Impatience, Incentives, and Obesity[*]

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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

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 the greatest degree of present bias gain the most weight when food prices fall. The interacevidence 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

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 ( ) 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 depends on Weight ( ), food intake (

The …rst-order conditions are thus:

$$\frac{}{{}_t} = \frac{{}_t}{{}_t} + \frac{}{{}_{t+1}}\frac{{}_{t+1}}{{}_t} - \frac{}{{}_{t+1}}\frac{{}_{t+1}}{{}_t} = 0 \tag{3}$$

$$\frac{}{{}_t} = \frac{{}_t}{{}_t} - \frac{}{{}_{t+1}}\frac{{}_{t+1}}{{}_t} = 0 \tag{4}$$

which implies that at the optimum:

$$\frac{{}_t}{{}_t} + \frac{}{}$$

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 $\frac{\partial V}{\partial W_{t+1}} \quad 0$ then as $\to 1$, $\frac{\partial f}{\partial p}$ increases and becomes less negative. Consider a 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 ($25 \leq$ 30), Class I obese ($30 \leq$ 35), or severely obese (≥ 35), with the omitted category re‡ecting 25.

Our independent variables of interest are time preference measures computed from two

"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 (2) to compute annualized (via simple multiplication) discount factors – named "Discount Factor 2" (2) – through the following formula:

$$2 = \frac{1}{12 \; \frac{1000}{1000+\text{amount2}} - 11} \tag{7}$$

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 …t an individual's responses to both intertemporal questions using the quasi-hyperbolic discounting speci…cation, whereby individuals discount outcomes periods away at The parameter re‡ects an individual's "long-run" level of patience, whereas re‡ects any disproportionate weight given to the immediate present at the expense of all future periods (Phelps and Pollak, 1968; Laibson, 1997). If $= 1$ then quasi-hyperbolic discounting reduces to traditional, time-consistent discounting, whereas 1 re‡ects potentially time-inconsistent impulsivity and present-bias.

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

$$\begin{aligned} \tfrac{1}{12} &= \frac{1000}{1000 + \qquad 2} \\ &= \frac{1000}{1000 + \qquad 1} \end{aligned}$$

yielding $= (\frac{1000+\text{amount2}}{1000+\text{amount1}})^{\frac{12}{11}}$ and $= \frac{1000}{(1000+\text{amount1})}$ To assess the relative contribution of impulsivity versus impatience towards obesity, our main regressions include both and 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

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

inverted U-shaped relationship between income and BMI (Lakdawalla and Philipson, 2002). Finally, is the measure of risk preference. We include the sets of control variables in an e¤ort to isolate the ceteris paribus relationship between time preference and BMI. If levels of patience and BMI both di¤er 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 $_1$ or $_2$. 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 and with the simple patience measures of 1 with 2.

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 and long-run patience are statistically signi…cant and negatively associated with BMI in all six speci…cations, suggesting that impulsivity and time-consistent impatience are separately and signi…cantly associated with BMI. Including the demographic and human capital controls in columns (2) and (3) attenuates the coe¢ cient estimate for somewhat, TJ/F4479.297(o)12(e)9(a)1(d)-283.(s)8(e)9(t)8(s)-293(o)J/F4811(r)-358(

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and severe obesity rates. Similar results hold using 1 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

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 and long-run patience . 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 and with food prices provides a preliminary test of this theory.

