

## INTERNET APPENDIX

### A.1. Robustness Tests and Extensions

#### A.1.1. Weight Categories, The Financial Crisis, and Other Measures of Financial Distress

In this section, we consider robustness tests in several dimensions. First, delinquency is not the only indicator of financial distress in the NLSY. Respondents also declare when they have filed for bankruptcy in the 2004 and 2008 interviews and how many maxed-out credit cards they have in 2008. Finding a similar association between excess weight and other measures of financial distress would further validate our interpretation. Second, it would be interesting and informative to know how delinquency risk varies across the range of BMI. Third, our sample period partially overlaps with the financial crisis. To assess the temporal robustness of our main result, we use 2000 survey data to predict delinquencies reported in 2004.

Results are displayed in Table A.4. In panel A, we use year 2004 covariates to predict 2008 outcomes, and in panel B we use year 2000 covariates to predict 2004 outcomes. Being obese is associated with a 0.9 percentage point greater incidence of bankruptcy and a 2.8 percentage point greater incidence of reaching a credit card limit. While statistically insignificant, the 0.9 percentage point impact of obesity on bankruptcies in 2008 is economically large (0.9 percentage points relative to the 3.87% incidence rate amounts to a 23% higher bankruptcy rate). Also, with the exception of the thinly populated underweight category, we find that financial distress risk increases for the most part across the BMI classifications.

Interestingly, there are almost twice as many delinquent respondents than respondents with maxed-out credit cards. Why would people fall behind on their payments if they have

additional borrowing capacity? First, the survey question about the number of maxed-out credit cards refers to the year 2008, while delinquencies refer to the previous five years. Second, households may choose to fall behind on a payment despite having additional borrowing capacity, because the additional funds do not suffice to cover the bill, the late charges are less than the interest rate on the credit card, or because the household needs the liquidity for more important expenditures in the near future (e.g., see Cohen-Cole and Morse (2010)).

One potential drawback to predicting 2008 financial distress is the interference of the financial crisis that began in August 2007. Note that the delinquency rate in our sample rises only modestly from 18.17% in 2004 to 18.49% in 2008, suggesting that delinquencies reported in the 2008 interview do not yet fully reflect the changing economic environment. The 2008 NLSY interviews were conducted between January 2008 and April 2009, with 65% of the observations taken by the end of the first quarter in 2008, and 82% by the end of the second quarter. As is evident from Figure A.3, national delinquency rates for consumer loans and mortgages began rising in 2006, albeit at a very slow pace. Growth in mortgage delinquencies accelerated in mid-2007, but growth in consumer loan delinquencies and the unemployment rate accelerated only in mid-2008. The NLSY79 data show a similar pattern. Respondents who answered the survey in the first quarter of 2008 have lower incidences of delinquency and unemployment than respondents who answered the survey later, but the magnitude of the difference is relatively small.<sup>1</sup>

The caveat to using surveys prior to 2004 to predict financial distress in 2004 is the lack of detailed information on assets and debts (e.g., no information on credit card or student loans) and no information on credit histories. Some of our control variables will be measured

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<sup>1</sup>The financial crisis obscures out-of-sample tests that use risk scores obtained from the 2004–2008 period to predict financial distress in 2010 or 2012. With the financial crisis in full swing, the composition of loan types and underlying causes drastically changes (e.g., mortgage defaults rise by more than other consumer credit defaults and strategic motives become relatively more prevalent). Any shock that is common to the obese and non-obese will obfuscate obesity risk in observed defaults.

differently (e.g., debt-to-income and debt-to-asset ratios) or be excluded from the 2000 credit risk model (e.g., credit history). Therefore, the estimated marginal effects of the various BMI categories on delinquencies are not directly comparable between the 2000 and 2004 credit risk models. Nevertheless, the results in panel B are qualitatively similar to those in panel A. We conjecture that the link between obesity and financial distress that we document in the cross-section is stable over time and not driven by the financial crisis.

