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IMPATIENCE, INCENTIVES, AND OBESITY

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ABSTRACT

This paper explores the relationship between time preferences, economic incentives, and body mass index (BMI). Using data from the 1979 cohort of the National Longitudinal Survey of Youth, we first show that greater impatience increases BMI even after controlling for demographic, human capital, and occupational characteristics as well as income and 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 ŭ). Both long-run patience (ŭ) and present-bias (ϐ) predict BMI, suggesting obesity is partly attributable to rational intertemporal tradeoffs but also partly to time inconsistency.

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1 Introduction

Obesity, defined as having a body mass index (BMI) of at least 30, has become a leading public health concern in the developed world in recent decades.[1] The most dramatic rise has occurred in the United States (US), where the obesity rate skyrocketed from 13% in 1960 to 34% in 2006 (Flegal et al., 1998; National Center of Health Statistics, 2008). 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 in the US (Sturm, 2002; Flegal et al., 2005). Treating obesity-related conditions costs the US 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 (2010), Currie et al. (2010), and Anderson and Matsa (2011). 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, 2009; Nonnemaker et al., 2008; Courtemanche, 2009a), gasoline prices (Courtemanche, 2011), Walmart Supercenters (Courtemanche and Carden, 2011), urban sprawl (Eid et al., 2008; Zhao and Kaestner, 2010), 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.

A growing body of research examines the link between time preference and BMI.[3] Komlos et al. (2004), Smith et al. (2005), Borghans and Golsteyn (2006), and Zhang and Rashad (2008) all document a connection between proxy variables for time preference and weight.[4] More recent work utilizes direct measures of time preference elicited through questions on intertemporal trade-offs. These include small-sample laboratory studies of adults in the Boston area (Chabris et al., 2008), college students in Birmingham, AL (Weller et al., 2008), and children in Austria (Sutter et al., 2013), as well as larger-sample surveys of Japanese adults (Ikeda et al., 2010), Dutch adults (Van der Pol, 2011), and US children (Seeyave et al., 2009).[5]

While important progress has been made in understanding the time preference-BMI connection, two important questions remain unanswered. First, even if it time preference does influence BMI, is not clear whether this relationship can help to explain the *trend* in BMI as opposed to merely the level. Percoco and Nijkamp (2009) and Borghans and Golysten (2006)

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

[4] 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 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.

[5] Chabris et al. (2008) find a relationship between discount rate and BMI, as well as other health behaviors such as smoking and exercise. Weller et. al. (2008) show that obese women exhibit greater discounting than non-obese women. Sutter et. al. (2013) estimate a significant correlation between time preferences and BMI, along with alcohol and cigarette consumption. Seeyave et. al. (2009) find that time preference measured at age 4 is correlated with being overweight at age 11. 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 . Van der Pol (2011) examines the effect of education on health outcomes, including BMI, when controlling for time preference. Other papers look at the effect of time preference on health outcomes besides BMI, e.g. smoking and exercise (Song 2011), drinking and exercise (Chiteji 2010), disease screening (Bradford et. al. 2010), behaviors to prevent hypertension (Axon et. al. 2009), or healthy behaviors in general (Bradford 2010).

found no evidence that rates of time preference have systematically changed over time.[6] 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 second 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 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.[7] He further describes biological reasons to expect time 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 both of these fronts using data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY). This survey includes questions on body weight and hypothetical intertemporal trade-offs along

[6] 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. 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.

[7] Scharff (2009) shows that the caloric consumption of obese individuals is less responsive to nutritional information than that of other individuals, which he argues is evidence of hyperbolic discounting among the obese. 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.

with a rich array of other individual information that enables the construction of a detailed set of control variables. We begin by demonstrating the validity of our time preference measure and verifying that the connection between time preference and BMI observed in other contexts exists in our sample as well. Greater impatience is associated with higher BMI even after controlling for demographic characteristics, IQ, education, work hours, occupation type, income, and risk preference. The effects are strongest for whites and males. Falsification tests provide no evidence of a link between time preference and either height or health conditions that are less directly tied to eating and exercise, helping to validate the results for BMI.

We then proceed with our two main contributions. The first 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 across a wide range of specifications, including both cross-sectional and individual fixed effects models. Our preferred estimate implies that the food price elasticity of BMI ranges from -0.1 for the least patient individuals to statistically indistinguishable from 0 among those with higher levels of patience. This interaction effect can potentially 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 fallen for most 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 help to explain trends in BMI and obesity even if individuals have not become more impatient over time.[8]

[8]Heterogeneity in food price changes could also explain some of the increasing variance of the BMI distribution. For instance, Chung and Myers (1999) provide evidence that the absence of chain stores in poor neighborhoods in the Twin Cities increases the poor's food prices.

Our second main contribution is to 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.[9] Female BMI appears more strongly driven by present-bias than time-consistent impatience, whereas 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 then briefly discuss extending the model to analyze time-inconsistent preferences.

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

[9] 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.

weight, and that further weight gains are increasingly aversive.[10] 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

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

The first-order condition is

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

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 $\frac{\partial w}{\partial p}$ using the chain rule on $w = g(f)$ and the 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 $\frac{\partial w}{\partial \delta}$ in the

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

same manner as above

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

Again the denominator is negative and g' is positive. The numerator $\square V'(f)$ 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 $\frac{\partial w}{\partial p}$ 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, $\frac{\partial^2 w}{\partial \delta \partial p} > 0$.

To calculate this cross-partial derivative, we evaluate the derivative of $\frac{\partial w}{\partial p}$ 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

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

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 ($\square g' \cdot V''$) 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 ($\square g'' \cdot V'$) 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.[11] We thus leave it to our empirical work to determine with more certainty the sign of this cross-partial derivative. A similar theoretical result is found in a model of rational addiction in Becker et. al. (1991, footnote 3). They derive conditions under which relatively impatient addicts are more responsive to current prices.

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)). However, prices have fallen for most consumers, yet the growth in BMI 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 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.

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 inves-

[11] 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.

tigate time-inconsistent preferences, so we can consider 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. We do not present details of the model here, but they are available by the authors upon request. The model demonstrates that weight is negatively affected by food price and by both discount factors. 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.

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 $\frac{\partial^2 w}{\partial\delta\partial p}$ and $\frac{\partial^2 w}{\partial\beta\partial p}$ 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.

For simplicity, our model ignores the quality of diet and assumes that all food has the same effect on weight. An extension to the model considers two types of food ("healthy" and "unhealthy") with two distinct prices, only one of which affects future weight ("unhealthy" food). We show that the unhealthy food price has a negative effect on weight and the discount factor still has an unambiguously negative effect on weight. Details of this extension are available from the authors upon request.

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 and biennially thereafter.[12] We use two different samples. The first consists of only the 2006

[12]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

cross-section, as 2006 is the only year in which time preference information is available. The second (which we will refer to as the "full sample") consists of most of the panel, starting in 1986 to match our access to price data.[13] The 1986, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, 2000, 2002, 2004, and 2006 surveys include body weight, so the full sample includes 13 waves spanning 21 years. The respondents were between 14 and 22 years old at the start of the panel, making our age range 41 to 50 in 2006 and 21 to 50 in the full sample. Height is reported in 2006 and also slightly before our sample period in 1985. Since all respondents were adults throughout the sample, the 1985 and 2006 heights are very similar. We use 2006 height and have verified that the results are very similar using 1985 height or the average of the two years.

Our main dependent variable is BMI, which we compute from these self-reports of weight and height. 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 the 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 nearly identical if we do not employ the correction.[14]

Our independent variables of interest are time preference measures computed from two questions on hypothetical intertemporal trade-offs available in the 2006 NLSY survey.[15] The

throughout the analysis.

[13] Our price data begin in 1985, but we will be including one lag of price, which necessitates starting the sample in 1986.

[14] We use the 2005-2006 NHANES wave for this correction to provide the best possible match to our 2006 sample. It is possible that using correction coefficients from 2005-2006 to predict height and weight in all the years of our full sample could introduce some measurement error. However, the fact that the results are virtually identical if we do not employ the correction suggests that such out-of-sample predictions are not introducing systematic bias. It is not possible to construct an NHANES sample to span the entire time horizon of our full sample, as it did not become continuous until 1999.

[15] DellaVigna and Paserman (2005) utilize the NLSY (and PSID) to explore the implications of impatience for job search decisions. The authors construct a measure of impatience via factor analysis of several proxies for impatience, such as smoking, life insurance, and contraceptive use. Cadena and Keys (2011) use NLSY

first question is,

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

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

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

The second question is,

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

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

$$DF2 = \left(\frac{1000}{1000 + amount2}\right)^{12}. \tag{7}$$

$DF1$ 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

data to investigate the effects of impatience on human capital formation. Their measure of impatience comes from the survey interviewer's assessment of the subject.