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

$$_{ic} = {}_0 + {}_1 {}_{ic} + {}_2 {}_{ic} + \alpha_3 \mathrm{DEMO}_{ic} + \alpha_4 \mathrm{HC}_{ic} + \alpha_5 \mathrm{LABOR}_{ic} + \alpha_6 \mathrm{FIN}_{ic} + {}_7 {}_{ic}$$

$$+ {}_8 {}_c + {}_9 ({}_i * {}_c) + {}_{10} ({}_i * {}_c) + {}_{11} {}_c + {}_i \qquad (10)$$

where 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 and , 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

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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

8 and 9 and signi…cant in 9. The interaction term $*$ is signi…cant at the 5% level in all regressions and positively associated with BMI, supporting the prediction that greater impulsivity (lower) strengthens individuals' response to food prices. The coe¢ cient estimates for the interaction term are all within a standard error of each other, ranging from 3.07 to 4.39. The interaction term $*$ is also positively associated with BMI in all speci…cations, with coe¢ cient estimates ranging from 1.23 to 1.52. However, $*$ is only signi…cant 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 speci…cations using discount factors instead of and (columns (7) and (8) of Table 8), the interaction terms are both signi…cant at the 5% level and suggest that greater impatience (lower 1 and 2) strengthens the food price e¤ect.

Figure 2 uses the estimates from the full model from column (6) of Table 8 to show how the marginal e¤ect of food price on BMI changes from the 1st to 99th percentiles of the impulsivity distribution. This range spans a large present bias of $= 0\ 33$ to a slight future bias of $= 1\ 11$. The solid line shows the marginal e¤ect, while the dashed lines represent the endpoints of the 95% con…dence 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 e¤ect weakens as increases, gradually approaching zero. The con…dence intervals show that the food price e¤ect is statistically signi…cant up to approximately the 23rd percentile of $= 0\ 62$. The entire statistically detectable e¤ect of food prices on BMI is therefore concentrated among the most impulsive individuals.

Figures 3-5 illustrate how this heterogeneity in the food price e¤ect can a¤ect the variance of the BMI distribution. We perform a median split, de…ning individuals with a "high present bias" as those with $\leq 0\ 845$ and those with a "low present bias, time consistent preferences, or future bias" as those with 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 di¤erence 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 results potentially help to explain the rightward shift in the BMI distribution in recent decades

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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 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

(0:44) 0 512 (0:41:0:40) 14 1 11 −0 (0:44)

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	–22)	0 –	0 –					

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 (0:61)**	−0 54 (0:67)	–	–	−1 10 (0:53)**	0 26 (0:72)	–	–
Delta	−0 24 (0:37)	−0 81 (0:35)**	–	–	−0 57 (0:32)*	−0 24 (0:35)	–	–
Discount factor 1	–	–	−0 70 (0:50)	−1 31 (0:49)***	–	–	−1 12 (0:41)***	−0 20 (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 signi..cant 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 Pro[redacted]s

Dependent Variable: B[redacted]

Variable	Coe¢ cient Estimate	Marginal E¤ects Overweight	Marginal E¤ects Obese (Class 1)	Marginal E¤ects Severely Obese	Coe¢ cient Estimate	Marginal E¤ects Overweight	Marginal E¤ects Obese (Class 1)	Marginal E¤ects 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

= 5982. See notes for Table 5.

Table 7 – Falsi…cation Tests [redacted] Using V[redacted]alt[redacted] Condition[redacted]

Depend[redacted]es:

Height	Arthritis	Asthma	Kidney/ Bladder	[redacted]