### **A.1.2. Estimates from Propensity Scoring**

The purpose of adding the many factors to our credit risk model was to account for differences between the obese and non-obese, so that we do not mistakenly attribute delinquencies to obesity. An alternative way to achieve this goal is to use propensity scoring. The propensity score is the predicted probability that a respondent is obese based on his/her observed characteristics, which we obtain from a probit regression of obesity on the full set of credit risk attributes. The weights emphasize the comparison of obese and non-obese persons who are similar in their observable characteristics (see DiNardo et al. (1996) for an early application and Nichols (2007, 2008) for details on the implementation).<sup>2</sup>

Figure A.4 displays the distribution of propensity scores for the obese and non-obese before and after reweighting. The upper panel utilizes the observable and permissible characteristics (see Table 4) for propensity scoring; the lower panel also includes the factors that are prohibited or unobservable to the lender (see Table 6). The left-hand panels indicate that the credit risk factors are strongly correlated with obesity. The right-hand panels indicate that the distributions overlap almost perfectly over the entire range of propensity

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<sup>2</sup>Propensity score methods are often considered a valid approach to causal inference, albeit less convincing than experiments, regression discontinuity designs, or instrumental variables. Nevertheless, we caution against the causal interpretation of our results, both due to data constraints and our use of obesity as a proxy for or signal of credit risk. A causal interpretation of the results is not necessary for the objective of our paper; we merely attempt to establish that obesity is incrementally informative about the likelihood of the repayment of debt.

scores after we reweight the observations, which suggests that we have sufficient variation in obesity across the spectrum of observable credit risk factors.

In Table A.5 we display the estimates from regressing delinquency on obesity after propensity scoring. We implement propensity scoring in two ways: including the score as a control variable in the regression (columns 1 and 3) and using the score to reweight the observations (giving more weight to the more typical observations; columns 2 and 4). Restricting the regressions to the common support is superfluous, as the common support covers almost the entire range of the propensity scores. We find that the likelihood of delinquency among the obese is about 4.0 percentage points higher than among the non-obese, with a standard error of about 1.4 percentage points. This estimate based on propensity scoring is very close to the benchmark estimate of 3.8 percentage points.

## A.2. Measurement Error

Our primary variables of interest, obesity and delinquency, rely on survey data and are potentially mismeasured. The following discussion is largely based on Bound et al. (2001). Due to the nature of our data, the measurement error cannot be of the classical form: (i) BMI is the ratio of weight squared and height, which implies that classical measurement error in the inputs would no longer be classical for BMI; (ii) obesity and delinquency are binary variables, and therefore measurement error must be mean reverting. We will therefore focus our discussion of measurement error on the potential consequences of misclassification of obesity and delinquency.

Whereas classical measurement error in continuous dependent variables does not bias the coefficient estimates, misclassification error in the dependent variable causes the estimates to be biased in probit models. Assuming that delinquency is the only mismeasured variable, the marginal effect of obesity on the *observed* delinquency rate will differ from the marginal

effect of obesity on the *true* delinquency rate by a factor of  $1 - \tau_{01} - \tau_{10}$ , where  $\tau_{01}$  is the probability of unreported delinquencies conditional on actually being delinquent (false negatives) and  $\tau_{10}$  captures false positives (Hausman et al. (1998)). We can obtain a rough estimate of the misclassification probability by comparing the bankruptcy rate reported by NLSY respondents to the national bankruptcy rate based on court filings. Measured over years 2004 to 2008, the bankruptcy rate among NLSY respondents is 26% lower than the national rate. Assuming that classification error stems from underreporting only, the marginal effect of obesity on the observed delinquency rate is 74% of the marginal effect on the true delinquency rate.<sup>3</sup>

Turning to misclassification in obesity, let us assume that the measurement error is non-differential (i.e., conditional on true obesity, the error is independent of delinquency). Based on Aigner (1973), Bound et al. (2001) show that the bias factor is

$$1 - \frac{\pi_{01}\pi}{\pi_{01}\pi + (1 - \pi_{10})(1 - \pi)} - \frac{\pi_{10}(1 - \pi)}{\pi_{10}(1 - \pi) + (1 - \pi_{01})\pi}, \quad (\text{A.1})$$

where  $\pi$  is the true prevalence of obesity,  $\pi_{01}$  is the probability of false negatives, and  $\pi_{10}$  is the probability of false positives. The estimated coefficient on obesity will be biased towards zero, but — for sufficiently high degrees of misclassification — can lead to a sign reversal on the estimated coefficient (i.e., the factor would turn negative).

To quantify the potential downward bias in the obesity estimate, we obtain estimates of the various probabilities from Grabner (2012), who compares the extent of bias between self-reported and measured height and weight and the effect on BMI and obesity across various data sets. Survey respondents tend to overstate their height and underreport their weight, leading primarily to false negatives in the obesity classification. According to Grabner’s Fig-

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<sup>3</sup>Additional bias may arise from inconsistent estimation of the coefficients. Implementing the solution proposed by Hausman et al. (1998) — explicitly allowing for misclassification in the likelihood function — yields an estimate of the marginal effect of obesity on delinquency that is about 35% higher than the benchmark estimate. The Stata routine is available at <http://www.utexas.edu/cola/depts/economics/faculty/ja8294?tab=139>.