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.[16]

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 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 time-inconsistent present-bias. Assuming annual periods, an individual's joint responses to these two questions imply that

$$\beta\delta^{\frac{1}{12}} = \frac{1000}{1000 + amount2} \quad (8)$$

$$\beta\delta = \frac{1000}{1000 + amount1} \quad (9)$$

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 our intertemporal discounting questions, 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) and Madden et al. (2003) find no significant difference between the discounting of real versus hypothetical monetary

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

amounts, and Ubfal (2012) finds no significant difference between discounting of real versus hypothetical consumable goods as well as money. Although some studies demonstrate a difference between real and hypothetical time discounting decisions, there is no consensus over the direction of bias. 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.

Table 1 presents the correlations between each of the time preference measures from the 2006 sample. The correlation between the annual $DF1$ and the monthly $DF2$ is 0.58. $DF1$ is more closely associated with long-run patience δ whereas $DF2$ is more closely related to present bias β. We also demonstrate the validity of the time preference questions by correlating our four time preference measures to several economic variables with an obvious intertemporal component. A more patient response to the annual discounting question, $DF1$, is correlated with more educational attainment, a greater percentile score on the Armed Forces Qualification Test (AFQT), and a greater net worth.[17] Individuals with patient responses were also less likely to have any credit card debt, less likely to have maxed-out credit cards, less likely to have ever declared bankruptcy, and less likely to be smokers. Our β and δ parameters are identified from an individual's joint responses to the monthly and annual questions, and one concern might be that these parameters simply reflect calculation errors. However, Table 1 reveals that the β and δ parameters are similarly correlated with education, credit card debt, bankruptcy, and smoking, which suggests that individuals' responses to these questions are not simply noise but are reflective of intertemporal preferences.

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

[17] Net worth is computed by the NLSY based on respondents' answers to a variety of questions on income sources, assets, and liabilities.

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 controls are age and dummies for gender, race, and marital status. AFQT percentile proxies for intelligence.[18] 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.[19] We also control for total household income.[20]

The NLSY also contains a health module administered to respondents the first survey after their 40th birthdays – either 1998, 2000, 2002, 2004, or 2006. Information on chronic conditions allows for the construction of indicator variables for arthritis, anemia, chronic kidney or bladder problems, and chronic stomach problems. These dummies serve as dependent variables in the falsification tests. Since these variables are only recorded once for each

[18]The AFQT is the exam taken by prospective entrants into the United States military. It consists of vocabulary, reading comprehension, analytical, and mathematics components. It was administered to all NLSY respondents, regardless of sex or military status, in 1985.

[19]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.

[20]In order to retain as much of the sample as possible, we impute missing values of the controls by taking the midpoint of the previous and subsequent survey waves. We considered adding a set of dummies indicating whether these variables were imputed but they were highly insignicant and had no meaningful impact on the results. We did not impute missing values of BMI; these observations were dropped.

respondent, we only conduct the falsification tests with the cross-sectional sample.

We match these individual-level data to local price information from the C2ER's American Chamber of Commerce Researchers Association Cost of Living Index (ACCRA COLI). The ACCRA COLI computes quarterly 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 first compute annual prices for each market by averaging over all quarters in the year in which prices for the market are available. We then use the county identifiers from the restricted version of the NLSY to match each respondent in each year 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 respondents living in counties greater than 50 miles from the closest ACCRA COLI area (approximately 11% of the sample). The conclusions reached are similar using 30, 40, 60, and 70 mile distance cutoffs. Our food price variable is the average price of the 16 reported food items, weighted by their share as given by the ACCRA COLI.[21] The same set of weights is used for all areas. Table 2 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. Additionally, in some specifications we use separate prices for the fruit/vegetable, meat, and other (generally unhealthy) food items, as denoted in Table 2.

Tables 3 and 4 report the names, descriptions, means, and standard deviations for the variables that will be used in the regression analyses, both for the 2006 and full 1986-2006 samples. Since the time and risk preference variables are only available in 2006, for the other years of the full sample we assign respondents their 2006 values. In other words, we assume

[21] Despite the weighting, it should be noted that the food basket is not necessarily representative of average food consumption, as it is missing many important components such as dairy products, pasta, and rice. Nonetheless, the ACCRA COLI provides the most appropriate price data for our analysis because of the narrow geographic level at which the data are available.

time and risk preferences are stable across the sample period. We discuss the implications of this assumption in Section 4.2. Similarly, AFQT score is only reported in 1985, so we assign the 1985 value to all years.

Turning to the summary statistics for the key variables, the average BMI is 28.3 in 2006 and 26.3 in the full sample. 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 $\beta > 1$. This asymmetry of β about 1 suggests that this variable is not merely representing noise from subjects' misreporting.

The average inflation-adjusted price of the basket of 16 foods is \$3.69 in the full 1986-2006 sample. There is substantial time-series and cross-sectional variation in food price in our sample. Food prices fell for 87% of respondents during the sample period, with average price dropping from \$3.91 in 1986 to \$3.53 in 2006. The range of food prices observed in the average year is \$2.16, or a sizeable 59% of the mean. There is also considerable within-individual variation in food price, as the correlation between current food price and its first lag is only 0.61 in the full sample.

4 Empirical Analysis

4.1 Discount Factor and BMI

The two main objectives of this paper are to examine the interaction effect of time preference and food price on BMI, and to test whether the effect of time preference on BMI is driven by time-consistent patience or present-bias. Before turning to these questions, it is important to verify that the previously-documented connection between time preference and BMI exists in our sample. We therefore begin by estimating the association between discount factor and BMI using the 2006 sample and conducting falsification tests to assess the validity of the results. Our main regression equation is

$$BMI_i = \alpha_0 + \alpha_1 DF1_i + \boldsymbol{\alpha}_2 \mathbf{DEMO}_i + \boldsymbol{\alpha}_3 \mathbf{HC}_i + \boldsymbol{\alpha}_4 \mathbf{LABOR}_i + \boldsymbol{\alpha}_5 \mathbf{INCOME}_i + \alpha_6 RISK_i + \varepsilon_i \tag{10}$$

where i indexes individuals.[22] $DF1$ 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. **INCOME** consists of real income and its square 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

[22] In an unreported regression (full results available upon request), we use BMI category rather than BMI as the outcome variable and estimate an ordered probit model. The categories are healthy weight (BMI<25), overweight but not obese (25≤BMI<30), class I obese (30≤BMI<35), and severely obese (BMI≥35).The marginal effect of discount factor on P(Overweight but not Obese) is small and insignificant, but 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.

on the basis of age, gender, race, marital status, intelligence, education, income, time spent working, or risk preference, failing to adequately control for these variables may bias the estimators of α_1.[23]

Table 5 reports the key results; full regression output is available upon request. 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 -0.97 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 0.24 to 0.27 units, or 1.6 to 1.8 pounds at the sample mean height of 67.55 inches. Columns (7) and (8) show that the results are 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.

Table 6 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 slightly insignificant for women.[24] When stratifying

[23] We do not control for some of the variables shown to be correlated with discount factor in Table 1 – net worth, credit card debt, maxed-out credit cards, bankruptcy, and smoking – because in our judgment the literature strongly suggests that they are causally affected by time preference. Including them could therefore lead to an over controlling problem in which we "control away" some of the mechanisms through which time preference causally affects BMI. In unreported regressions, we do control for these variables and they only slightly attenuate the association between discount factor and BMI. Less obvious over controlling problems could also exist for some of the variables we do include in the reported regressions, such as AFQT score, education, work hours, and income. 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.

[24] Ikeda et. al. (2010) provide similar findings. In their regressions (from data on a Japanese subject pool), the coefficient on the discount rate is larger for males than for females, though not significantly so in the regressions with demographic controls. Without demographic controls, the coefficient for males is about twice as high as that for females, and only the coefficient on males is significant. While we are unsure why the

by race, discount factor's impact is strong and significant for whites but small and insignificant for non-whites.

We close this section with a series of falsification tests. First, we re-estimate equation (10) 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: arthritis or rheumatism; kidney or bladder problems; stomach, liver, intestinal, or gall bladder problems; and anemia. We also consider a dependent variable representing the total number of these conditions reported. While it is difficult to find health outcomes that are completely independent of health behaviors, we expect that these conditions should at least be less directly tied to behaviors than obesity. A large "effect" of discount factor on these outcomes would therefore suggest 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.

connection between time preference and BMI is stronger for men than women, the fact that similar results have been found in Japan suggests that cultural factors unique to the US do not provide a sufficient explanation.

