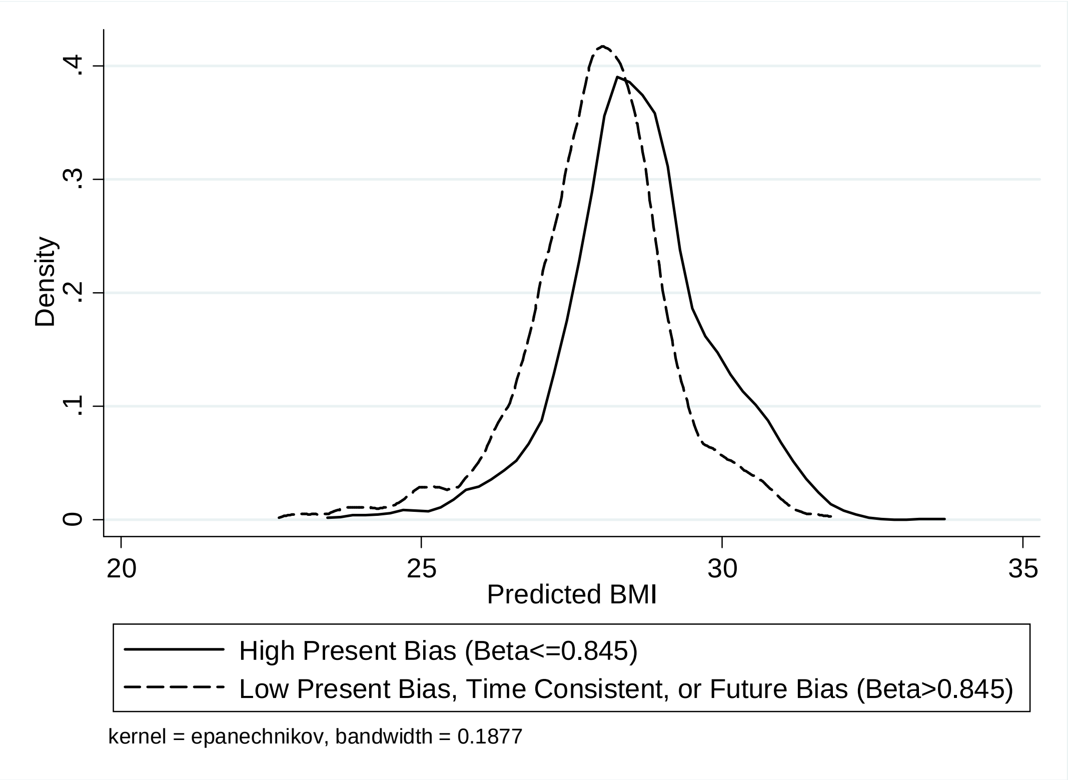


Figure 5 – BMI Distributions by Degree of Present Bias at Estimated Food Price=$2.95