ure 1.2.a, average measured BMI in the National Health and Nutrition Examination Survey (NHANES) is about 1.5 units higher than average self-reported BMI in the National Health Interview Survey (NHIS) and the Behavioral Risk Factor Surveillance System (BRFSS). Adding the difference to each respondent’s reported BMI in NLSY raises the prevalence of obesity in our sample from 27.7% to 37.3%. With  $\pi_{01} = 9.6/37.3$  as the misclassification rate and  $\pi = 37.3\%$  as the true obesity prevalence, we obtain from eq. (A.1) a factor of 0.87. That is, the amount of misclassification inherent in obesity suggests that our estimate of the obesity effect is downward biased by about 13%. Alternatively, Grabner’s Figure 1.2.b suggests a true obesity rate of about 35% (based on measured NHANES data), and a misclassification rate of 28.6% (underreporting of obesity by 10 percentage points in NHIS/BRFSS data). These assumptions also yield an estimated downward bias of 13%.<sup>4,5,6</sup>

Looking at measurement error in obesity and delinquency independently suggests that the true relationship between the variables is stronger than what we capture in the benchmark specification. However, in theory systematic joint misreporting of weight, height, and delinquency could induce a positive correlation between obesity and delinquency. Suppose that in the true state of the world the obese and non-obese are equally likely to be delinquent. Yet, individuals who are self-conscious and insecure are more likely to understate BMI *and* delinquency, as both are perceived negatively in society. Thus, compared to the true state of

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<sup>4</sup>The heading to Figure 1.2.b states that it depicts class I obesity rates, but in private correspondence Grabner has confirmed that it reflects the overall obesity rate.

<sup>5</sup>A second concern is that BMI does not distinguish between fat and muscle mass or bone structure, which leads to substantial measurement error. Utilizing results from Burkhauser and Cawley (2008), we estimate bias factors of 0.5 (based on classification errors and prevalence without the threshold adjustment) and 0.4 (with the threshold adjustment).

<sup>6</sup>Sometimes, researchers attempt to correct for misreporting bias with regression-based adjustments, calibrated on the difference between reported and measured height and weight data from NHANES. While BMI and obesity prevalence estimates are affected substantially, the relationship between BMI or obesity and various outcomes appears to be insensitive to the self-reporting bias. For example, Lakdawalla and Philipson (2002) and Zagorsky (2005) report that adjustments to BMIs calculated from NLSY data do not substantively alter their results. More recently, Grabner (2012) concludes that self-reported BMIs from other data sets (such as BRFSS and NHIS) are valid sources for BMI trends and associations despite their bias, but cautions against adjusting self-reported data based on NHANES-calibrated corrections due to significant differences in self-reports across the data sets.

the world, misreporting would lead to more non-obese respondents and a lower delinquency rate among them in the data.

The most extreme form of dependence in misclassification — when every stigma-concerned respondent denies being obese and delinquent if afflicted (i.e., no one cares only about weight *or* delinquency stigma) — would just be enough to generate the difference in delinquency rates we observe between the obese and non-obese in the data even if none existed. Without any prior empirical evidence on whether weight and delinquency stigma tend to occur jointly or separately, our best guess is to maintain the prior of independent misclassification of obesity and delinquency. If they are independently misclassified, our estimate would be biased downward by 36.0%, and the degree of dependence would have to be severe to not only offset the downward bias, but to generate an upward bias sufficiently strong to drive our results.

Finally, we acknowledge the possibility that using classically mismeasured values in place of true values in control variables (e.g., income and wealth) only partially controls for the confounding effects of the correctly measured variables on the estimate of the effect of obesity on delinquency (Bound et al. (2001)).

In conclusion, there are several reasons to believe that the estimated effect of obesity on delinquency is biased downward, and a few reasons for why the effect might be biased upward. Taken together, it is difficult to assess the relative magnitudes of the potential biases inherent in the data, but there is no indication that the obesity effect is fully attributable to measurement error.

### **A.3. Attrition and Selection Bias**

Attrition bias occurs due to systematic nonparticipation in the 2008 survey by individuals who experience obesity and/or financial distress. Attrition bias in the direction of our result

would result from attrition of (a) obese nondelinquents and (b) non-obese delinquents. The (a) group would drive up the estimated delinquency rate among the obese who remain in the sample; the (b) group would lower the delinquency rate among the non-obese. 475 out of 7,470 individuals with 2004 BMI do not provide delinquency information in 2008 (an attrition rate of 6.36%).

