Impatience, Incentives, and Obesity

Department of Economics Working Paper Series

Charles Courtemanche
University of Louisville

Garth Heutel
University of North Carolina at Greensboro

Patrick McAlvanah
Federal Trade Commission

March 2011 (Revised September 2011)
Working Paper 11-09

www.uncg.edu/bae/econ/

Impatience, Incentives, and Obesity*

Charles Courtemanche† Garth Heutel‡ Patrick McAlvanah§

September 2011

Abstract

This paper explores the relationship between time preferences, economic incentives, and body mass index (BMI). Using data from the 2006 National Longitudinal Survey of Youth, we first show that greater impatience increases BMI and the likelihood of obesity even after controlling for demographic, human capital, occupational, and financial characteristics as well as risk preference. Next, we provide evidence of an interaction effect between time preference and food prices, with cheaper food leading to the largest weight gains among those exhibiting the most impatience. The interaction of changing economic incentives with heterogeneous discounting may help explain why increases in BMI have been concentrated amongst the right tail of the distribution, where the health consequences are especially severe. Lastly, we model time-inconsistent preferences by computing individuals' quasi-hyperbolic discounting parameters (β and δ). Both long-run patience (δ) and present-bias (β) predict BMI, suggesting obesity is partly attributable to rational intertemporal tradeoffs but also partly to time inconsistency.

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

---

*This research was conducted using restricted data from the Bureau of Labor Statistics. The views expressed in this paper do not reflect those of the BLS. We thank Dan Becker, Tim Classen, Stephen Holland, Debra Holt, Pauline Ippolito, Brian Rowe, Chris Ruhm, Steven Schmeiser, Ken Snowden, Chris Wheeler, Erez Yoeli, and Harry Zhang for helpful comments. Seminar participants at the University of North Carolina at Greensboro, Federal Trade Commission, Canadian Competition Bureau, International Health Economics Association World Congress, and Southern Economic Association Annual Meeting provided useful feedback.

†Corresponding author. University of Louisville, College of Business, Department of Economics, Louisville, KY 40292. National Bureau of Economic Research, Cambridge, MA. Email: cjcour02@louisville.edu.

‡University of North Carolina at Greensboro, Bryan School of Business and Economics, Department of Economics, PO Box 26165, Greensboro, NC 27402. National Bureau of Economic Research, Cambridge, MA. Email: gaheutel@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). As shown in Figure 1, the rise in obesity has resulted from both increases in the mean and variance of BMI, as the largest weight gains have been concentrated amongst the right tail of the BMI distribution.

A large literature attempts to characterize the rise in obesity as an economic phenomenon driven by changes in economic incentives. Particular attention has been paid to the lower monetary and time costs of food consumption resulting from falling food prices and increasing restaurant density.[2] Such aggregate-level variables might help explain the growth in average BMI, but they cannot explain the increasing variance unless some people respond more strongly to changing economic incentives than others. This paper argues that such heterogeneity is partly attributable to differences in individuals' time preferences. We provide a theoretical and empirical investigation of the interplay between time preferences and food prices, finding that impatience both increases BMI and strengthens one's response to food

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

[2] For examples of papers studying the influence of food prices on BMI, see Lakdawalla and Philipson (2002), Philipson and Posner (2003), Chou et al. (2004), Lakdawalla et al. (2005), and Goldman et al. (2010). For examples of papers studying the role of restaurants, see Chou et al. (2004), Rashad et al. (2006), Dunn (2008), Currie et al. (2010), and Anderson and Matsa (forthcoming). Other economic factors linked to obesity include time costs of food preparation (Cutler et al., 2003), on-the-job physical activity (Philipson and Posner, 2003; Lakdawalla and Philipson, 2002), work hours (Courtemanche, 2009b), cigarette prices (Chou et al., 2004; Gruber and Frakes, 2006; Baum, 2008; Nonnemaker et al., 2008; Courtemanche, 2009), gasoline prices (Courtemanche, 2011), Walmart Supercenters (Courtemanche and Carden, 2011), health insurance coverage (Bhattacharya et al., 2010), urban sprawl (Ewing et al., 2003; Frank et al., 2004; Plantinga and Bernell, 2007; Eid et al., 2008; Zhao and Kaestner, 2010), the minimum wage (Meltzer and Chen, forthcoming), and the unemployment rate (Ruhm, 2000 and 2005).

prices. We also fit a quasi-hyperbolic specification and provide evidence that these estimated relationships are at least partly driven by time inconsistency.

Researchers have recently begun examining the link between time preference and BMI.[3] Komlos et al. (2004) illustrate a time-series relationship between obesity and both the savings rate and debt-to-income ratio in the US, and also show that developed countries with low savings rates have higher obesity rates. Smith et al. (2005) conduct an individual-level analysis with data from the National Longitudinal Survey of Youth (NLSY), finding some evidence of a connection between savings behavior – a proxy for time preference – and 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. Zhang and Rashad (2008) 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 subjects from the Boston area. Ikeda et al. (2010) estimate a connection between time preference – measured either by the discount rate or a proxy variable relating to debt – and BMI in a Japanese survey.

While important progress has been made in understanding the time preference-BMI relationship, three important questions remain unanswered. First, does the association represent a ceteris paribus impact of time preference on BMI or merely a spurious correlation? Omitted variable bias could result from associations between impatience and potential determinants of BMI such as education, income, wealth, work hours, occupation, and risk preference. Of the aforementioned studies, only Zhang and Rashad (2008), Chabris et al. (2008), and Ikeda et al. (2010) control for education; only Smith et al. (2005), Zhang and Rashad (2008), and

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

Ikeda et al. (2010) control for income; only Ikeda et al. (2010) control for work hours and risk preference; and none control for wealth or occupation type. Reverse causality is another possible concern, as obesity could reduce expected longevity and cause individuals to optimize over a shorter time horizon.

The second question is whether time preference can help to explain the *trend* in BMI, as opposed to merely the level. Meta-analyses and longitudinal studies have not found evidence that rates of time preference have systematically changed over time.[4] In the absence of such changes, it is unclear how time preference could have played a role in the nearly three-fold increase in the obesity rate over the past half-century.

A third open question is the extent to which the time preference-BMI connection is the result of time-inconsistency as opposed to rational intertemporal substitution. If time-inconsistent preferences are a cause of obesity, then there is a potential economic rationale for policies designed to alter eating decisions (Cutler et al., 2003). The existing evidence that quasi-hyperbolic discounting contributes to obesity is mostly circumstantial. Citing the National Institute of Diabetes and Digestive and Kidney Diseases (2008), Ruhm (2010) notes that over 200,000 Americans a year have bariatric surgery to reduce the size of their stomachs, presumably as a commitment device to limit susceptibility to self-control problems. He also documents the high prevalence of weight loss attempts, while showing that such attempts are positively related to BMI. Dieting can be considered an admission of past mistakes, possibly resulting from time inconsistency.[5] He further describes biological reasons to expect time

[4] In a meta-analysis of experimental and field studies on time preferences published from 1978-2002, Percoco and Nijkamp (2009) find no 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. Further, Borghans and Golsteyn (2006) examine trends in some of their proxy variables for time preference and find no evidence that individuals have become systematically less patient.

[5] Ikeda et al. (2010) show that a proxy variable for procrastination influences BMI but do not find a statistically significant impact of their more direct measure of hyperbolic discounting – a dummy variable for whether the respondent discounted the future more heavily for a shorter delay than a longer delay. Royer et al. (2011) document individuals voluntarily engaging in self-funded committment contracts to exercise, and show that the effects of these contracts were strongest for those who had previously struggled to maintain regular exercise patterns.

inconsistency to be a factor in determining body weight. The human brain consists of both a rational deliberative system and an affective system driven by chemical reactions to stimuli. The more the affective system is in control, the further one's weight is likely to deviate from her rational optimum.

We contribute to the literature on time preferences and BMI along all three of these fronts. First, we push further than prior research toward establishing that the association between time preference and BMI is in fact a ceteris paribus relationship. We do this by using the 2006 NLSY, which includes questions on body weight and hypothetical intertemporal trade-offs along with a rich array of other individual information that enables the construction of a detailed set of control variables. Building up from a simple regression to a model that includes demographic characteristics, IQ, education, work hours, occupation type, income, net worth, and risk preference, we show that greater impatience consistently increases BMI and that the coefficient estimate is stable once demographic characteristics and education are added. The effects are strongest for white males and are accompanied by related effects on the probabilities of being obese and severely obese. We also conduct falsification tests that provide no evidence of a link between time preference and either height or health conditions that are less directly tied to eating and exercise, further supporting a causal interpretation of the results.