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.

4.2.1 Cross-Sectional Regressions

Our initial regression is similar to equation (10) but adds local food prices ($PFOOD$), non-food prices (PNF), and the interaction of food prices with discount factor:

$$\begin{aligned} BMI_{ic} &= \alpha_0 + \alpha_1 DF1_{ic} + \boldsymbol{\alpha}_2 \mathbf{DEMO}_{ic} + \boldsymbol{\alpha}_3 \mathbf{HC}_{ic} + \boldsymbol{\alpha}_4 \mathbf{LABOR}_{ic} + \boldsymbol{\alpha}_5 \mathbf{INCOME}_{ic} \quad (11) \\ &\quad + \alpha_6 RISK_{ic} + \alpha_7 PFOOD_c + \alpha_8 (DF1_{ic} * PFOOD_c) + \alpha_9 PNF_c + \varepsilon_i \end{aligned}$$

where c indexes counties.[25] Controlling for non-food prices helps ensure that the estimated effect of food price is not simply capturing a more general price effect. Because of the addition of county-level variables, we now cluster standard errors by county.

Table 8 displays the results from estimating equation (11) using the 2006 sample. We again start with a model with no controls, gradually build up to the full specification in column (6), and experiment with the alternative discount factor measures $DF2$ and $\overline{DF}$ in columns (7) and (8). Consistent with results from the literature (e.g. Chou et al., 2004), the coefficient estimate for food price is negative across all eight specifications in Table 8 and

[25] Our model assumes that the effect of food price on BMI changes linearly across the discount factor distribution. We have also estimated models using a quadratic functional form for discount factor, as well as a series of dummies splitting the discount factor distribution into thirds and fifths. We did not observe clear evidence of nonlinearities, so we present the results from the simple linear specification.

significant at the 5% level or better in seven of the eight. The interaction term is positively associated with BMI and significant at the 10% level or better in all eight regressions. These results support the intuitive 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 well within each other's confidence intervals, ranging from 1.98 to 3.17. Aside from the regression that computes discount factor exclusively from the monthly delay question (column (7)), the estimates are all within the narrower range of 3.02 to 3.17 and significant at the 5% level.

4.2.2 Panel Regressions

This cross-sectional strategy has two important limitations. First, identification of the food price effect requires the strong assumption that no unobservable determinants of BMI are correlated with food prices. Areas with high demand for food may have both higher food prices and higher BMI, while other local area-level economic variables such as food store and restaurant densities may influence both food prices and BMI. Second, a cross-sectional equation ignores the dynamics of the food price effect. Our theoretical framework treats weight as a function of food prices in the *prior* period, as weight is a capital stock that is determined by past eating "investments." Accordingly, Goldman et al. (2010) provide evidence that the long-run effect of food prices on BMI is stronger than the short-run effect.

To address both of these issues, we also consider a specification that utilizes the full sample of 1986-2006. The panel nature of the NLSY allows for the inclusion of individual fixed effects to control for unobservable characteristics that are stable over time. The identifying assumption for the food price effect therefore becomes merely that *changes over time* in unobservable determinants of BMI are uncorrelated with *changes over time* in food prices.[26] It also allows for the matching of individuals to lagged food prices without having to impose

[26] Results (available upon request) are similar if we include both individual and county fixed effects, though the estimates are slightly less precise. This is not surprising, as county fixed effects only provide new information for people who move during the sample period.

the assumption that people remain in the same county over time.

On the other hand, using a panel strategy to test whether impatient individuals gain more weight in response to falling food prices requires the assumption that time preferences are stable across the entire period. Some evidence suggests that time preferences are relatively stable within an individual. 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. Moreover, even if time preferences do change within individuals, this measurement error would lead to attenuation bias that would cause us to *underestimate* the interaction effect of time preference and food prices. In other words, the results from the panel regressions can perhaps be viewed as conservative.

Our panel specification adds individual and year fixed effects to equation (11), while dropping the time-invariant covariates discount factor, risk preference, AFQT score, race, and gender. Importantly, the *interaction* of discount factor with food price does not drop out of the model, as food price varies over time. We experimented with different lag lengths, finding that the first lag of food price and the interaction of food price with discount factor were consistently significant but that second, third, or fourth lags were consistently insignificant. We therefore include one lag of food price and the interaction term in the model. We also add one lag of each of the controls to guard against bias from lagged price being correlated with lagged controls.[27] The resulting regression equation is

$$\begin{aligned} BMI_{ict} = \; & \alpha_0 + \boldsymbol{\alpha}_{11}\mathbf{DEMO}_{ict} + \boldsymbol{\alpha}_{12}\mathbf{DEMO}_{ic,t-1} + \boldsymbol{\alpha}_{21}\mathbf{HC}_{ict} + \boldsymbol{\alpha}_{22}\mathbf{HC}_{ic,t-1} + \\ & \boldsymbol{\alpha}_{31}\mathbf{LABOR}_{ict} + \boldsymbol{\alpha}_{32}\mathbf{LABOR}_{ic,t-1} + \boldsymbol{\alpha}_{41}\mathbf{INCOME}_{ict} + \boldsymbol{\alpha}_{42}\mathbf{INCOME}_{ic,t-1} + \\ & \alpha_{51}PFOOD_{ct} + \alpha_{52}PFOOD_{c,t-1} + \alpha_{61}(DF1_{ic} * PFOOD_{ct}) + \\ & \alpha_{62}(DF1_{ic} * PFOOD_{c,t-1}) + \alpha_{71}PNF_{ct} + \alpha_{72}PNF_{c,t-1} + \mu_i + \tau_t + \varepsilon_{ict} \end{aligned} \qquad (12)$$

[27] Recall that our full sample consists of 13 waves spanning 21 years. The average lag length is therefore approximately 1.6 years, with some lags being one year and others being two years.

where t denotes survey year, **DEMO** no longer includes the gender and race dummies, **HC** no longer includes AFQT score, and μ_i and τ_t are the individual and year fixed effects. Of particular interest are the "total effects" of food price and the interaction of discount factor with food price. These are simply the sum of the contemporaneous and lagged effects: $\alpha_{51} + \alpha_{52}$ and $\alpha_{61} + \alpha_{62}$, respectively.

Table 9 reports the results from the fixed effects regressions, gradually adding controls up to the full model in column (5), with columns (6) and (7) utilizing the alternative discount factor measures.[28] All 14 coefficient estimates for food price and lagged food price are negative, and 13 of the 14 are significant. Consistent with the intertemporal nature of our theoretical framework, lagged food price appears to have about twice as strong an effect on BMI than contemporaneous food price. All 14 coefficient estimates for the interaction term and the lagged interaction term are positive and significant, with the lagged interaction of discount factor with food price having roughly twice as strong an effect on BMI as the contemporaneous interaction. Turning to the total effects, the "total food price effect" is always significant at the 5% level or better while the "total interaction effect" is always significant at the 1% level. Compared to the estimates from the cross-sectional regressions, the total effects of food price and the interaction of discount factor with food price are both smaller in the fixed effects regressions but they are also both much more precisely estimated. In fact, the estimated total effects from Table 9 are always within the 95% confidence interval of the corresponding estimate from Table 8. In other words, it is possible that the apparent differences in magnitudes could simply be due to the imprecision of the cross-sectional estimates.

To summarize, both the cross-sectional and panel regressions provide robust evidence that the effect of food price on BMI is strongest for impatient individuals. The cross-sectional regressions suggest stronger heterogeneity in the food price effect, which could be the result of upward bias in the cross-sectional estimator, attenuation bias in the fixed effects estimator, or simply the imprecision of the cross-sectional estimates. To err on the side of caution, we

[28] Table 9 has one less column than Table 8 because risk preference is dropped from the model since it is time invariant in our data.

focus on the fixed effects estimates throughout the rest of this section.

4.2.3 Simulations

Figure 2 uses the estimates from the fixed effects model with the full set of controls (column (5) of Table 9) 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 (27% of the sample mean) decreases the BMIs of the most impatient individuals by 0.6 units, or 4 pounds at the sample mean height. This is a decrease of 2.3% of the sample mean BMI, implying a food price elasticity of BMI of -0.1. The effect of food prices on BMI steadily weakens with additional patience, reaching zero at a discount factor of 0.69. Though the sign flips to positive after that point, the marginal effect does not become positive and significant at the 5% level until the very top of the discount factor distribution.