No reliable statistical methods exist to overcome attrition bias, as it is the correlation between unobserved determinants of delinquency and unobserved determinants of attrition that causes the bias in estimates. Based on our observables, the observed delinquency differential between the obese and non-obese almost vanishes in the raw data only under the most extreme assumption that all obese nonrespondents were delinquent and that all obese nonrespondents were nondelinquent. However, without a plausible economic or psychological reason for why obese nondelinquents and non-obese delinquents would leave the NLSY survey between 2004 and 2008 we believe that this scenario is difficult to justify.

Moreover, under this most extreme assumption, the delinquency rate among those who drop out of the sample would be 75%, an implausible value in light of those survey participants' relatively lower average credit risk. As shown in Fig. A.5, those in the attrition group tend to have slightly lower BMIs and significantly lower predicted credit risk (based on the assumption that the credit risk model coefficients estimated from those who remain also apply to those who drop out). We find a lower predicted credit risk both among the obese and non-obese. Undisclosed estimates further show that obesity interacted with credit risk score quintiles explain a very small fraction of the variation in attrition outcomes (a Pseudo- $R^2$  of only 3.2%).

Selection bias, which occurs when individuals with missing data for 2004 are systematically related to obesity and/or delinquency, is unlikely to have a substantial effect on our estimates. Our estimation specification accommodates individuals with missing covariates in 2004. We only drop 161 individuals with missing BMI in 2004 to maintain the same sample



size across tables. Individuals with missing BMI in 2004 on average reported somewhat higher BMIs in earlier survey rounds than respondents whose BMI is not missing in 2004. Table A.7 shows the benchmark risk model estimates when including respondents with missing BMI in the estimation sample. Interestingly, the delinquency rate is much higher among those for whom we lack BMI. If obesity were priced in credit markets based on our data, admitting to being obese would be cheaper than not responding at all. Since respondents with missing BMI in 2004 are more than twice as likely to have missing data for other covariates, it is possible that missing BMI captures the effect of poor information availability and quality.

## A.4. Additional Figures and Tables

Figure A.1: Delinquency Rates Across BMI Categories

**Description:** This graph displays the delinquency rate across the BMI categories (brackets denote the 95% confidence interval). Delinquency is defined as having completely missed a payment or having been late by at least 2 months on any bill over the last 5 years. Data source: NLSY79.

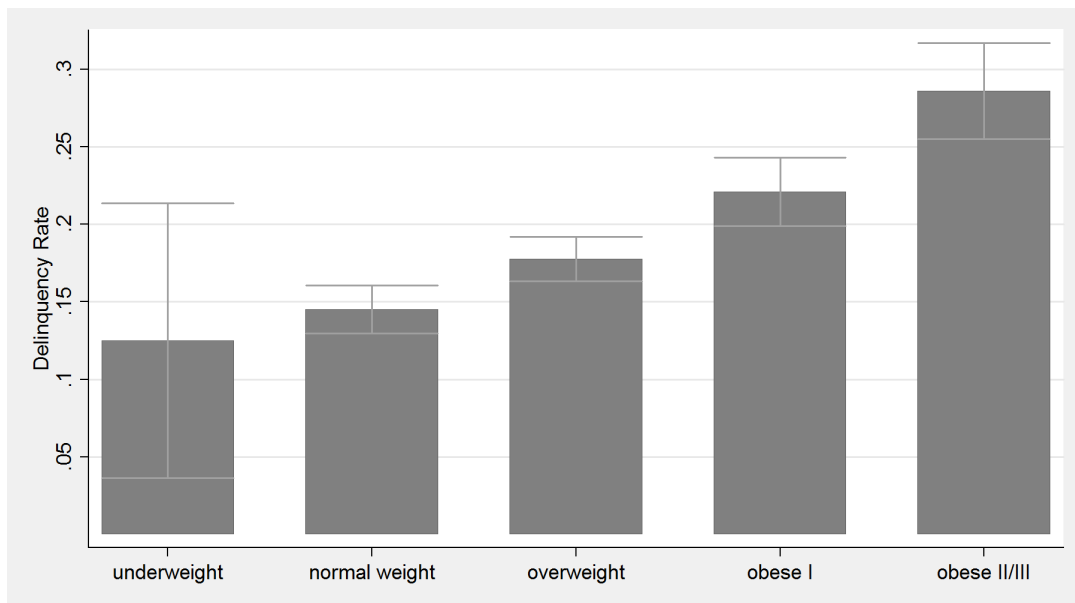


Figure A.2: Bankruptcy Rates Across BMI Categories

**Description:** This graph displays the bankruptcy rate across the BMI categories (brackets denote the 95% confidence interval). Bankruptcy refers to bankruptcies declared between 2004 and 2008. Data source: NLSY79.