Our second contribution is to propose and test the theory that the magnitude of the effect of food prices on BMI varies with time preference. Intuitively, less-patient consumers care relatively more about utility in the present. Food prices are a present cost, so as prices fall, less-patient consumers respond with a larger increase in food consumption than do more-patient consumers. Matching the NLSY to local price data from the Council for Community and Economic Research (C2ER), we show that the interaction of time preference and food price is a statistically significant predictor of BMI regardless of the control variables included or the basket of goods used to construct the food price measure. The estimates imply that the food price elasticity of BMI ranges from -0.23 for the least patient individuals to statistically indistinguishable from 0 among the most patient. This interaction effect can help explain why increases in BMI have been concentrated in the right tail of the distribution as food has become cheaper and more readily available. Although food prices have decreased roughly uniformly for all consumers, their decrease has caused a larger increase in BMI for the least patient consumers, individuals who already disproportionately comprised the right tail of the BMI distribution. This heterogeneous response to decreasing food prices can explain trends in BMI and obesity even if individuals have not become more impatient over time.

Finally, we provide a preliminary attempt to disentangle the relative contributions of time inconsistency versus rational intertemporal substitution to these estimated relationships. Using responses to the NLSY's intertemporal trade-off questions, we calculate each individual's quasi-hyperbolic ($\beta\delta$) discounting parameters, decomposing time preferences into a present bias component β and a long-run component δ. We then re-run the previous BMI regressions using these two discounting parameters, finding evidence that obesity is partly attributable to both present bias and time-consistent impatience.[6] Female BMI appears more strongly driven by present-bias than time-consistent impatience, while the reverse is true for males. The effects of both components of time preference are stronger for whites than minorities. We also interact β and δ with the price of food and show that both present-bias and long-run discounting strengthen price responsiveness, though only the interaction of β with food price is consistently statistically significant.

2 Theoretical Model

We begin by theoretically modeling the roles of time preference and food prices in determining body weight. A consumer chooses food consumption (f), which provides instantaneous consumption utility and affects her future weight. Our simple model provides the intuition behind the impact of prices and the discount factor on food consumption and weight. We

[6] In contrast to Ikeda et al. (2010), our approach accounts for not only whether individuals exhibit any present-bias but also the degree of that bias, an important distinction given that almost 85% of our sample is present-biased. The utilization of this additional information allows us to obtain clearer results.

then briefly discuss extending the model to analyze time-inconsistent preferences.

2.1 Two-Period Model with Time-Consistent Preferences

We first consider a two-period model. The consumer receives an instantaneous utility from food consumption in the first period $U(f)$ and pays a per-unit price of p. In the following period, the consumer's weight is a function of food consumption: $w = g(f)$, where g is increasing in f. The consumer receives a utility from her weight $V^*(w)$. We assume that the second-period utility is decreasing in weight, or that the consumer is at or over her ideal weight, and that further weight gains are increasingly aversive.[7] To simplify the notation, define $V(f) \equiv V^*(w) = V^*(g(f))$. First-period utility is increasing and concave in food consumption: $U' > 0, U'' < 0$. Second-period utility is decreasing and concave in food consumption: $V' < 0, V'' < 0$. The discount factor applied between the two periods is δ.

The consumer's full maximization problem is thus

$$\max_f U(f) - pf + \delta V(f) \tag{1}$$

The first-order condition is

$$U'(f) - p + \delta V'(f) = 0 \tag{2}$$

From an additional unit of consumption, the consumer receives a marginal benefit from instantaneous utility now, pays a marginal cost now, and suffers a marginal cost from weight in the future. We now show how the consumer's weight depends on the price of food p, the discount factor δ, and how the sensitivity to price varies with the discount factor.

Intuitively, a higher food price should lead to less food consumption and thus lower weight. This can be verified by evaluating the derivative $\frac{dw}{dp}$ using the chain rule on $w = g(f)$ and the

[7] This is a reasonable assumption for the vast majority of our sample, as only 0.8% are underweight (BMI<18.5).

implicit function theorem on equation (2).

$$\frac{\partial w}{\partial p} = g'(f) \times \frac{\partial f}{\partial p} = g'(f) \times \frac{1}{U''(f) + \delta V''(f)} < 0 \tag{3}$$

The denominator is negative and g' is positive. Higher food prices lead to less food consumption and therefore lower weight.

Our second intuitive prediction is that more patient consumers should have lower weight, because the disutility from being overweight occurs only in the future. We evaluate $\frac{dw}{d\delta}$ in the same manner as above

$$\frac{\partial w}{\partial \delta} = g'(f) \times \frac{\partial f}{\partial \delta} = g'(f) \times \frac{-V'(f)}{U''(f) + \delta V''(f)} < 0 \tag{4}$$

Again the denominator is negative and g' is positive. The numerator $-V'(f)$ is positive, since we assume the consumer is above her ideal weight and thus gets negative utility from additional weight in the future. A higher discount factor indicates a more patient consumer and leads to less food consumption and lower weight.

Our third intuitive prediction is that the least patient individuals should be the most responsive to food prices. The total cost of food is the sum of the explicit monetary price, paid in the current period, and the health cost, paid in the future period. Impatient people are relatively more concerned with present costs, and therefore should be more responsive to the monetary price, i.e. their $\frac{dw}{dp}$ should be higher in absolute value (more negative). Patient peoples' response to food price changes are tempered by their recognition of the future health costs. Mathematically, $\frac{d^2w}{d\delta dp} > 0$.

To calculate this cross-partial derivative, we evaluate the derivative of $\frac{dw}{dp}$ with respect to δ, taking care to observe that within that derivative (equation (3)), f is also a function of δ and the chain rule must be applied accordingly. The cross-partial derivative is

$$\frac{\partial^2 w}{\partial \delta \partial p} = \frac{1}{(U'' + \delta V'')^2} \times \left[-g' \cdot V'' - g'' \cdot V' + g' \cdot V' \times \frac{U''' + \delta V'''}{U'' + \delta V''} \right] \tag{5}$$

where the arguments of the functions have been dropped for clarity. Our intuitive prediction was that this derivative should be positive, but in fact its sign is ambiguous. The coefficient in front of the brackets is positive. The first term in the brackets $(-g' \cdot V'')$ is positive, and it represents the direct intuitive effect that we described above: less patient consumers care less about the current price and therefore their weight responds less to the price. However, the two remaining terms pick up indirect effects, and these may be positive or negative. The second term $(-g'' \cdot V')$ is the same sign as g'', about which we make no assumptions. If $g'' \geq 0$, so that food consumption increases weight either constantly or convexly, then this second term is non-negative, consistent with our intuitive prediction. Lastly, the third term in the brackets has the same sign as the numerator in the fraction, which involves third derivatives of U and V. We make no assumptions about these third derivatives. If both are positive, as would be the case under CRRA preferences, or if both are zero, as would be the case under quadratic utility, then this term is non-negative and our intuition stands. However, there are possible cases in which this second derivative may in fact be negative, contrary to our intuition.[8] We thus leave it to our empirical work to determine with more certainty the sign of this cross-partial derivative.

This cross-partial derivative can potentially help to explain a fact about recent growth in consumers' BMI. Real food prices have fallen, which may have contributed to the growth in average BMI (equation (3)). But prices have fallen roughly uniformly for all consumers, yet the growth in BMI is not uniform; it is concentrated in the right tail (Figure 1). This can be explained with two facts from our model. First, those initially among the right of the BMI distribution are likely those with lower discount factors (less patient), as predicted by equation (4). Second, if the second derivative in equation (5) is positive, then these impatient people will respond more strongly to the falling prices, and therefore the growth in BMI will be right-skewed.

Although we will not directly test the theory that this helps to explain the right-skewed

[8]By making assumptions about functional forms and parameter values we are able to numerically find some cases where this second derivative is in fact negative, though it is positive in most cases.

growth in BMI, we test the predictions of equations (3) and (4), and we test for the sign of equation (5). The empirical evidence supports both of our predictions and supports the claim that the second derivative is positive, consistent with our explanation for the right-skewed growth in BMI.