Table 8 – Interaction E¤ects of Food Prices with Time Preference

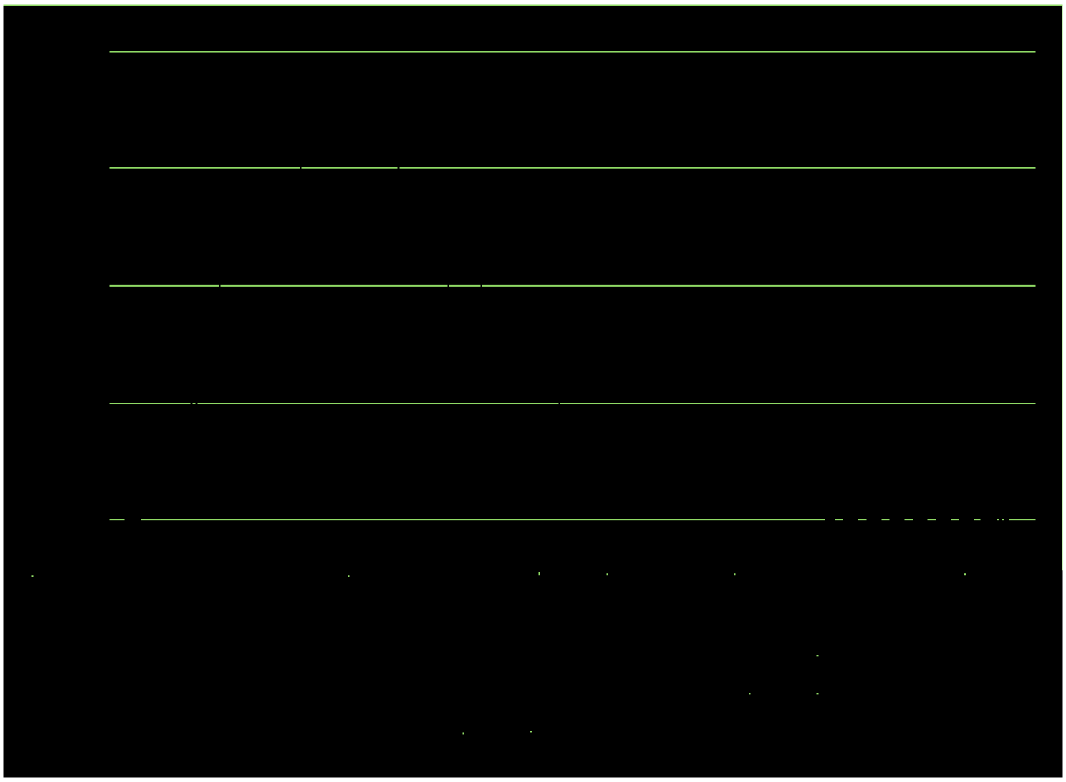
Dependent Variable: BMI

Table 9 – Interaction E¤ects: Additional Robustness Checks

Dependent Variable: BMI

	Alternate food price measures					Interactions of Food Price and Controls
	13-item basket	6-item basket	2-year lag	4-year lag	6-year lag	
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)