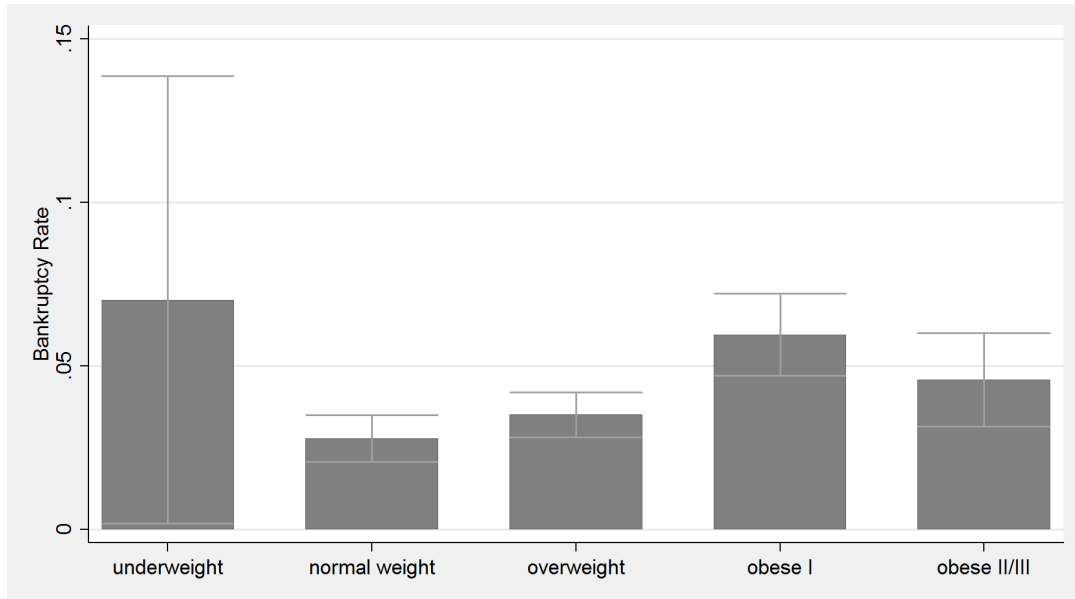


Figure A.3: Economic Environment Before and During the Sample Period

**Description:** To gauge the impact of the financial crisis on the delinquency rate reported in the 2008 NLSY interview, we plot the unemployment rate and the residential real estate loan and consumer loan delinquency rates over time. The 2008 NLSY interviews were conducted between January 2008 and April 2009, with 65% of the observations taken by the end of Q1 2008, and 82% by Q2. Data sources: BLS and Federal Reserve Bank.

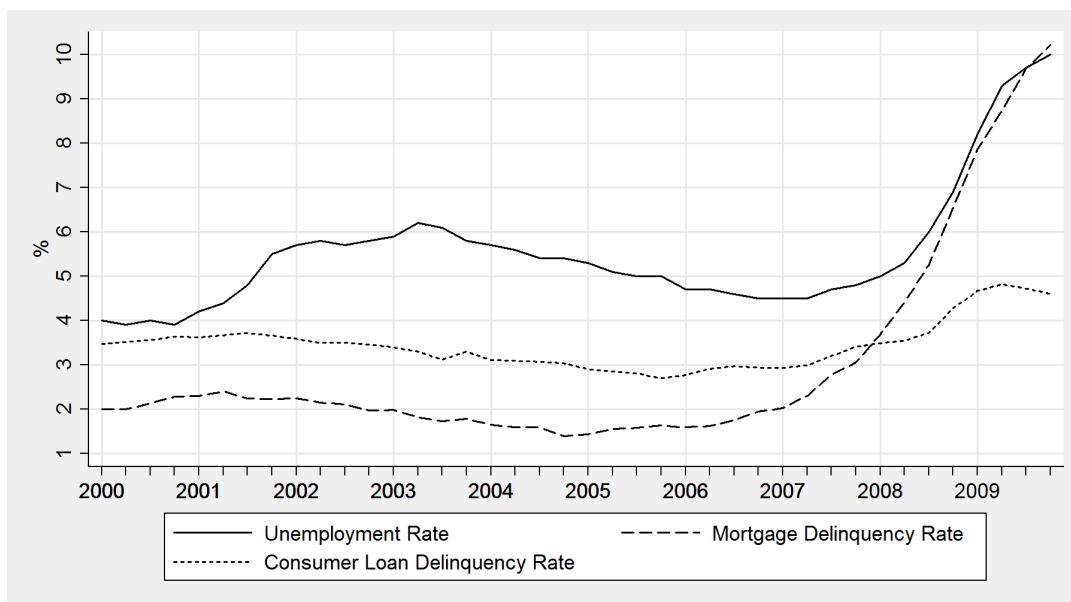


Figure A.4: Comparability of Obesity Propensity Scores Before and After Reweighting