2.2 Three-Period Model with Time-Inconsistent Preferences

The two-period model provides the basic intuition and testable hypotheses regarding the interaction between food prices, discount factors, and weight. It does not allow us to investigate time-inconsistent preferences, so we next move to a three-period extension of the model that allows for a consumer with quasi-hyperbolic discounting. The long run discount factor is δ and the present-bias is β. To keep the model as simple as possible, we consider only the consumer's decision over present food consumption f, and we allow that level of consumption to affect weight in both the second and third periods.[9] Allow the consumer's weight in the second period to be given by the function $g(f)$ and her weight in the third period $h(f)$. The reduced form instantaneous utility as a function of food consumption is $V(f)$ in the second period and $W(f)$ in the third period. Assume again that the consumer is above her ideal weight in all periods, so that V and W are both decreasing in f, and furthermore assume that V'' and W'' are both negative. The consumer's first-period maximization problem is

$$\max_f U(f) - pf + \beta\delta V(f) + \beta\delta^2 W(f) \tag{6}$$

and the first-order condition is

$$U'(f) - p + \beta\delta V'(f) + \beta\delta^2 W'(f) = 0 \tag{7}$$

Here, the consumer receives an instantaneous benefit from food consumption now, pays for

[9] A more complicated model that explicitly models the consumer's second- and third-period consumption decisions and their differential effects on weight in each period is available upon request from the authors, but it does not provide any additional intuition beyond the simpler model here.

it now, and faces utility costs in the second and third periods. The implicit function theorem can be used on this first-order condition to find the effect of each discount factor on weight, as well as the effect of food price on weight:[10]

$$\frac{dw}{dp} = g'(f) \times \frac{df}{dp} = g'(f) \times \frac{1}{U''(f) + \beta\delta V''(f) + \beta\delta^2 W''(f)} < 0 \tag{8}$$

$$\frac{dw}{d\delta} = g'(f) \times \frac{df}{d\delta} = g'(f) \times \frac{-\beta V'(f) + 2\beta\delta W'(f)}{U''(f) + \delta V''(f)} < 0 \tag{9}$$

$$\frac{dw}{d\beta} = g'(f) \times \frac{df}{d\beta} = g'(f) \times \frac{-\delta V'(f) + \delta^2 W'(f)}{U''(f) + \delta V''(f)} < 0 \tag{10}$$

Food consumption and therefore weight decrease as the food price increases. As consumers discount the future more over the long run (lower δ), or as consumers become more present-biased (lower β), food consumption and weight increase. As in the two-period model, these intuitive first-derivative results remain, whether patience is measured by the long-run discount factor or by present bias.

Also as with the two-period model, the cross-partial derivative of weight with respect to either δ or β is theoretically ambiguous. Intuition suggests that as consumers become more present-focused, either because of a lower δ or because of a lower β, they should respond more strongly to price, but the expressions for both $\frac{d^2w}{d\delta dp}$ and $\frac{d^2w}{d\beta dp}$ contain a positive-definite term and other terms with ambiguous sign. As before, we turn to empirical analysis to find the sign of these effects.

3 Data

We test these intuitive and 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

[10] These results refer to weight in the second period, $g(f)$. The effect of weight in the third period, $h(f)$, is found by replacing g with h in all the equations below, and is the same sign as the effects presented.

and then biennially through 2008.[11] 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 after dropping observations with missing information our analysis sample is 5,982. The respondents were between 14 and 22 years old at the start of the panel, so the age range in the sample is 41 to 49.

Our main dependent variable is BMI, which we compute from self-reported weight and 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 adjusted BMI to construct indicator variables for whether 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

[11] 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.

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:

$$DF1 = \frac{1000}{1000 + amount1}. \tag{11}$$

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 discount factors (via exponential annualization) – named "Discount Factor 2" ($DF2$) – through the following formula:

$$DF2 = \left(\frac{1000}{1000 + amount2}\right)^{12}. \tag{12}$$

$DF1$ is our preferred measure of time preference since it is computed directly from the question about an annual delay, and thus is not subject to the compounding of response error that the annualized question based on monthly delay will be. We utilize $DF2$ as well as the average of $DF1$ and $DF2$ (denoted $\overline{DF}$) in some of the robustness checks. Our conclusions are not sensitive to the use of discount rates instead of factors.[12]

We exploit the fact that the 2006 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

[12] Note that the above discount factor computations implicitly assume linear utility.

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 individual's joint responses to these two questions imply that

$$\beta\delta^{\frac{1}{12}} = \frac{1000}{1000 + amount2} \tag{13}$$

$$\beta\delta = \frac{1000}{1000 + amount1} \tag{14}$$

yielding $\delta = (\frac{1000+amount2}{1000+amount1})^{\frac{12}{11}}$ and $\beta = \frac{1000}{\delta(1000+amount1)}$.

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.

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?"

Other information available in the NLSY allows us to construct a detailed set of control variables. The demographic variables are age and dummies for gender, race, and marital status. Percentile score on the Armed Forces Qualification Test (AFQT) proxies for intelligence. We measure educational attainment with dummy variables for high school degree but no college, some college but less than a four-year degree, and college degree or higher. The omitted category is less than a high school degree. Hours worked per week and indicator variables for white collar, blue collar, or service occupation (relative to the omitted category of no paid work) reflect labor market activity.[13] Total household income and net worth, our financial controls, are computed by the NLSY based on respondents' answers to a variety of questions on income sources, assets, and liabilities. All control variables are from the 2006 survey except for the AFQT score and net worth, taken from the 1985 and 2004 surveys respectively.

The NLSY also contains a health module administered to respondents the first survey

[13] We classify an individual as "white collar" if she reports an occupation of executive, administrative, and managerial; management related; mathematical and computer scientists; engineers, architects, and surveyers; engineering and related technicians; physical scientists; social scientists and related; life, physical, and social science technicians; counselors, social, and religious; lawyers, judges, and legal support; teachers; education, training, and library; media and communications; health diagnosing and treating; health care technical and support; sales and related; or office and administrative support. We classify an individual as "blue collar" if her occupation is entertainers and performers, sports and related; farming, fishing, and forestry; construction trade and extraction; installation, maintenance, and repairs; production and operating; setters, operators, and tenders; transportation and material moving; military specific; or armed forces. We classify an individual as "service" if her occupation is protective service; food preparation and serving related; cleaning and building service; entertainment attendants and related; funeral related; personal care and service; sales and related; office and administrative support; or food preparation.

after their 40th birthdays – either 1998, 2000, 2002, 2004, or 2006. Information on chronic conditions allows for the construction of indicator variables for arthritis, asthma, anemia, chronic kidney or bladder problems, chronic stomach problems, frequent colds, and frequent headaches. These dummies serve as dependent variables in the falsification tests.

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 28.3; 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 0.3 using the monthly delay question, corresponding to a 66% and 257% 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. 7% of respondents reported perfect patience on both questions and are therefore exactly time-consistent with $\beta = 1$. 8% 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 discount factor and BMI. Our main regression equation is

$$BMI_i = \alpha_0 + \alpha_1 DF1_i + \boldsymbol{\alpha}_2 \mathbf{DEMO}_i + \boldsymbol{\alpha}_3 \mathbf{HC}_i + \boldsymbol{\alpha}_4 \mathbf{LABOR}_i + \boldsymbol{\alpha}_5 \mathbf{FIN}_i + \alpha_6 RISK_i + \varepsilon_i \quad (15)$$

where i indexes individuals. $DF1$ is the preferred annual discount factor measure described in Section 3. **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 AFQT score 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. Our model contains a more detailed set of covariates than the 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. (2010) control for only age, gender, college degree, work hours, smoking, and risk preference.[14]

Table 4 reports the results. We begin in column (1) with a simple regression of BMI on discount factor and then gradually add the sets of controls to build up to the full model in column (6). As robustness checks, in columns (7) and (8) we replace $DF1$ with $DF2$ and $\overline{DF}$, respectively. Discount factor is statistically significant and negatively associated with BMI in all eight regressions, suggesting that greater patience decreases weight. Including the demographic and human capital controls in columns (2) and (3) attenuates the coefficient estimate for α_1 somewhat, but across columns (3) to (6) the effect stabilizes at -0.92 to -1.08 units. The results from columns (3) to (6) imply that a one standard deviation increase in discount factor (0.25) decreases BMI by an average of 0.23 to 0.27 units, or 1.5 to 1.8 pounds at the sample mean height of 67.55 inches. Columns (7) and (8) show that the results are

[14] We do not control for smoking in any of our reported specifications given its clear endogeneity. In unreported regressions, we added a dummy for whether or not the individual smoked as of 1998 – the last year in which the NLSY included smoking questions – and verified that the results remain similar. Less obvious endogeneity problems could also exist for some of the variables we do include in the reported regressions, such as education, work hours, income, and net worth. This highlights the importance of showing that the estimated effect of discount factor remains similar across a number of specifications with different combinations of control variables.

similar using the alternative discount factor measures. Though we are of course unable to control for every potential confounding factor, the robustness of the link between discount factor and BMI increases our confidence that the relationship is causal rather than spurious.