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 fixed effects model in column (5) of Table 9 to plot the predicted BMI distributions for the two groups at the approximate high end of the food price range observed in our full sample ($5.50), the approximate low end of this range ($2.50), and the midpoint of this range ($4.00).[29] Underneath the figures, we also report the mean BMI, percentage overweight or obese (BMI$\geq$ 25), percentage obese (BMI$\geq$ 30), and percentage severely obese (BMI$\geq$ 35) for the impatient and patient groups at each price point. Figure 3 shows that at a relatively high food price, the BMI distributions of patient and impatient individuals are very similar, as are their mean BMIs and rates of being in unhealthy weight categories. Figure 4 shows that at a medium food price a gap

[29]Predicted BMI is computed simply by adding to actual BMI the difference between simulated ($5.50, $4, or $2.50) and actual food price times the coefficient estimate for food price, and the difference between the interaction term at the simulated and actual food price times the coefficient estimate for the interaction term.

begins to emerge between the BMI distributions of the patient and impatient groups, with the overweight, obesity, and severe obesity rates becoming 4, 3, and 2 percentage points greater for the impatient group. Figure 5 shows that at a low food price the difference between the BMI distributions of patient and impatient individuals becomes quite pronounced. The rates of overweight, obesity, and severe obesity are now 8, 5, and 4 percentage points greater for those who are impatient. These are sizeable differences, representing 13%, 18%, and 36% of the overweight, obesity, and severe obesity rates of the patient group, respectively.

4.2.4 Robustness Checks and Extensions

We close our investigation of the interaction effect of discount factor and food prices by estimating some additional variants of the fixed effects model using the full sample. Table 10 reports the results from several robustness checks to help further increase our confidence that the results from Table 9 can be considered causal. The first through third columns test for reverse causality between BMI and food prices by controlling for future food price. The first column includes food price in the subsequent year, the second column includes food price in the second subsequent year, and the third column adds both of these leads.[30] 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 fourth column of Table 10 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. Finally, the fifth column controls for interactions of discount factor with county fixed effects. This tests for the possibility that the estimated effect of the interaction of discount factor and food price could simply reflect heterogeneous effects of patience on BMI across geographic regions. As shown in Table 10, the estimates of interest remain very similar to those from Table 9 in all these robustness checks. Additionally,

[30] Since we have ACCRA COLI data through 2008, adding two leads does not require us to drop any observations.

future food prices are not statistically associated with BMI, so there is no evidence of reverse causality.[31]

Finally, we address the potential concern 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. We divide the 16 food items into three categories: fruits/vegetables (lettuce, bananas, potatoes, peas, peaches, and corn), grocery meats (steak, beef, chicken, sausage, eggs, tuna), and other foods (white bread, cereal, and the three restaurant meals). The fruits/vegetables category contains the most unambiguously healthy foods, so one might expect their prices – and the interaction of their prices with discount factor – to have little or no effect on BMI. In contrast, the "other foods" category contains items that are either high in starchy carbohydrates, fats, or both, and therefore could be considered the most unambiguously unhealthy. Their price effects may therefore be the strongest. The "grocery meats" category is perhaps in between the other two categories in terms of healthfulness, as they are relatively calorie-dense but high in protein and low in carbohydrates.

Table 11 reports the results from estimating a fixed effects regression with prices for each of these three different types of foods, along with their interactions with discount factor:

$$\begin{aligned} BMI_{ict} = \; & \alpha_0 + \boldsymbol{\alpha}_{11}\mathbf{DEMO}_{ict} + \boldsymbol{\alpha}_{12}\mathbf{DEMO}_{ic,t-1} + \boldsymbol{\alpha}_{21}\mathbf{HC}_{ict} + \boldsymbol{\alpha}_{22}\mathbf{HC}_{ic,t-1} + \\ & \boldsymbol{\alpha}_{31}\mathbf{LABOR}_{ict} + \boldsymbol{\alpha}_{32}\mathbf{LABOR}_{ic,t-1} + \boldsymbol{\alpha}_{41}\mathbf{INCOME}_{ict} + \boldsymbol{\alpha}_{42}\mathbf{INCOME}_{ic,t-1} + \\ & \alpha_{51}PFRVEG_{ct} + \alpha_{52}PFRVEG_{c,t-1} + \alpha_{61}(DF1_{ic} * PFRVEG_{ct}) + \\ & \alpha_{62}(DF1_{ic} * PRVEG_{c,t-1}) + \alpha_{71}PMEAT_{ct} + \alpha_{72}PMEAT_{c,t-1} + \\ & \alpha_{81}(DF1_{i} * PMEAT_{ct}) + \alpha_{82}(DF1_{ic} * PMEAT_{c,t-1}) + \alpha_{91}POTHER_{ct} + \\ & \alpha_{92}POTHER_{c,t-1} + \alpha_{10,1}(DF1_{ic} * POTHER_{ct}) + \alpha_{10,2}(DF1_{ic} * \\ & POTHER_{c,t-1}) + \alpha_{11,1}PNF_{ct} + \alpha_{11,2}PNF_{c,t-1} + \mu_i + \tau_t + \varepsilon_{ict} \end{aligned} \tag{13}$$

[31] In unreported regressions, we repeated the falsification exercises with height and the other health conditions as the dependent variables and the full set of controls. Neither discount factor nor its interaction with food prices was ever statistically significant.

where $PFRVEG$, $PMEAT$, and $POTHER$ are the prices of fruits/vegetables, meats, and other foods. The results are as expected. We find no evidence that fruit/vegetable price or its interaction with discount factor influence BMI. The total effects of meat prices, other food prices, and their interactions with discount factor are all significant at the 10% level or better and have the same signs as the earlier estimates using the entire basket. However, both the price and interaction effects are larger in magnitude for other foods than meats, consistent with our assumption that the foods in the "other" category are the least healthy.

4.3 Time-Inconsistent Discounting and BMI

The final section of our empirical analysis provides 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. 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

$$BMI_i = \theta_0 + \theta_1\beta_i + \theta_2\delta_i + \theta_3\mathbf{DEMO}_i + \theta_4\mathbf{HC}_i + \theta_5\mathbf{LABOR}_i + \theta_6\mathbf{INCOME}_i + \theta_7 RISK_{ic} + \eta_i \tag{14}$$

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

$$\begin{aligned} BMI_i \quad = \quad & \theta_0 + \theta_1\beta_i + \theta_2\delta_i + \theta_3\mathbf{DEMO}_i + \theta_4\mathbf{HC}_i + \theta_5\mathbf{LABOR}_i + \theta_6\mathbf{INCOME}_i + \\ & \theta_7 RISK_i + \theta_8 PFOOD_c + \theta_9(\beta_i * PFOOD_c) + \theta_{10}(\delta_i * PFOOD_c) + \theta_{11} PNF_c + \eta_i. \end{aligned} \tag{15}$$

and the fixed effects model using the full sample is

$$\begin{aligned} BMI_{ict} = \; & \theta_0 + \boldsymbol{\theta}_{11}\mathbf{DEMO}_{ict} + \boldsymbol{\theta}_{12}\mathbf{DEMO}_{ic,t-1} + \boldsymbol{\theta}_{21}\mathbf{HC}_{ic} + \boldsymbol{\theta}_{22}\mathbf{HC}_{ic,t-1} + \quad (16) \\ & \boldsymbol{\theta}_{31}\mathbf{LABOR}_{ict} + \boldsymbol{\theta}_{32}\mathbf{LABOR}_{ic,t-1} + \boldsymbol{\theta}_{41}\mathbf{INCOME}_{ict} + \boldsymbol{\theta}_{42}\mathbf{INCOME}_{ic,t-1} + \\ & \theta_{51}PFOOD_{ct} + \theta_{52}PFOOD_{c,t-1} + \theta_{61}(\beta_{ic} * PFOOD_{ct}) + \\ & \theta_{62}(\beta_{ic} * PFOOD_{c,t-1}) + \theta_{61}(\delta_{ic} * PFOOD_{ct}) + \theta_{62}(\delta_{ic} * PFOOD_{c,t-1}) + \\ & \theta_{71}PNF_{ct} + \theta_{72}PNF_{c,t-1} + \mu_i + \tau_t + \varepsilon_{ict}. \quad (17) \end{aligned}$$

To conserve space, we only report the results from the full-sample regressions with all the control variables, along with those from the regressions evaluating heterogeneity by gender, race, and food category. We have, however, re-estimated all the robustness checks and falsification tests from Tables 5-10 replacing discount factor with β and δ and verified that our findings are not sensitive to specification. These results are available upon request.

The results in the first column of Table 12 show that both present-bias β and long-run patience δ are statistically significant and negatively associated with BMI. Present bias and long-run impatience therefore both separately influence weight. The magnitudes imply that a one standard deviation increase in β (decrease in present bias) reduces BMI by 0.2 units, or 1.3 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 but δ is not significant, whereas the reverse pattern holds for men. This suggests that the relationship between intertemporal preferences and BMI is driven by 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.