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

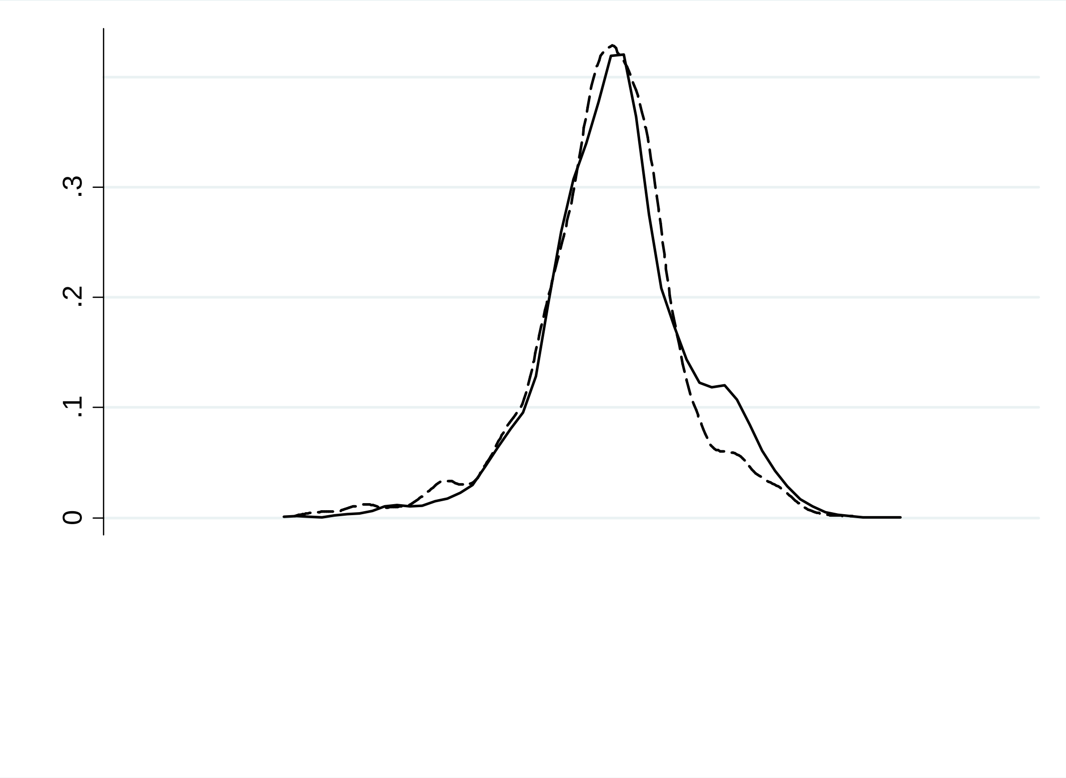


Figure 4 – BMI Distributions by Degree of Present Bias at 2006 Food Price=$3.35

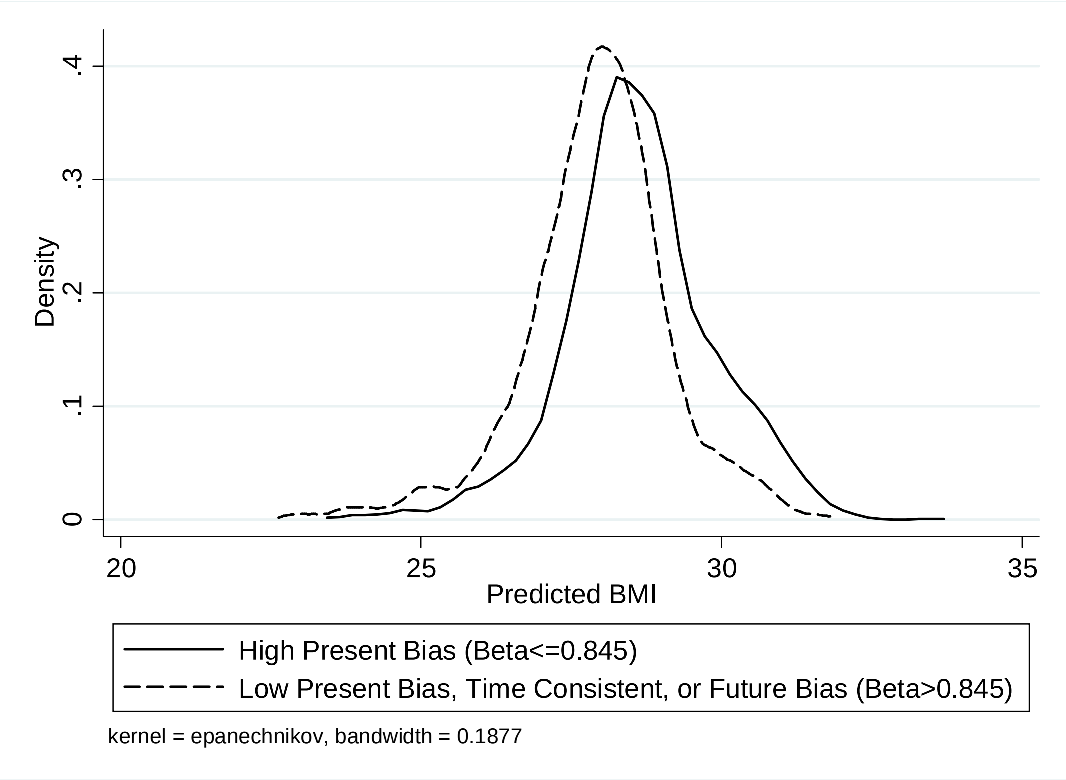


Figure 5 – BMI Distributions by Degree of Present Bias at Estimated Food Price=$2.95