The results for the control variables are generally consistent with prior research. Being male, black, married, not having a college degree, having a lower net worth, and working longer hours are 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, AFQT score, 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 estimates of α_1 splitting the sample by gender and race, using $DF1$ and the full set of control variables. The effect of discount factor on BMI is strong and significant for men, and still negative but smaller and insignificant for women. When stratifying by race, discount factor's impact is strong and significant for whites but small and insignificant for non-whites.[15]

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

[15] The lack of a significant effect for non-whites should be interpreted with caution, as it could simply reflect the limited size of the subsample or heterogeneity within the subsample. To illustrate, the point estimates for whites are within the 95% confidence intervals for non-whites. In unreported regressions (available upon request) we further stratified non-whites into subsamples of blacks, Hispanics, and others, but the sample sizes were too small to obtain meaningful precision.

accompanied by increased odds of becoming overweight or obese. We estimate

$$P(CATEGORY_i = j) = \Phi(\theta_j - (\gamma_0 + \gamma_1 DF1_i + \gamma_2 \mathbf{DEMO}_i + \gamma_3 \mathbf{HC}_i + \gamma_4 \mathbf{LABOR}_i + \gamma_5 \mathbf{FIN}_i + \gamma_6 RISK_i + \mu_i)) \quad (16)$$

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 estimate of γ_1 as well as the marginal effects of discount factor on the probabilities of being overweight, obese, or severely obese. Discount factor is statistically significant at the 5% level and its coefficient estimate is negative, indicating that greater patience is associated with a lower BMI category. The marginal effect of discount factor on P(Overweight) is small and insignificant, indicating that the number of individuals transitioning from healthy weight to overweight are cancelled out by those transitioning from overweight to obese. The marginal effects of discount factor on P(Class I Obese) and P(Severely Obese) are -0.027 and -0.033 and are significant at the 5% level. These effects are sizeable relative to the sample Class I obesity and severe obesity rates of 20% and 12%.

We close this section with a series of falsification tests. First, we re-estimate (15) 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. Discount factor is never significant at even the 10% level. 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 prediction that impatience strengthens the response to food prices by examining heterogeneity in the effect of local food prices on BMI on the basis of discount factor. 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 an effect of the interaction of discount factor and food prices provides a preliminary test of this theory.

The regression equation is similar to (15) but adds local food prices ($PFOOD$), non-food prices (PNF), and the interaction of food prices with discount factor:

$$\begin{aligned} BMI_{ic} &= \alpha_0 + \alpha_1 DF1_{ic} + \boldsymbol{\alpha}_2 \mathbf{DEMO}_{ic} + \boldsymbol{\alpha}_3 \mathbf{HC}_{ic} + \boldsymbol{\alpha}_4 \mathbf{LABOR}_{ic} + \boldsymbol{\alpha}_5 \mathbf{FIN}_{ic} \\ &\quad + \alpha_6 RISK_{ic} + \alpha_7 PFOOD_c + \alpha_8 (DF1_i * PFOOD_c) + \alpha_9 PNF_c + \varepsilon_i \end{aligned} \tag{17}$$

where c indexes counties.[16] Controlling for non-food prices helps ensure that the estimated effect of food price is not simply capturing a more general price effect. The endogeneity of food prices is a natural concern. However, note that the regressor of interest in equation (17) is the interaction of food price with discount factor, 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 discount factors. It is not obvious why this would be the case. Further, the natural direction of 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 still estimate an inverse relationship between food prices and BMI, so any upward bias is not preventing us from obtaining the sign predicted by economic theory.[17]

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 $DF2$ and $\overline{DF}$. Table 9 contains additional robustness checks. One potential concern is that the food basket used to compute market prices contains both healthful and unhealthful items, whereas the rise in obesity may be the result of cheaper junk food rather than lower across-the-board food prices.

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

[17] 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.

The first two columns of Table 9 therefore experiment with dropping the (arguably) more healthful items from the food basket in an attempt to isolate the price of unhealthful 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.[18] The third through fifth columns of Table 9 test for reverse causality between BMI and food prices by controlling for future food price. The third column includes the price of the original 19-item food basket in the second quarter of 2007, the fourth column includes the price of this basket in the second quarter of 2008, and the fifth column adds both of these leads.[19] If future food prices predict contemporaneous BMI conditional on current food prices, the BMIs of a city's residents likely influence the market price of food rather than the other way around. The sixth column of Table 9 controls for state fixed effects as well as a dummy variable for whether the respondent lives in an urban area. This addresses potential omitted variable bias from unobserved geographic variables correlated with both local food prices and population weight. Finally, the last column of Table 9 controls for 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.

Consistent with results from the literature (e.g. Chou et al., 2004), the coefficient estimate for food price is negative across all 15 specifications in Tables 8 and 9 and significant at the 10% level or better in 12 specifications. The interaction term is positively associated with

[18] 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 discount factor. The coefficient estimates for price and the interaction of price and discount factor 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 significant. We therefore consider these findings speculative and do not present them in the paper.

[19] The ACCRA COLI cities vary somewhat from quarter to quarter. For cities that do not have second quarter prices in 2007 or 2008 available, we use the first quarter. If the first quarter is also not available, we use the third quarter, then the fourth quarter. If no price information is available for a city from any of the four quarters, all observations matched to that city are dropped. The sample size is therefore slightly smaller in the regressions that control for future food prices.

BMI in all regressions and significant at the 5% level in 14 of the 15 specifications. These results support the prediction that more patient people respond less strongly than impatient people to changes in food prices. The coefficient estimates for the interaction term are all within each other's confidence intervals, ranging from 1.40 to 3.27. Aside from the regression that computes discount factor exclusively from the monthly delay question (column (7) of Table 8), the estimates are all within the narrower range of 2.61 to 3.27. Additionally, future food prices are not statistically associated with BMI (third through fifth columns of Table 9), so there is no evidence of reverse causality.

Figure 2 uses the estimates from the full model in column (6) of Table 8 to show how the marginal effect of food price on BMI changes across the discount factor distribution. 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 impatient individuals by almost 2 units, or 13 pounds at the sample mean height. This is a decrease of 7% of the sample mean BMI, implying a food price elasticity of BMI of -0.23. The effect of food prices on BMI steadily weakens with additional patience, reaching zero at a discount factor of 0.66. Though the sign flips to positive after that point, at no point in the distribution is the marginal effect positive and significant.

Figures 3-5 illustrate how this heterogeneity in the food price effect can affect the variance of the BMI distribution. We perform an approximate median split and define "impatient" individuals as those with discount factors below 0.5 and "patient" individuals as those with discount factors above 0.5. We use the regression results from the full model in column (6) of Table 8 to plot the predicted BMI distributions for the two groups at the sample mean food price of $3.34, 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.[20] Figure 3 therefore

[20]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%.

represents the predicted BMI distributions of patient and impatient individuals 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 impatient and patient people are virtually on top of each other. As food prices fall to 2006 levels in Figure 4, a difference between the two distributions emerges and impatient individuals have higher predicted BMIs than patient individuals. Figure 5 projects that if real food prices fall further in the future the gap between the two groups will widen even more.

4.3 Time-Inconsistent Discounting and BMI

We close the empirical analysis by providing a preliminary attempt to determine the degree to which the observed relationship between time preference and BMI reflects rational intertemporal substitution as opposed to self-control problems. As described in Section 3, the 2006 NLSY contains two intertemporal discounting questions, one over a monthly interval and the other over an annual interval, allowing us to fit the β (present-bias) and δ (long-run patience) parameters of a quasi-hyperbolic specification. The three-period theoretical model predicted that both β and δ should influence BMI, in which case both impulsivity and impatience would contribute to weight gain. We test these predictions by replacing the univariate measure of discounting from our previous regressions with both β and δ. The main BMI regression takes the form

$$BMI_i = \theta_0 + \theta_1\beta_i + \theta_2\delta_i + \theta_3\mathbf{DEMO}_i + \theta_4\mathbf{HC}_i + \theta_5\mathbf{LABOR}_i + \theta_6\mathbf{FIN}_i + \theta_7 RISK_i + \eta_i \quad (18)$$

while the specification adding prices and the interactions of food prices with β and δ is

$$\begin{aligned} BMI_i &= \theta_0 + \theta_1\beta_i + \theta_2\delta_i + \theta_3\mathbf{DEMO}_i + \theta_4\mathbf{HC}_i + \theta_5\mathbf{LABOR}_i + \theta_6\mathbf{FIN}_i + \\ & \quad \theta_7 RISK_i + \theta_8 PFOOD_c + \theta_9(\beta_i * PFOOD_c) + \theta_{10}(\delta_i * PFOOD_c) \\ & \quad +\theta_{11} PNF_c + \eta_i. \end{aligned} \tag{19}$$

To conserve space, we only report the results from the full-sample regressions with all the control variables, along with those from the regressions for the gender and race subsamples. We have, however, re-estimated all the robustness checks and falsification tests from Tables 4-9 replacing discount factor with β and δ and verified that our findings are not sensitive to specification. These results are available upon request.