Table 13 presents the results for the interaction of β and δ with food prices. The first column uses the 2006 sample and cross-sectional research design, the second column uses the full sample and fixed effects approach, and the third column uses the fixed effects model with multiple food categories. We focus our discussion on the "total effects" of the interactions of β and δ with food prices. These are simply the coefficient estimates for the contemporaneous interaction terms in the cross-sectional model, and the sum of the estimates for the contemporaneous and lagged interaction terms in the two fixed effects models. The cross sectional and fixed effects results both indicate 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. When multiple food categories are used, the interactions of β with meat and "other food" prices both significantly increase BMI, while the interactions of δ with meat and "other food" prices are also positively associated with BMI but are insignificant. In all, the evidence that time-inconsistent 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 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 discount factor with food prices reveals that the gap between the weights of impatient and patient individuals is larger in counties with lower food prices. 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 help 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.

Our results suggest several potentially interesting directions for future research. First, future work 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. Future research should also test our theory across a broader time period, as our data only span two of the nearly four decades of the sharp rise in obesity. Further study of how the effects differ across different demographic groups could also have interesting implications. For instance, from 1960 to 1994 the rise in obesity was similar for men and women, but from 1999 to 2010 obesity prevalence only increased for men (Flegal et al., 1998; Ogden et al., 2012). We find a stronger connection between overall time preference and BMI for men, but a stronger connection between present-bias and BMI for women. If these results prove to be generalizable, time-consistent patience may be more relevant for the recent portion of the rise in obesity than it was for the earlier decades, but the reverse may be true for present-bias.

It is also worth noting that the theory of rational addiction makes a similar prediction to ours about the interaction effect: addicts who are more patient are less responsive to current prices (Becker et. al. 1991). Townsend (1987) and Chaloupka (1991) test this prediction with data on cigarette consumption, but with proxies for patience (class and education, respectively). Though not in the context of a model of rational addiction, our tests using the interaction of food prices and individual time preferences are the first such tests of this prediction utilizing a direct measure of patience rather than indirect proxies.

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, which has potential policy 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, 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. Time inconsistency could provide a different rationale for interventions that move more of the costs of overeating into the present period, such as taxes on unhealthy foods. Such a conclusion 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.

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Table 1 – Correlation of Time Preference Measures with Intertemporal Variables

Discount Factor Measure	DF1	DF2	Beta	Delta
Annual DF1	□	□	□	□
Monthly DF2	0.58	□	□	□
	(0.00)***			
Beta	0.50	0.75	□	□
	(0.00)***	(0.00)***		
Delta	0.73	0.09	□0.13	□
	(0.00)***	(0.00)***	(0.00)***	
High school	□0.06	□0.06	□0.08	□0.01
	(0.00)***	(0.00)***	(0.00)***	(0.43)
Some college	□0.01	0.002	0.01	□0.01
	(0.61)	(0.84)	(0.27)	(0.39)
College	0.10	0.07	0.11	0.02
	(0.00)***	(0.00)***	(0.00)***	(0.12)
AFQT	0.13	0.11	0.22	□0.02
	(0.00)***	(0.00)***	(0.00)***	(0.11)
Net worth	0.11	0.08	0.11	0.03
	(0.00)***	(0.00)***	(0.00)***	(0.01)**
Any credit card debt	□0.07	□0.02	□0.03	□0.03
	(0.00)***	(0.12)	(0.01)**	(0.01)***
Maxed-out credit cards	□0.08	□0.07	□0.07	□0.03
	(0.00)***	(0.00)***	(0.00)***	(0.01)**
Ever Bankrupt	□0.05	□0.03	□0.03	□0.02
	(0.00)***	(0.04)**	(0.01)**	(0.18)
Smoker	□0.07	□0.02	□0.07	□0.03
	(0.00)***	(0.11)	(0.00)***	(0.05)**

Notes: Pairwise correlations with p-values in parentheses. *** statistically significant at the 1% level; ** 5% level; *10% level. Observations are weighted using the NLSY sampling weights.

Table 2 – ACCRA COLI Food Items (2006)

Item	Average Price	Weight
Fruits and vegetables		
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
Meats		
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
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
Other foods		
24 oz. white bread	1.175	0.0861
18 oz. box of corn flakes; Kellogg's or Post	2.987	0.0399
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 BMI, Time Preference, and Food Price Variables

Variable Name	Description	Mean (SD) 2006	Mean (SD) Full
BMI	Body mass index (kg/m^2)	28.26 (5.76)	26.31 (5.43)
Beta	Computed using quasi-hyperbolic discounting specification	0.80 (0.20)	0.80 (0.20)
Delta	Computed using quasi-hyperbolic discounting specification	0.75 (0.33)	0.75 (0.33)
Discount factor 1	Based on amount needed to wait a year to receive $1000	0.59 (0.25)	0.59 (0.26)
Discount factor 2	Based on amount needed to wait a month to receive $1000	0.28 (0.34)	0.28 (0.34)
Food price	Weighted average price of 16 food items (2006$)	3.53 (0.28)	3.69 (0.38)
Non-food index	Weighted average price index of non-food price categories	106.01 (18.64)	109.24 (22.69)
Fruit/vegetable price	Weighted average price of 6 fruits/vegetables (2006$)	1.47 (0.20)	1.51 (0.23)
Meat price	Weighted average price of 5 grocery meats (2006$)	2.94 (1.30)	3.04 (0.34)
Other food price	Weighted average price of 5 other foods (2006$)	4.64 (0.39)	4.31 (0.35)

Note: Observations are weighted using the NLSY sampling weights. $n = 5982$ in the 2006 analysis sample, and $63,950$ in the 1986-2006 analysis sample. SD=standard deviation.

Table 4 – Summary Statistics for Control and Falsification Test Variables

Variable Name	Description	Mean (SD)	
		2006	Full
Age	Age in years	44.87 (2.230)	34.47 (6.59)
Female	1 if female	0.48 (0.50)	0.48 (0.50)
Race: black	1 if race is black	0.13 (0.34)	0.14 (0.34)
Race: other	1 if race is neither black nor white	0.03 (0.16)	0.02 (0.16)
Married	1 if married	0.64 (0.48)	0.60 (0.49)
AFQT	Percentile score on armed forces qualifying test in 1985	48.97 (28.54)	49.19 (28.66)
High school	1 if highest grade completed=12	0.41 (0.49)	0.42 (0.49)
Some college	1 if 13≤highest grade completed≤15	0.24 (0.42)	0.23 (0.42)
College	1 if highest grade completed≥16	0.28 (0.45)	0.26 (0.44)
White collar	1 if current occupation is white collar	0.56 (0.50)	0.52 (0.50)
Blue collar	1 if current occupation is blue collar	0.23 (0.42)	0.28 (0.45)
Service	1 if current occupation is service	0.10 (0.30)	0.11 (0.31)
Hours worked	Average hours worked per week in the preceding year	35.92 (19.40)	35.27 (18.69)
Income	Total household income ($10,000s; 2006$)	8.31 (8.41)	7.33 (11.77)
Risk	Amount ($1,000s) to forego a 50% chance of $10,000 or $0	4.79 (3.27)	4.79 (3.26)
Arthritis	1 if ever had arthritis or rheumatism	0.12 (0.32)	□
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)	□

□ indicates these variables are not used in the 1986-2006 sample. See other notes for Table 3.

Table 5 – Discount Factor and BMI

Dependent Variable: BMI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discount factor	□1.44	□1.30	□1.08	□1.07	□0.97	□1.02	□0.87	□1.20
	(0.35)***	(0.35)***	(0.35)**	(0.35)***	(0.35)***	(0.35)***	(0.26)***	(0.34)***
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
Income	NO	NO	NO	NO	YES	YES	YES	YES
Risk	NO	NO	NO	NO	NO	YES	YES	YES
D. factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF2$	$\overline{DF}$
Observations	5982	5982	5982	5982	5982	5982	5982	5982

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. "Income" controls include income and income^2. "Risk" control is the measure of risk preference.

Table 6 – Heterogeneity by Gender and Race

Dependent Variable: BMI

	Gender		Race	
	Women	Men	White	Non-White
Discount factor	□0.74	□1.36	□1.17	□0.22
	(0.50)	(0.49)***	(0.41)***	(0.54)
Demographics	YES	YES	YES	YES
Human capital	YES	YES	YES	YES
Labor	YES	YES	YES	YES
Income	YES	YES	YES	YES
Risk	YES	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$
Observations	2989	2993	3894	2088

See notes for Table 5.