**Description:** Numerous observable predictors of obesity are also known credit risk factors. These graphs illustrate the comparability of obese and non-obese respondents. The figures on the left display the kernel density estimates of the probability density functions of unadjusted propensity scores (i.e., predicted probabilities that individuals are obese) for the obese and non-obese. The figures on the right display propensity-score-reweighted densities (i.e., giving more weight to observations that are representative of the population average). The upper panel is based on the permissible and observable characteristics (Table 4, column 2). The lower panel also includes the additional covariates from Table 6 (e.g., race and gender). Data source: NLSY79.

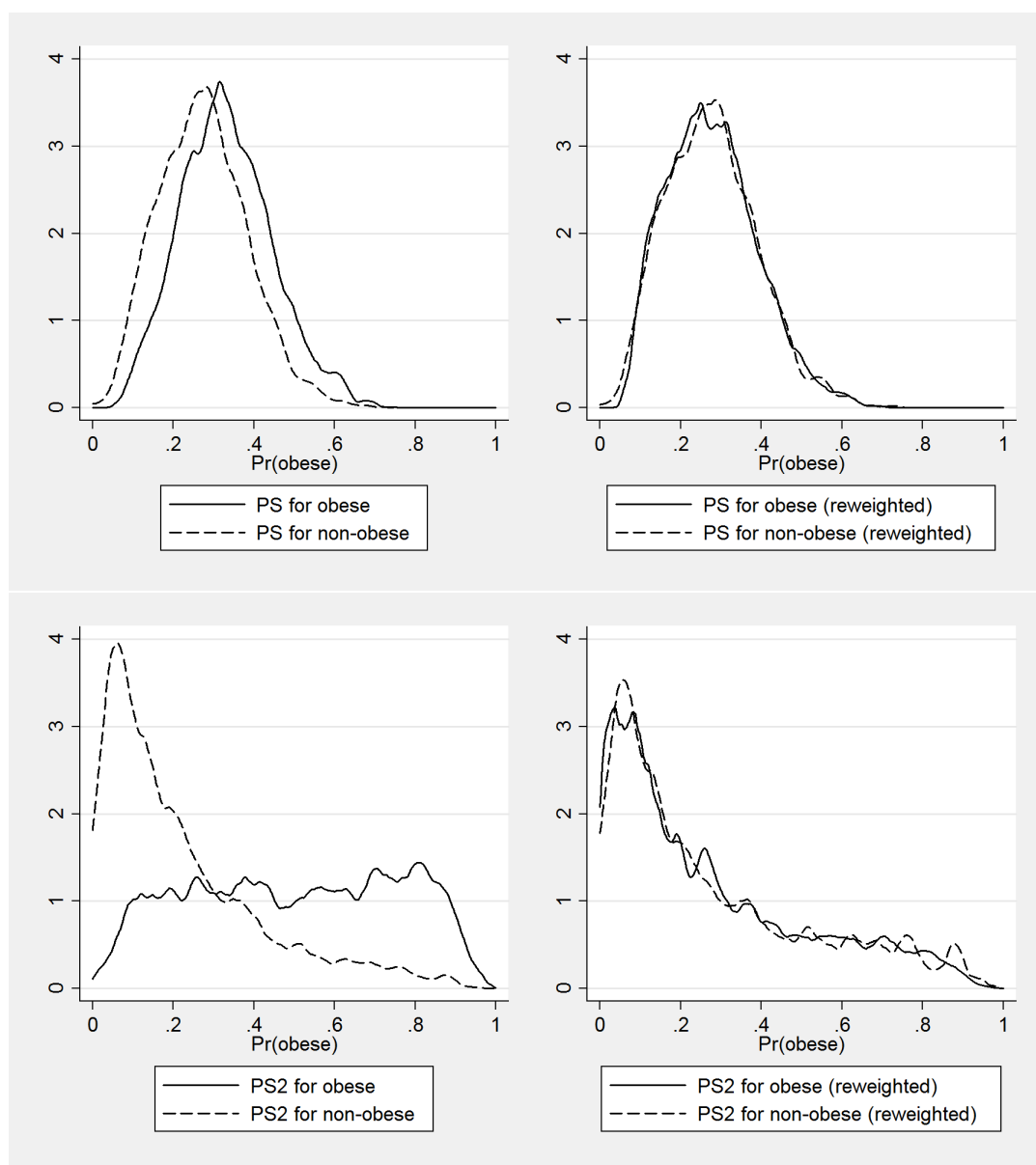


Figure A.5: Comparing the Composition of Nonattrition vs. Attrition Groups

**Description:** Comparison of distributions of BMI and predicted delinquency risk (based on the benchmark credit risk model) between respondents who remain in the sample between 2004 and 2008 and those who drop out. Data source: NLSY79.