The full-sample results in the first column of Table 10 show that both present-bias β and long-run patience δ are statistically significant and negatively associated with BMI. Impulsivity and long-run impatience therefore both separately influence weight. The magnitudes imply that a one standard deviation increase in β (decrease in impulsivity) reduces BMI by 0.18 units, or 1.2 pounds at the sample mean height, while a standard deviation increase in δ (time-consistent patience) reduces weight by 0.17 BMI units or 1.1 pounds. The second and third columns reveal that the coefficient on β is negative and statistically significant for women whereas δ is not significant, whereas the reverse pattern holds for men. This suggests that the relationship between intertemporal preferences and BMI is driven by impulsivity and present bias for females, but time-consistent impatience for males. Stratifying by race shows that both β and δ predict the BMI of whites, but there is no evidence that either influence the weight of non-whites. Finally, the last column shows that the interaction of β and food prices is positive and statistically significant, while the interaction of δ and food prices is also positive but marginally insignificant. The evidence that impulsive individuals respond more strongly to food prices is therefore clearer than the evidence regarding the interaction of time-consistent impatience and food prices.

5 Conclusion

This study investigates the connection between time preferences, economic incentives, and BMI. Our theoretical model predicts that greater impatience increases BMI and might strengthen individuals' responses to food prices. We test these predictions using the 2006 NLSY matched with local price data from C2ER. Impatience is associated with BMI and the probabilities of being overweight and obese across a wide range of specifications. Interacting the discount factor with food prices reveals that impatient individuals experience the largest increases in weight when food prices fall. Finally, we consider time-inconsistent quasi-hyperbolic discounting. Both present bias (β) and the long-run discount factor (δ) are negatively correlated with BMI, and their interactions with food prices are positively correlated with BMI, though only the interaction with β is statistically significant.

Our study aims to combine two strands of the literature on the economic causes of obesity in an effort to explain why the BMI distribution has not only shifted to the right but also thickened in the right tail. The majority of the literature focuses on the influence of economic factors such as food prices on weight. While society-wide changes in economic incentives can explain the shift to the right in the BMI distribution, they alone cannot explain why individuals in the right tail of the distribution have experienced the largest weight gains while others in the left tail have not gained any weight. Another portion of the literature links time preference to BMI, but has left unclear whether this link can help to explain the rise in obesity since the best available evidence suggests time preferences are reasonably stable. We propose that incentives and impatience interact to explain the changes in the BMI distribution in recent decades. As economic factors lower the opportunity cost of food consumption, impatient individuals gain weight while the most patient individuals do not. Mean BMI therefore rises but the rise is concentrated among a subset of the population. We provide a preliminary test of this theory in the context of food prices. Future research should examine whether the interaction of time preference with other economic incentives, such as those that affect the opportunity cost of physical activity rather than eating, also predict BMI.

Our paper also provides the first attempt to explicitly model quasi-hyperbolic discounting parameters β and δ and test their separate influences on BMI and obesity. The results suggest that the intertemporal trade-offs that determine body weight are at least partly due to time-inconsistent discounting. The policy implications of this time inconsistency are an important topic for future research, but here we briefly summarize possible implications. The standard rationale for policies aimed at curbing obesity comes from externalities associated with obesity, such as medical expenditures paid by the government or other members of a private insurance pool. However, if consumers' time-inconsistency explains their obesity, then there may be justification for policy intervention even if there are no externalities associated with obesity.[21] Whether time inconsistency alone justifies policy intervention depends on how we ought to conduct welfare analysis under time-inconsistent preferences. One argument is that we should treat the present bias as a "mistake" or a type of market/behavioral failure, and the social planner should maximize using a welfare function that does not include β. This is the approach taken by Heutel (2011), O'Donoghue and Rabin (2006) and Gruber and Koszegi (2001). Others, e.g. Bernheim and Rangel (2009), propose a different set of welfare criteria and do not find that present bias justifies policy intervention in all cases. Our contribution to this topic is merely to identify time inconsistency as a contributor to obesity, rather than to make policy recommendations.

References

Anderson, L., Mellor, J., 2008. "Predicting health behaviors with an experimental measure of risk preference." *Journal of Health Economics* 27, 1260-1274.

Anderson, M., Matsa, D., forthcoming. "Are restaurants really supersizing America?" *American Economic Journal: Applied Economics.* Available http://www.aeaweb.org/forthcoming/output/accepted_APP.php.

Baum, C., 2009. "The effects of cigarette costs on BMI and obesity." *Health Economics* 18, 3–19.

[21] In fact, Bhattacharya and Sood (2011) argue that there are no externalities from obesity, i.e. that the costs of obesity are paid for by the obese person himself or herself through either out-of-pocket medical costs or foregone wages.

Bernheim, B., and Rangel, A., 2009. "Beyond Revealed Preference: Choice-Theoretic Foundations for Behavioral Welfare Economics." *Quarterly Journal of Economics*, vol. 124(1), 51-104.

Bhattacharya, J., Bundorf, M., Pace, N., Sood, N., forthcoming. "Does health insurance make you fat?" Grossman, M., and Mocan, N., eds., *Economic Aspects of Obesity.*

Bhattacharya, J., and Sood, N., 2011. "Who Pays for Obesity?" *Journal of Economic Perspectives*, vol. 25(1), 139-158.

Borghans, L., Golsteyn, B., 2006. "Time discounting and the body mass index: Evidence from the Netherlands." *Economics and Human Biology* 4, 29-61.

Cawley, J., 1999. "Rational addiction, the consumption of calories, and body weight." Ph.D. dissertation. University of Chicago, Chicago, IL.

Chabris, C., Laibson, D., Morris, C., Schuldt, J., Taubinsky, D., 2008. "Individual laboratory-measured discount rates predict field behavior." *Journal of Risk and Uncertainty* 37, 237-269.

Chou, S., Grossman, M., Saffer, H., 2004. "An economic analysis of adult obesity: results from the behavioral risk factor surveillance system." *Journal of Health Economics* 23, 565–587.

Chou, S., Grossman, M., Saffer, H., 2006. "Reply to Jonathan Gruber and Michael Frakes." *Journal of Health Economics* 25, 389–393.

Coller, M. Williams, M., 1999. "Eliciting individual discount rates." *Experimental Economics* 2, 107-127.

Courtemanche, C., 2009a. "Rising cigarette prices and rising obesity: coincidence or unintended consequence?" *Journal of Health Economics* 28, 781–798.

Courtemanche, C., 2009b. "Longer hours and larger waistlines? The relationship between work hours and obesity." *Forum for Health Economics and Policy* 12(2), Article 5.

Courtemanche, C., 2011. "A silver lining? The connection between gasoline prices and obesity." *Economic Inquiry* 49, 935-957.

Courtemanche, C., Carden., A., 2011. "Supersizing supercenters? The impact of Walmart Supercenters on body mass index and obesity." *Journal of Urban Economics* 69, 165-181.

Currie, J., DellaVigna, S., Moretti, E., Pathania, V., 2010. "The effect of fast food restaurants on obesity and weight gain." *American Economic Journal: Economic Policy* 2, 32–63.

Cutler, D., Glaeser, E., Shapiro, J., 2003. "Why have Americans become more obese?" *Journal of Economic Perspectives* 17, 93–118.

Dunn, R. 2010. "Obesity and the availability of fast-food: an analysis by gender, race/ethnicity and residential location." *American Journal of Agricultural Economics* 92, 1149-1164.

Dunn, R., 2008. "Obesity and the availability of fast-food: An instrumental variables approach." Working Paper, University of Wisconsin-Madison.

Eid, J., Overman, H., Puga, D., Turner, M., 2008. "Fat city: questioning the relationship between urban sprawl and obesity." *Journal of Urban Economics* 63, 385–404.