Table 7 – Falsification Tests Using Various Health Conditions

	Dependent Variables:					
	Height	Arthritis	Kidney/ Bladder	Stomach	Anemia	Number of Conditions
Discount factor	□0.15 (0.16)	0.015 (0.019)	0.011 (0.010)	□0.012 (0.017)	□0.004 (0.008)	0.003 (0.032)
Demographics	YES	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES	YES
Income	YES	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$
Observations	5982	5975	5971	5970	5970	5952

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

Table 8 – Interaction of Discount Factor with Food Prices: 2006 Sample

	Dependent Variable: BMI							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Discount factor	□12.45 (4.60)***	□12.19 (4.50)***	□12.48 (4.44)***	□12.29 (4.49)***	□12.39 (4.60)***	□12.34 (4.60)***	□8.16 (3.83)**	□12.53 (4.47)***
Food price	□2.05 (0.83)**	□2.18 (0.81)***	□2.14 (0.80)***	□2.09 (0.81)***	□1.83 (0.84)**	□1.82 (0.83)**	□0.47 (0.43)	□1.29 (0.62)**
Discount factor*food price	3.05 (1.31)**	3.02 (1.28)**	3.16 (1.26)**	3.11 (1.28)**	3.17 (1.31)**	3.14 (1.31)**	1.98 (1.09)*	3.11 (1.27)**
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
Income	NO	NO	NO	NO	YES	YES	YES	YES
Risk	NO	NO	NO	NO	NO	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF2$	$\overline{DF}$
Observations	5353	5353	5353	5353	5353	5353	5353	5353

Notes: Standard errors are heteroskedasticity-robust and clustered by county. See other notes for Table 5.

Table 9 – Interaction of Discount Factor with Food Prices: Full Sample

Dependent Variable: BMI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Food price	□0.20	□0.20	□0.21	□0.20	□0.19	□0.11	□0.19
	(0.08)**	(0.09)**	(0.09)**	(0.09)**	(0.08)**	(0.06)*	(0.08)**
Food price lag	□0.45	□0.46	□0.46	□0.46	□0.44	□0.18	□0.33
	(0.19)**	(0.19)**	(0.19)**	(0.19)**	(0.19)**	(0.11)	(0.16)**
Discount factor*food price	0.32	0.33	0.33	0.33	0.32	0.31	0.41
	(0.13)**	(0.13)**	(0.13)**	(0.13)**	(0.13)**	(0.15)**	(0.16)**
Discount factor*food price lag	0.64	0.66	0.67	0.67	0.62	0.40	0.61
	(0.27)**	(0.27)**	(0.27)**	(0.27)**	(0.27)**	(0.23)*	(0.28)**
Total food price effect	**□0.65**	**□0.66**	**□0.67**	**□0.67**	**□0.63**	**□0.28**	**□0.52**
	(0.19)*	**(0.19)***	**(0.19)***	**(0.19)***	**(0.19)***	**(0.12)**	**(0.15)***
Total interaction effect	**0.97**	**0.99**	**1.00**	**1.00**	**0.93**	**0.71**	**1.02**
	(0.27)*	**(0.27)***	**(0.27)***	**(0.27)***	**(0.27)***	**(0.23)***	**(0.27)***
Demographics	NO	YES	YES	YES	YES	YES	YES
Human capital	NO	NO	YES	YES	YES	YES	YES
Labor	NO	NO	NO	YES	YES	YES	YES
Income	NO	NO	NO	NO	YES	YES	YES
Discount factor measure	$DF1$	$DF1$	$DF1$	$DF1$	$DF1$	$DF2$	$\overline{DF}$
Observations	63950	63950	63950	63950	63950	63950	63950

Notes: Standard errors, heteroskedasticity-robust and clustered by county, in parentheses. *** statistically significant at 1% level; ** 5% level; * 10% level. Observations are weighted using the NLSY sampling weights. All regressions include individual and year fixed effects, as well as the non-food price index and its lag. Because of the individual fixed effects, the time-invariant variables discount factor, sex, race, AFQT, and risk preference are dropped. "Demographic" controls include age and marital status and its lag. "Human capital" controls include the education dummies and their lags. "Labor" controls include work hours and white collar, blue collar, and service indicators and their lags. "Income" controls include income, income^2, and their lags. "Total food price effect" is the sum of the coefficients on food price and lagged food price. "Total interaction effect" is the sum of the coefficients on discount factor*food price and discount factor*food price lag.

Table 10 – Robustness Checks: Full Sample

Dependent Variable: BMI

	Add Future Food Price			Add Interactions	
	1-year	2-year	Both	Food Price* Controls	DF* County FE
Food price	□0.18 (0.08)**	□0.18 (0.08)**	□0.18 (0.08)**	□0.30 (0.41)+	□0.18 (0.08)**
Food price lag	□0.41 (0.19)**	□0.42 (0.19)**	□0.41 (0.20)**	0.51 (0.49)+	□0.46 (0.20)**
Discount factor*food price	0.27 (0.11)**	0.28 (0.12)**	0.28 (0.12)**	0.27 (0.11)**	0.30 (0.12)**
Discount factor*food price lag	0.61 (0.27)**	0.63 (0.28)**	0.62 (0.28)**	0.60 (0.27)**	0.65 (0.28)**
Total food price effect	**□0.59 (0.19)*****	**□0.60 (0.19)*****	**□0.59 (0.19)*****	**0.21 (0.48)+**	**□0.64 (0.20)*****
Total interaction effect	**0.89 (0.27)*****	**0.90 (0.28)*****	**0.90 (0.28)*****	**0.86 (0.28)*****	**0.95 (0.28)*****
Food price in $t+1$	□0.037 (0.039)	□	□0.029 (0.037)	□	□
Food price in $t+2$	□	□0.032 (0.026)	□0.030 (0.024)	□	□
Demographics	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES
Income	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES
Observations	62360	61061	61061	63950	63950

See notes for Table 9. $^{+}$ indicates the coefficient estimates for food price and lagged food price and the "total food price effect" are uninformative in this specification since the overall effects of food prices are spread over all the interactions with the covariates.

Table 11 – Multiple Food Categories: Full Sample

Dependent Variable: BMI

	(1)
Fruit/vegetable price	□0.02
	(0.21)
Fruit/vegetable price lag	0.32
	(0.22)
Meat price	□0.01
	(0.01)*
Meat price lag	□0.26
	(0.14)*
Other food price	□0.38
	(0.12)***
Other food price lag	□0.13
	(0.12)
Discount factor*fruit/vegetable price	□0.11
	(0.30)
Discount factor*fruit/vegetable price lag	□0.44
	(0.32)
Discount factor*meat price	0.02
	(0.02)
Discount factor*meat price lag	0.40
	(0.21)*
Discount factor*other food price	0.61
	(0.19)***
Discount factor*other food price lag	0.16
	(0.18)
Total fruit/vegetable price effect	**0.30**
	(0.35)
Total meat price effect	**□0.28**
	(0.14)*
Total other food price effect	**□0.51**
	(0.15)***
Total discount factor*fruit/vegetable price effect	**□0.55**
	(0.50)
Total discount factor*meat price effect	**0.42**
	(0.21)**
Total discount factor*other food price effect	**0.77**
	(0.23)****
Demographics	YES
Human capital	YES
Labor	YES
Income	YES
Risk	YES
Observations	63950

See notes for Table 9.

Table 12 – Time Inconsistency and BMI

Dependent Variable: BMI

	All	Women	Men	White	Non-White
Beta	−0.98	−1.36	−0.60	−1.16	0.23
	(0.46)**	(0.62)**	(0.67)	(0.53)**	(0.71)
Delta	−0.51	−0.23	−0.84	−0.58	−0.24
	(0.25)**	(0.37)	(0.35)**	(0.32)*	(0.35)
Demographics	YES	YES	YES	YES	YES
Human capital	YES	YES	YES	YES	YES
Labor	YES	YES	YES	YES	YES
Income	YES	YES	YES	YES	YES
Risk	YES	YES	YES	YES	YES
Observations	5982	2989	2993	3894	2088

See notes for Table 5.