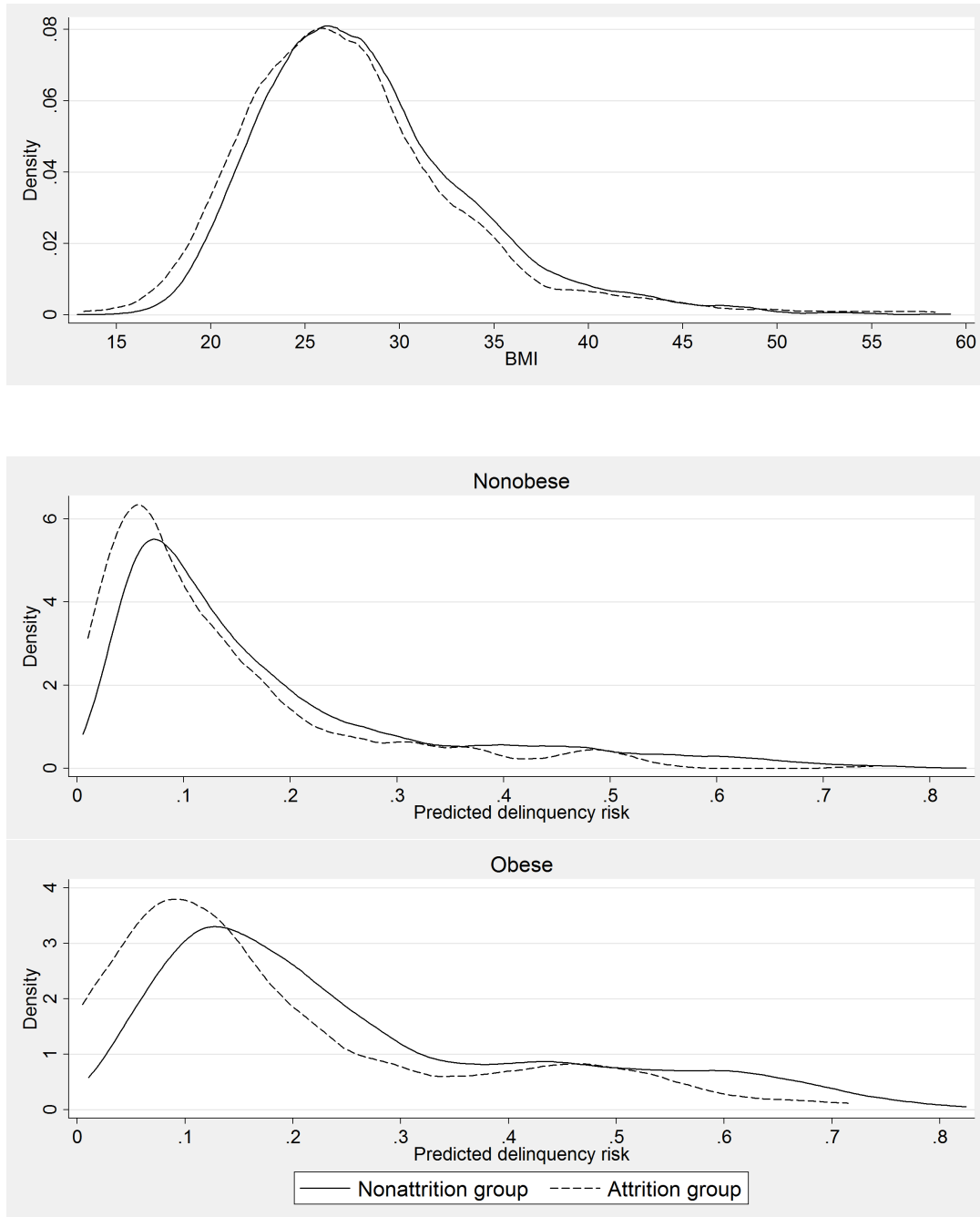


Table A.1: Marginal Effect of Obesity on Delinquency After Controlling for Income, Wealth, and Debt Capacity