Ewing, R., Schmid, T., Killingsworth, R., Zlot, A., Raudenbush, S., 2003. "Relationship between urban sprawl and physical activity, obesity, and morbidity." *American Journal of Health Promotion* 18, 47–57.

Finkelstein, E., Fiebelkorn, I., Wang, G., 2003. "National Medical Spending Attributable to Overweight and Obesity: How Much, and Who's Paying?" *Health Affairs*, Web Exclusives: W219-W226.

Flegal, K., Carroll, M., Kuczmarski, R., Johnson, C., 1998. "Overweight and obesity in the United States: prevalence and trends, 1960–1994." *International Journal of Obesity* 22, 39–47.

Flegal, K., Graubard, B., Williamson, D., Gail, M., 2005. "Excess deaths associated with underweight, overweight, and obesity." *Journal of the American Medical Association* 293, 1861–1867.

Frank, L., Andresen, M., Schmid, T., 2004. "Obesity relationships with community design, physical activity, and time spent in cars." *American Journal of Preventive Medicine* 27, 87–96.

Goldman, D., Lakdawalla, D., Zheng, Y., 2010. "Food prices and the dynamics of body weight." Forthcoming in Grossman, M., and Mocan, N., eds., *Economic Aspects of Obesity.* Available http://www.nber.org/chapters/c11817.pdf.

Gruber, J., Frakes, M., 2006. "Does falling smoking lead to rising obesity?" *Journal of Health Economics* 25, 183–187.

Gruber, J., and Koszegi, B., 2001. "Is Addiction "Rational"? Theory and Evidence." *Quarterly Journal of Economics*, vol. 116(4), 1261-1303.

Heutel, G., 2011. "Optimal Policy Instruments for Externality-Producing Durable Goods under Time Inconsistency," National Bureau of Economic Research Working Paper 17083.

Ikeda, S., Kang, M., Ohtake, F. 2010. "Hyperbolic discounting, the sign effect, and the body mass index." *Journal of Health Economics*, 29 (2010) 268-284.

Johnson, M.W., & Bickel, W.K. 2002. "Within-subject comparison of real and hypothetical money rewards in delay discounting." *Journal of the Experimental Analysis of Behavior*, 77,129–146.

Kirby, K., Marakovic, N., 1995. "Modeling myopic decisions: Evidence for hyperbolic delay-discounting within subjects and amounts." *Organizational Behavior and Human Decision Processes* 64, 22-30.

Komlos, J., Smith, P., Bogin, B., 2004. "Obesity and the rate of time preference: Is there a connection?" *Journal of Biosocial Science* 36, 209-219.

Laibson, D., 1997. "Golden Eggs and Hyperbolic Discounting." *The Quarterly Journal of Economics*, 112(2): 443-477.

Lakdawalla, D., Philipson, T., 2002. "The Growth of Obesity and Technological Change: A Theoretical and Empirical Investigation." National Bureau of Economic Research Working Paper 8965.

Lakdawalla, D., Philipson, T., Bhattacharya, J., 2005. "Welfare-enhancing technological change and the growth of obesity." *American Economic Review Papers and Proceedings* 95, 253–257.

Loewenstein, G., 1988. "Frames of mind in intertemporal choice." Management Science 34, 200-214.

Madden, G.J., Begotka, A.M., Raiff, B.R., & Kastern, L.L. 2003. Delay discounting of real and hypothetical rewards. *Experimental and Clinical Psychopharmacology*, 11, 139–145.

McAlvanah, P., 2010. "Subadditivity, Patience, and Utility: The Effects of Dividing Time Intervals," *Journal of Economic Behavior and Organization* 76, 2010, 325-337.

Meier, S., Sprenger, C. 2010. "Stability of Time Preferences," IZA Working Paper 4756.

Meltzer, D., Chen, Z., forthcoming. "The Impact of Minimum Wage Rates on Body Weight in the United States." Grossman, M., and Mocan, N., eds., *Economic Aspects of Obesity.*

National Center of Health Statistics, 2008. "Prevalence of Overweight, Obesity and Extreme Obesity among Adults: United States, Trends 1976–80 Through 2005–2006." Available http://www.cdc.gov/nchs/data/hestat/overweight/overweight_adult.pdf.

National Institute of Diabetes and Digestive and Kidney Diseases. 2008. "Longitudinal Assessment of Bariatric Surgery (LABS)", NIH publication No. 04-5573, November.

Nonnemaker, J., Finkelstein, E., Engelen, M., Hoerger, T., Farrelly, M., 2009. "Have efforts to reduce smoking really contributed to the obesity epidemic?" *Economic Inquiry* 47, 366–376.

O'Donoghue, T., and Rabin, M., 2006. "Optimal Sin Taxes," *Journal of Public Economics*, vol. 90(10-11), 1825-1849.

Percoco, M., Nijkamp, P., 2009. "Estimating individual rates of discount: a meta-analysis," *Applied Economics Letters*, vol. 16(12), pages 1235-1239.

Phelps, E. S., and Pollak, R., 1968. "On Second-Best National Saving and Game-Equilibrium Growth." *Review of Economic Studies*, 35(2): 185-199.

Philipson, T., Posner, R., 2003. "The long run growth of obesity as a function of technological change." *Perspectives in Biology and Medicine* 46, S87–S108.

Plantinga, A., Bernell, S., 2007. "The association between urban sprawl and obesity: is it a two-way street?" *Journal of Regional Science* 47, 857–879.

Rashad, I., Chou, S., Grossman, M., 2006. "The super size of America: an economic estimation of body mass index and obesity in adults." *Eastern Economic Journal* 32, 133–148.

Royer, H., Stehr, M., and Snydor, J., 2011. "Incentives, Commitments and Habit Formation in Exercise: Evidence from a Field Experiment with Workers at a Fortune-500 Company." Unpublished manuscript.

Ruhm, C., 2000. "Are recessions good for your health?" *Quarterly Journal of Economics* 115, 617–650.

Ruhm, C., 2005. "Healthy living in hard times." *Journal of Health Economics* 24, 341–363.

Ruhm, C., 2010. "Understanding overeating and obesity." National Bureau of Economic Research working paper 16149.

Shelley, M., 1993. Outcome signs, question frames, and discount rates. *Management Science* 39, 806-815.

Simpson, C., Vuchinich, R., 2000. "Reliability of a Measure of Temporal Discounting," *Psychological Record*, 50(1), 3-16.

Smith, P., Bogin, B., Bishai, D., 2005. "Are time preference and body mass index associated? Evidence from the National Longitudinal Survey of Youth." *Economics and Human Biology* 3, 259-270.

Strum, R., 2002. "The effects of obesity, smoking, and drinking on medical problems and costs." *Health Affairs* 21, 245–253.

US Department of Health and Human Services, 2001. "The Surgeon General's Call to Action to Prevent and Decrease Overweight and Obesity."

Zhang, L., Rashad, I., 2008. "Obesity and time preference: The health consequences of discounting the future." *Journal of Biosocial Science* 40: 97-113.

Zhao, Z., Kaestner, R., 2010. "Effects of Urban Sprawl on Obesity." *Journal of Health Economics* 29, 779–787.

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	0.28 (0.34)

Note: Observations are weighted using the NLSY sampling weights. All variables are from the 2006 survey unless otherwise indicated.