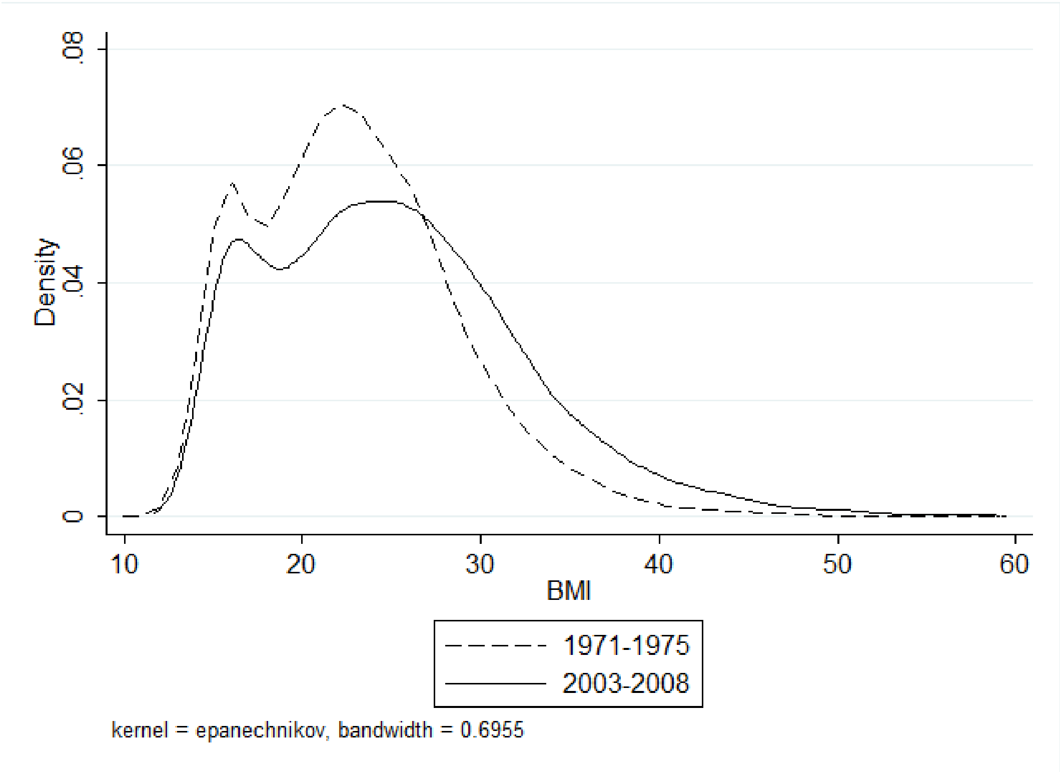
Table 13 – Interaction of Beta and Delta with Food Prices

Dependent Variable: BMI

	2006 Sample	Full Sample	Multiple Prices
Beta	□16.87 (5.88)***	□	□
Delta	□6.28 (3.49)*	□	□
Food price	□4.59 (1.70)***	□0.44 (0.19)**	□
Food price lag	□	□0.61 (0.36)*	□
Beta*food price	4.33 (1.67)***	0.52 (0.22)**	□
Beta*food price lag	□	0.38 (0.37)	□
Delta*food price	1.63 (1.00)	0.005 (0.114)	□
Delta*food price lag	□	0.34 (0.18)*	□
Fruit/vegetable price	□	□	0.07 (0.35)
Fruit/vegetable price lag	□	□	0.39 (0.42)
Beta*fruit/vegetable price	□	□	□0.07 (0.32)
Beta*fruit/vegetable price lag	□	□	□0.36 (0.39)
Delta*fruit/vegetable price	□	□	□0.14 (0.23)
Delta*fruit/vegetable price lag	□	□	□0.06 (0.24)
Meat price	□	□	□0.03 (0.03)
Meat price lag	□	□	□0.52 (0.26)**
Beta*meat price	□	□	0.05 (0.04)
Beta*meat price lag	□	□	0.40 (0.24)*
Delta*meat price	□	□	□0.01 (0.02)
Delta*meat price lag	□	□	0.23 (0.15)
Other food price	□	□	□0.80 (0.23)***
Other food price lag	□	□	-0.03 (0.24)
Beta*other food price	□	□	0.85 (0.22)***
Beta*other food price lag	□	□	□0.09 (0.24)
Delta*other food price	□	□	0.14 (0.15)
Delta*other food price lag	□	□	0.10 (0.12)
Total food price effect	**□4.59 (1.70)*** **	**□1.05 (0.36)*** **	□
Total food price*beta effect	**4.33 (1.67)*** **	**0.89 (0.37)** **	□
Total food price*delta effect	**1.63 (1.00)**	**0.34 (0.21)**	□
Total fruit/vegetable price effect	□	□	**0.46 (0.62)**
Total fruit/vege. price*beta effect	□	□	**□0.43 (0.56)**
Total fruit/vege. price*delta effect	□	□	**□0.20 (0.39)**
Total meat price effect	□	□	**□0.55 (0.26)** **
Total meat price*beta effect	□	□	**0.45 (0.24)* **
Total meat price*delta effect	□	□	**0.22 (0.16)**
Total other food price effect	□	□	**□0.83 (0.30)*** **
Total other food price*beta effect	□	□	**0.75 (0.31)** **
Total other food price*delta effect	□	□	**0.24 (0.18)**
Observations	5353	63950	63950

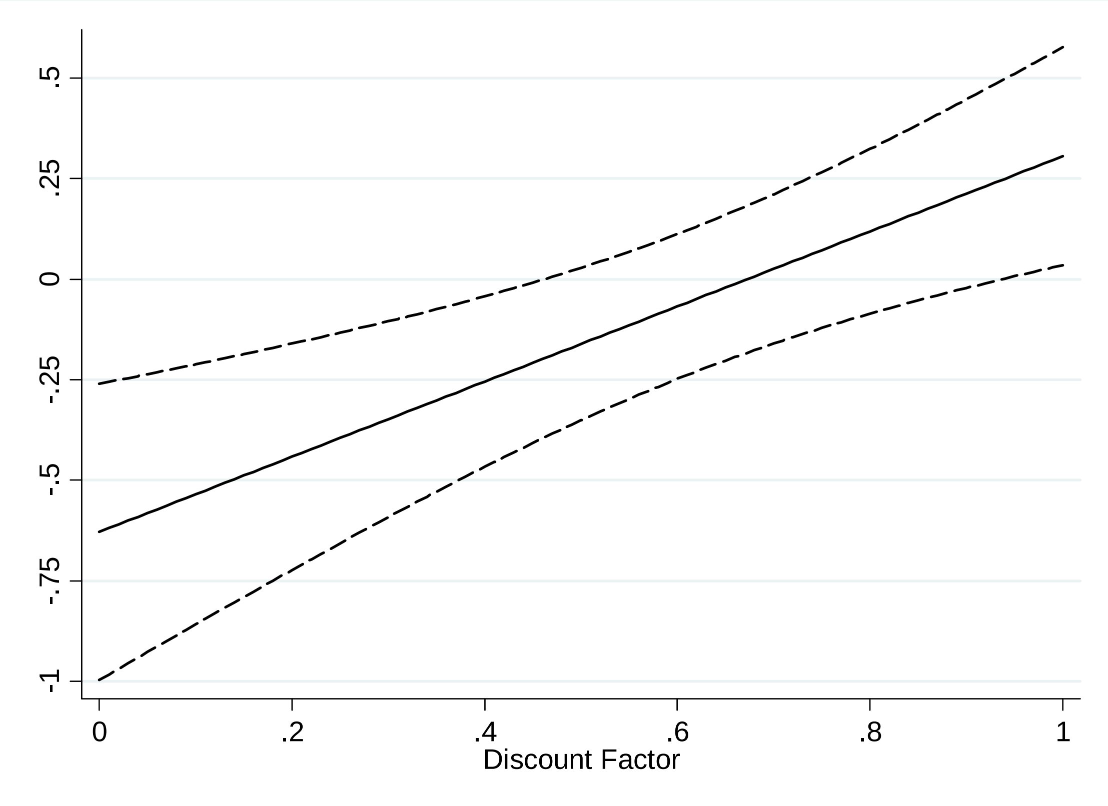
All controls are included. See other notes for Table 5 for the first regression, and Table 9 for the second and third.