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 – Discount Factor and BMI

Dependent Variable: BMI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discount factor	−1.44 (0.35)***	−1.30 (0.35)***	−1.08 (0.35)**	−1.07 (0.35)***	−0.92 (0.35)***	−0.98 (0.35)***	−0.84 (0.26)***	−1.16 (0.34)***
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)	0.05 (0.04)
Female	–	−0.73 (0.17)***	−0.71 (0.17)***	−0.54 (0.19)***	−0.57 (0.19)***	−0.57 (0.19)***	−0.55 (0.19)***	−0.56 (0.19)***
Race: black	–	2.15 (0.19)***	1.99 (0.22)***	2.01 (0.22)***	1.95 (0.22)***	1.96 (0.22)***	1.95 (0.22)***	1.94 (0.22)***
Race: other	–	0.61 (0.44)	0.50 (0.44)	0.50 (0.45)	0.53 (0.44)	0.54 (0.44)	0.51 (0.44)	0.52 (0.44)
Married	–	0.06 (0.19)	0.18 (0.19)	0.16 (0.19)	0.73 (0.22)***	0.73 (0.22)***	0.73 (0.22)***	0.73 (0.22)***
AFQT	–	–	−0.001 (0.004)	−0.004 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	0.002 (0.004)
High school	–	–	0.20 (0.38)	0.04 (0.38)	0.10 (0.38)	0.11 (0.38)	0.09 (0.38)	0.10 (0.38)
Some college	–	–	−0.07 (0.42)	−0.29 (0.42)	−0.13 (0.42)	−0.12 (0.41)	−0.13 (0.41)	−0.12 (0.41)
College	–	–	−1.10 (0.44)**	−1.38 (0.44)***	−0.88 (0.45)**	−0.87 (0.45)*	−0.89 (0.45)**	−0.88 (0.45)**
White collar	–	–	–	0.03 (0.28)	−0.02 (0.28)	−0.02 (0.28)	−0.02 (0.28)	−0.03 (0.28)
Blue collar	–	–	–	−0.32 (0.31)	−0.44 (0.32)	−0.44 (0.32)	−0.42 (0.32)	−0.43 (0.32)
Service	–	–	–	−0.37 (0.35)	−0.59 (0.35)*	−0.60 (0.35)*	−0.61 (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 (0.03)***
Income^2	–	–	–	–	0.001 (0.001)**	0.001 (0.001)**	0.002 (0.001)**	0.001 (0.001)**
Net worth	–	–	–	–	−0.006 (0.002)***	−0.006 (0.002)***	−0.006 (0.002)***	−0.006 (0.002)***
Risk	–	–	–	–	–	−0.027 (0.025)	−0.027 (0.025)	−0.030 (0.025)
D. factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF2$	$\overline{DF}$

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	White	Non-White
Discount factor	-0.70 (0.50)	-1.31 (0.49)***	-1.12 (0.41)***	-0.21 (0.55)
Demographics	YES	YES	YES	YES
Human capital	YES	YES	YES	YES
Labor	YES	YES	YES	YES
Financial	YES	YES	YES	YES
Risk	YES	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$
Observations	2989	2993	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 include income, income^2 and net worth.

Table 6 – Ordered Probit Results

Dependent Variable: BMI Category

Variable	Coefficient	Marginal Effects		
	Estimate	Overweight	Obese (Class 1)	Severely Obese
Discount factor	-0.17 (0.07)**	0.0006 (0.001)	-0.027 (0.011)**	-0.033 (0.013)**
Demographics	YES	YES	YES	YES
Human capital	YES	YES	YES	YES
Labor	YES	YES	YES	YES
Financial	YES	YES	YES	YES
Risk	YES	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$

Notes: $n = 5982$. See other 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
Discount factor	−0.15	0.015	−0.016	0.010	−0.010	−0.004	−0.043	−0.006	−0.072
	(0.16)	(0.019)	(0.014)	(0.010)	(0.017)	(0.008)	(0.027)	(0.017)	(0.081)
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
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$
Observations	5982	5975	5971	5971	5970	5970	5973	5973	5952

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

Table 8 – Interaction of Discount Factor with Food Prices

	Dependent Variable: BMI							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discount factor	−11.12	−10.79	−10.93	−10.67	−11.10	−11.03	−5.74	−9.89
	(4.44)**	(4.42)**	(4.40)**	(4.40)**	(4.39)**	(4.39)**	(3.15)*	(4.05)**
Food price	−1.64	−1.68	−1.86	−1.82	−1.99	−1.96	−0.55	−1.28
	(0.93)*	(0.92)*	(0.92)**	(0.92)**	(0.92)**	(0.92)**	(0.59)	(0.74)*
Non-food index	−0.007	−0.008	−0.003	−0.002	0.005	0.005	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Discount factor*food price	2.86	2.82	2.92	2.85	3.03	2.99	1.40	2.56
	(1.31)**	(1.31)**	(1.30)**	(1.30)**	(1.30)**	(1.30)**	(0.93)	(1.19)**
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	NO	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF2$	$\overline{DF}$

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

Table 9 – Interaction of Discount Factor with Food Prices: Additional Robustness Checks

Dependent Variable: BMI

	Alternate Food Baskets		Add Future Food Price			Geographic	Additional
	13 items	6 items	1-year	2-year	Both	Controls	Interactions
Discount factor	−11.31	−11.51	−11.07	−11.73	−11.12	−10.88	−11.99
	(4.52)**	(4.72)**	(4.38)**	(4.40)***	(4.39)**	(4.46)**	(4.54)***
Food price	−1.86	−1.57	−1.77	−2.53	−2.03	−1.02	−5.44
	(0.86)**	(0.77)**	(1.00)*	(1.07)**	(1.10)*	(1.01)	(6.34)
Non-food index	0.006	0.003	0.009	0.009	0.010	−0.005	0.004
	(0.008)	(0.006)	(0.008)	(0.008)	(0.008)	(0.010)	(0.008)
Discount factor*food price	2.81	2.61	3.07	3.24	3.08	2.94	3.27
	(1.22)**	(1.16)**	(1.30)**	(1.30)**	(1.30)**	(1.32)**	(1.34)**
Food price in $t+1$	–	–	−0.61	–	−0.76	–	–
			(0.58)		(0.62)		
Food price in $t+2$	–	–	–	0.23	0.40	–	–
				(0.65)	(0.70)		
Demographics	YES	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES	YES	YES
Financial	YES	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES	YES
State fixed effects	NO	NO	NO	NO	NO	YES	NO
Urban	NO	NO	NO	NO	NO	YES	NO
Food price*Controls	NO	NO	NO	NO	NO	NO	YES
Observations	5090	5090	4855	4853	4819	5030	5090

See notes for Table 5.

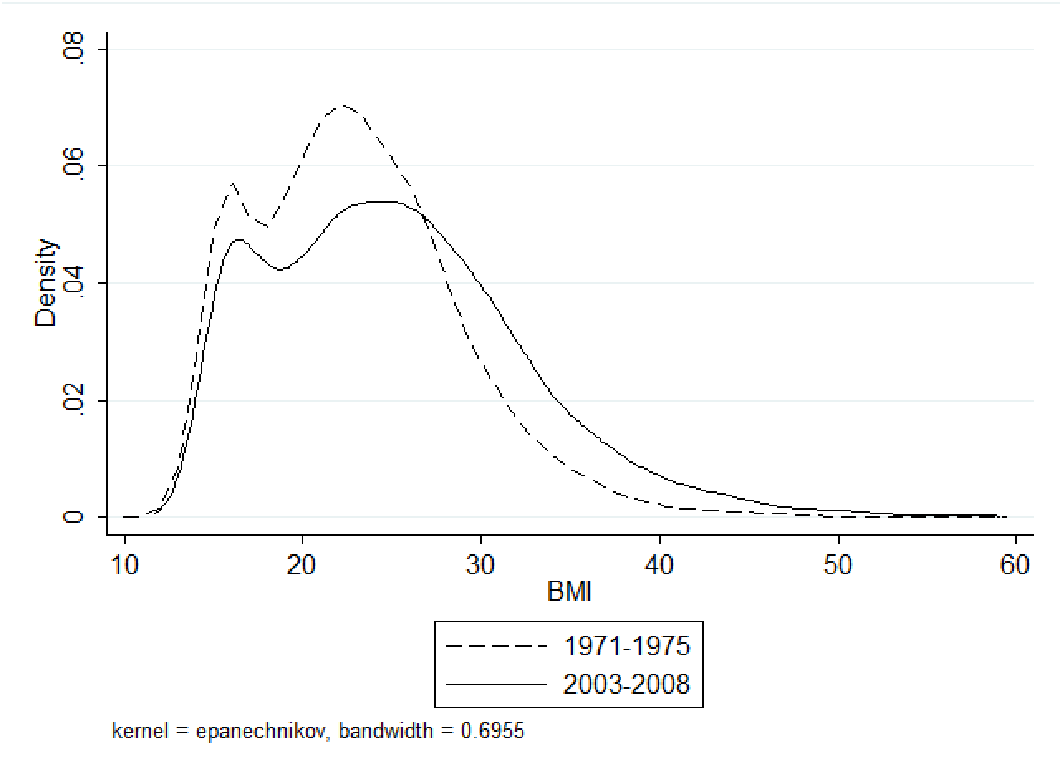
Table 10 – Time Inconsistency and BMI

Dependent Variable: BMI

	Full Sample	Women	Men	White	Non-White	Interactions
Beta	-0.92	-1.24	-0.54	-1.11	0.26	-13.80
	(0.46)**	(0.61)**	(0.67)	(0.53)**	(0.72)	(5.35)***
Delta	-0.50	-0.25	-0.81	-0.57	-0.25	-5.20
	(0.25)**	(0.37)	(0.35)**	(0.32)*	(0.35)	(3.13)*
Food price	–	–	–	–	–	-4.27
						(1.63)***
Non-food index	–	–	–	–	–	0.006
						(0.008)
Beta*food price	–	–	–	–	–	3.78
						(1.58)**
Delta*food price	–	–	–	–	–	1.43
						(0.94)
Demographics	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES
Financial	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES
Food price measure	–	–	–	–	–	1
Observations	5982	2989	2993	3894	2088	5090