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



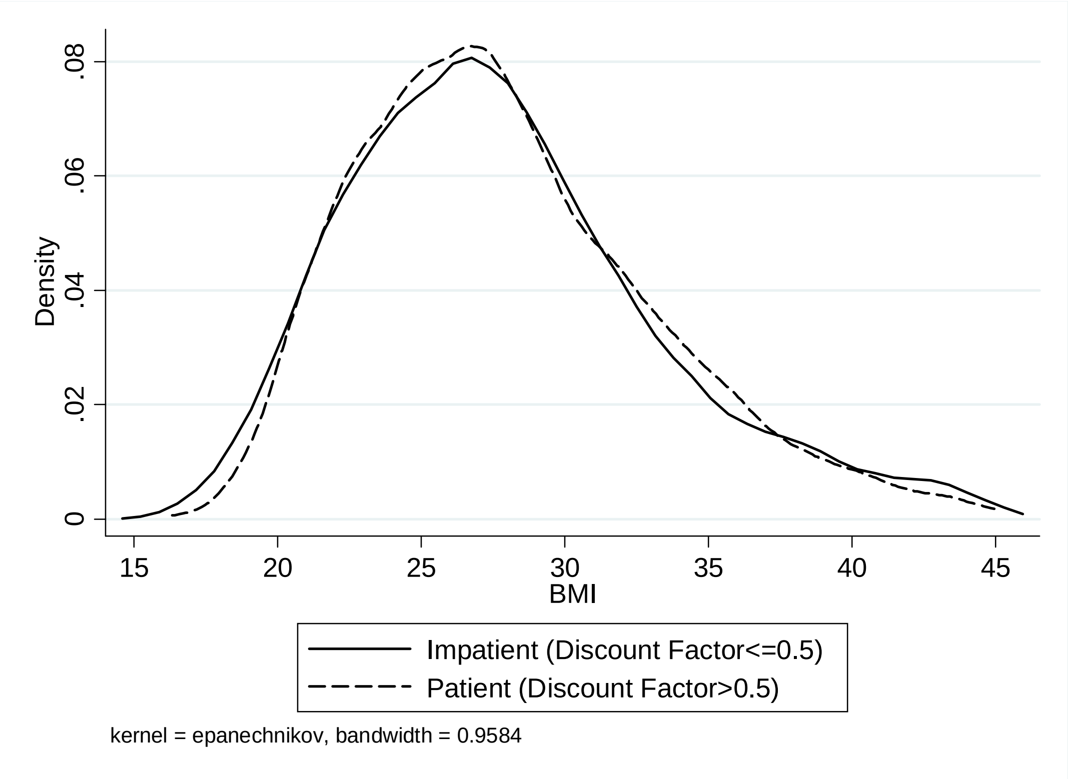
The 1971-1975 distribution is estimated using the National Health and Nutrition Examination Survey (NHANES) I, while the 2003-2008 distribution is estimated by pooling the 2003-2004, 2005-2006, and 2007-2008 NHANES. Between 1971-1975 and 2003-2008, the mean of the BMI distribution rose from 23.0 to 25.3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

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



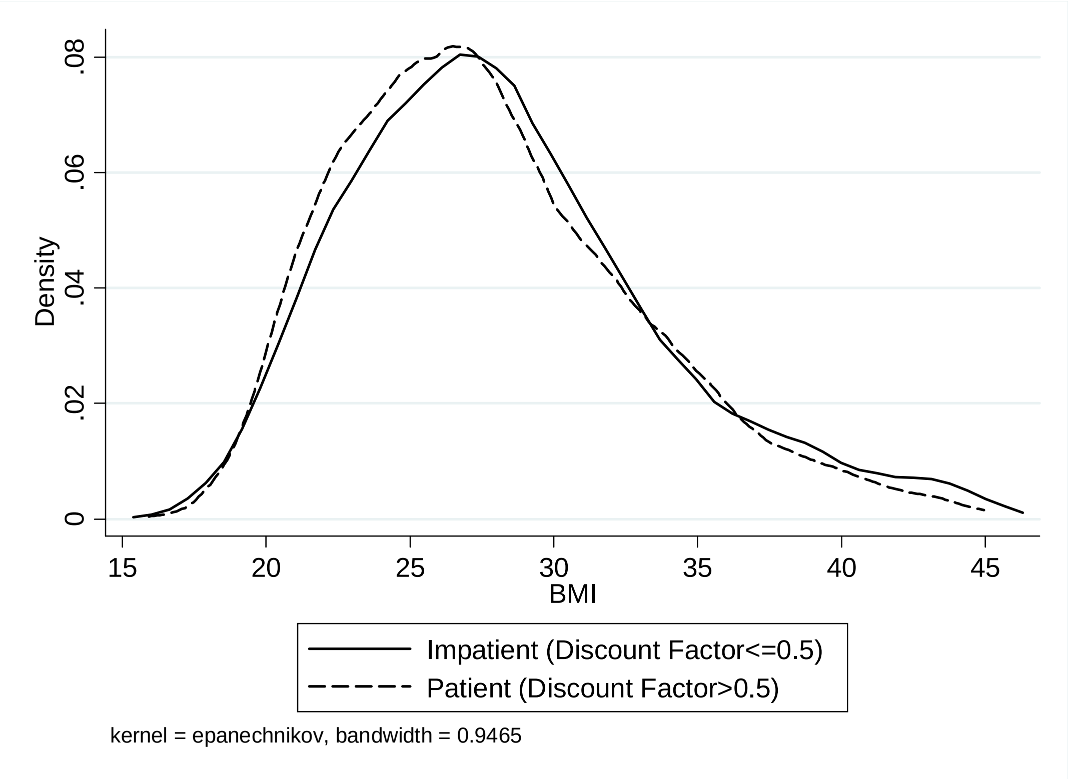
Solid line represents point estimate; dashed lines represent endpoints of 95% confidence interval.

Figure 3 – BMI Distributions by Degree of Patience at Food Price=$5.50



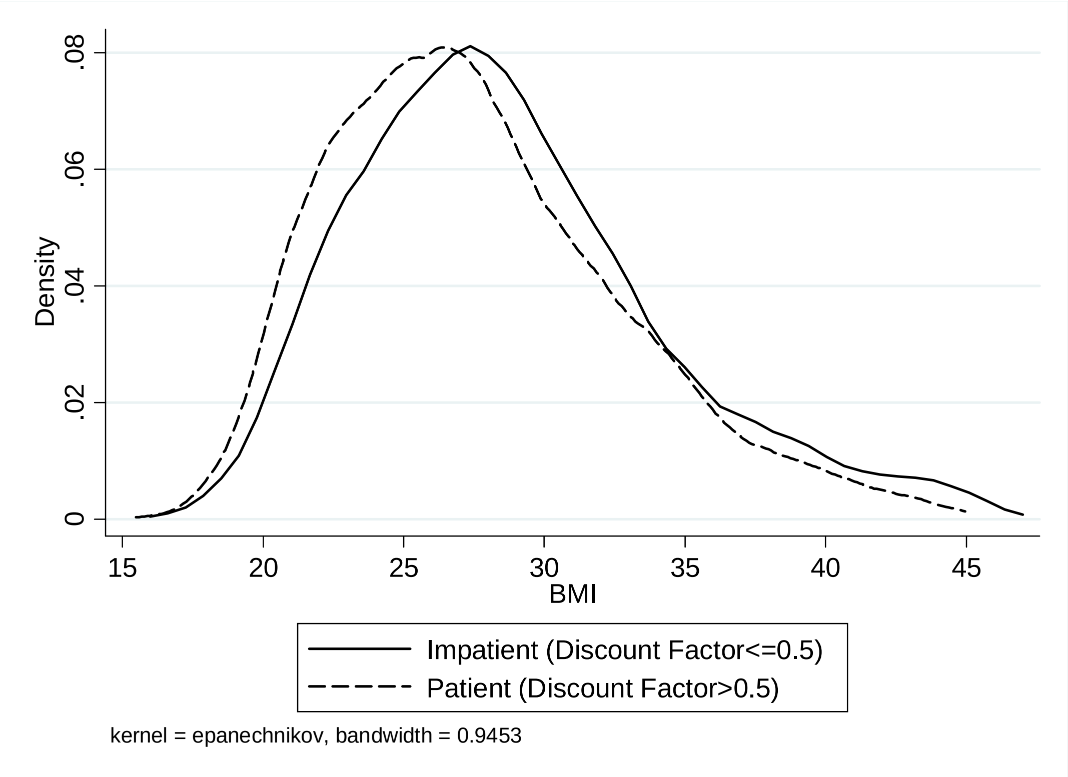
Mean BMI: 28.1 for impatient, 28.2 for patient
% Overweight or Obese: 67.8% for impatient, 68.7% for patient
% Obese: 30.8% for impatient, 31.1% for patient
% Severely Obese: 11.7% for impatient, 11.0% for patient

Figure 4 – BMI Distributions by Degree of Patience at Food Price=$4.00



Mean BMI: 28.5 for impatient, 28.0 for patient
% Overweight or Obese: 71.3% for impatient, 67.4% for patient
% Obese: 33.2% for impatient, 30.2% for patient
% Severely Obese: 12.8% for impatient, 10.8% for patient

Figure 5 – BMI Distributions by Degree of Patience at Food Price=$2.50



Mean BMI: 29.0 for impatient, 27.8 for patient
% Overweight or Obese: 74.0% for impatient, 65.6% for patient
% Obese: 35.4% for impatient, 30.0% for patient
% Severely Obese: 13.9% for impatient, 10.2% for patient