See 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 distribution 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

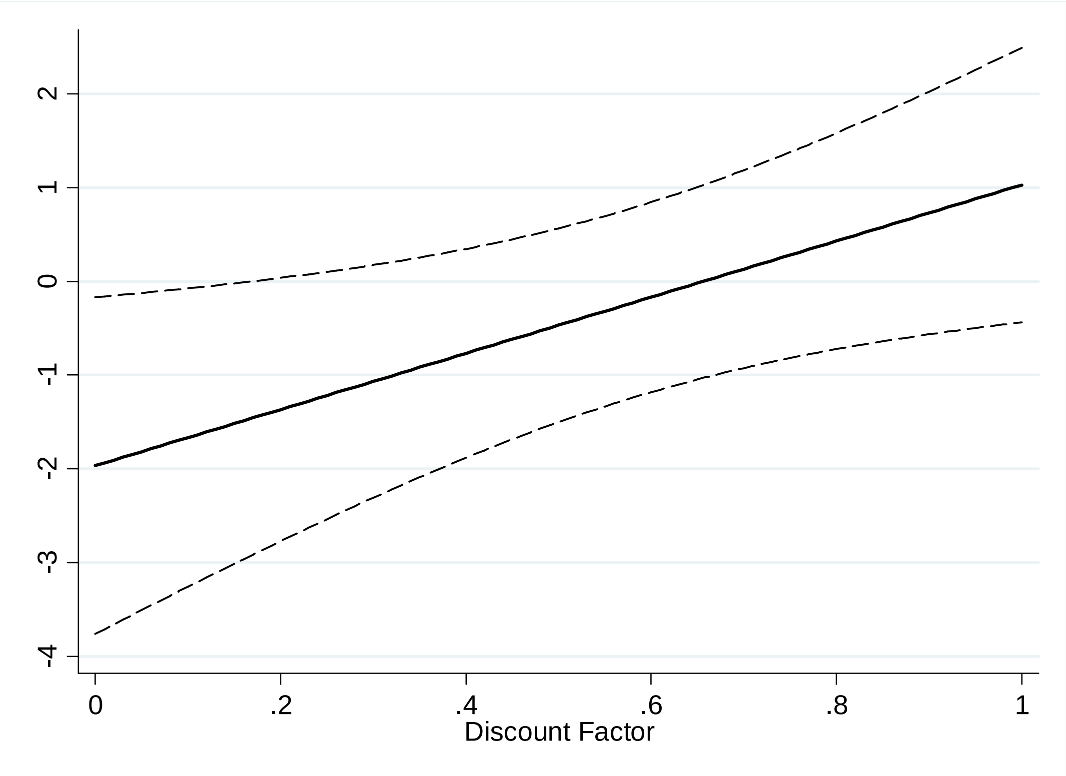


Figure 3 – BMI Distributions by Degree of Patience at Estimated 1956 Food Price=$3.74

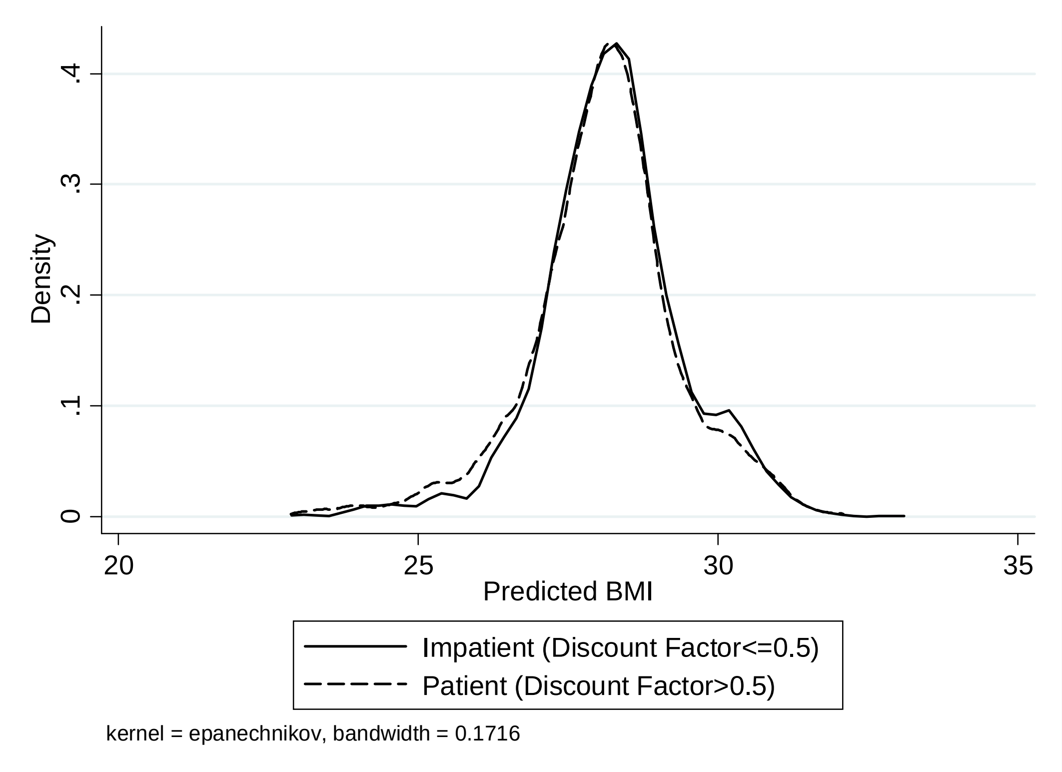


Figure 4 – BMI Distributions by Degree of Patience at 2006 Food Price=$3.34

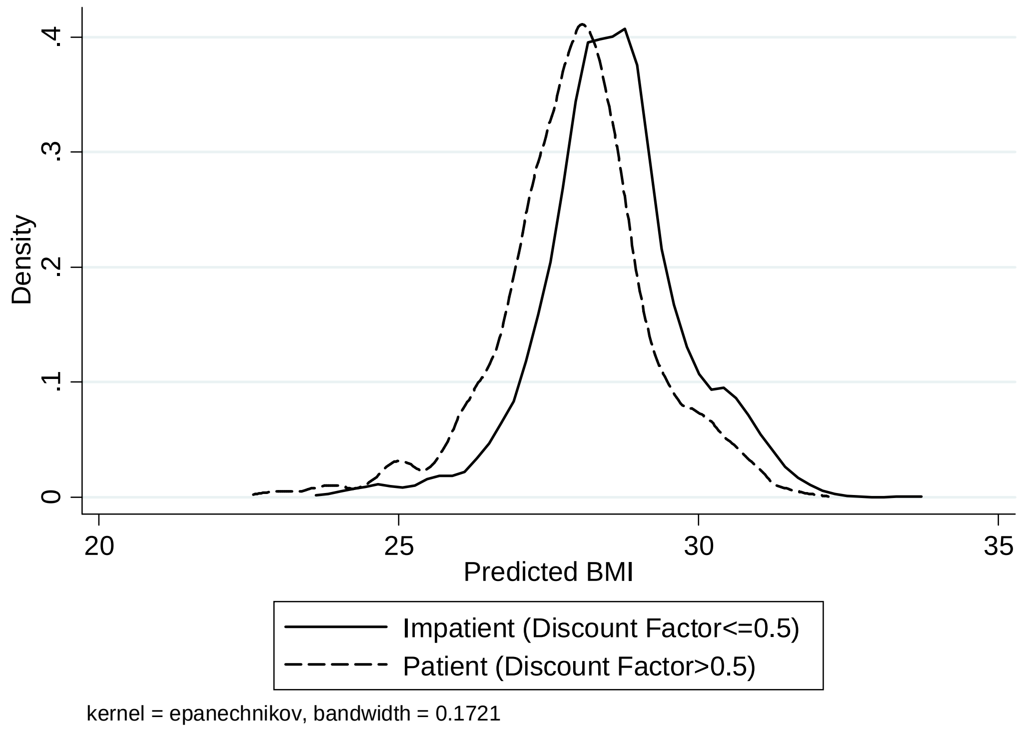


Figure 5 – BMI Distributions by Degree of Patience at Estimated Food Price=$2.94