**Description:** The table displays marginal effects of obesity on delinquency, estimated from credit risk probit models. All explanatory variables are from the 2004 survey; the dependent variable *Delinquent* comes from the 2008 survey. In columns 1–4, we individually introduce the income, wealth, debt characteristics as control variables. To achieve a flexible specification, each characteristic is represented by 6 attributes (5 attributes for the quintiles of the distribution and one attribute for missing responses). The first quintile represents the base category; estimates for the missing category are suppressed for brevity. In column 5 we control for all attributes simultaneously. In column 6, we increase the number of attributes by creating deciles. Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

	Quintile attributes					Deciles
	(1)	(2)	(3)	(4)	(5)	(6)
Obese	0.066*** (0.015)	0.057*** (0.015)	0.082*** (0.014)	0.070*** (0.015)	0.051*** (0.016)	0.050*** (0.016)
Income Q2	-0.068*** (0.021)				-0.055*** (0.020)	
Income Q3	-0.110*** (0.019)				-0.064*** (0.021)	
Income Q4	-0.150*** (0.011)				-0.083*** (0.017)	
Income Q5	-0.204*** (0.022)				-0.117*** (0.021)	
Wealth Q2		-0.070*** (0.024)			-0.073*** (0.025)	
Wealth Q3		-0.176*** (0.018)			-0.158*** (0.023)	
Wealth Q4		-0.196*** (0.017)			-0.165*** (0.022)	
Wealth Q5		-0.241*** (0.019)			-0.198*** (0.028)	
Debt/income Q2			0.024 (0.020)		0.040 (0.027)	
Debt/income Q3			-0.020 (0.017)		0.037 (0.028)	
Debt/income Q4			-0.021 (0.017)		0.034 (0.029)	
Debt/income Q5			0.027 (0.026)		0.043* (0.025)	
Debt/assets Q2				-0.027 (0.021)	0.037 (0.023)	
Debt/assets Q3				-0.022 (0.014)	0.039** (0.018)	
Debt/assets Q4				0.010 (0.018)	0.043* (0.025)	
Debt/assets Q5				0.148*** (0.017)	0.073*** (0.022)	
# of observations	6,995	6,995	6,995	6,995	6,995	6,995
Pseudo-R <sup>2</sup>	0.039	0.0615	0.012	0.036	0.075	0.083

Table A.2: Marginal Effect of Obesity on Delinquency After Controlling for Credit History (and Income, Wealth, and Debt Capacity)

**Description:** The table displays marginal effects from credit risk probit models, delinquency reported in 2008 being the dependent variable. All explanatory variables are from the 2004 survey. In all specifications, we include the set of controls used in column 5 of Table A.1, but suppress their average marginal effects to save space. For the credit attributes, the omitted category is *Did not apply for credit*. Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

	(1)	(2)	(3)	(4)
Obese	0.037*** (0.014)	0.049*** (0.016)	0.045*** (0.015)	0.035** (0.014)
Delinquent	0.260*** (0.014)			0.232*** (0.013)
Bankrupt		0.073** (0.031)		0.006 (0.024)
Credit approved			-0.014 (0.011)	-0.012 (0.012)
Credit denied			0.163*** (0.020)	0.091*** (0.019)
Credit expected to be denied			0.110*** (0.022)	0.043*** (0.016)
Controls from Table A.1	yes	yes	yes	yes
# of observations	6,995	6,995	6,995	6,995
Pseudo-R <sup>2</sup>	0.137	0.077	0.096	0.144



Table A.3: Marginal Effect of Obesity on Delinquency After Controlling for Employment Factors (and Income, Wealth, Debt Capacity, and Credit History)

**Description:** The table displays marginal effects from credit risk probit models, delinquency reported in 2008 being the dependent variable. All explanatory variables are from the 2004 survey, with the exception of *Income instability coefficient* which is based on survey years 1996–2004. In all specifications, we include the set of controls used in column 4 of Table A.2. The omitted category for education attainment is *Did not complete high school*. Industry and occupation dummies are based on 4-digit Census codes and follow the classification in the NLSY codebook. Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

	(1)	(2)	(3)	(4)	(5)	(6)
Obese	0.034*** (0.012)	0.038*** (0.014)	0.035** (0.014)	0.036*** (0.014)	0.038*** (0.013)	0.038*** (0.012)
Income instability Q2		0.022* (0.012)				0.017 (0.012)
Income instability Q3		0.014 (0.014)				0.008 (0.014)
Income instability Q4		0.038* (0.020)				0.030 (0.019)
Income instability Q5		0.063*** (0.018)				0.048*** (0.017)
High school degree			-0.013 (0.017)			-0.010 (0.016)
Some college			-0.008 (0.017)			-0.010 (0.020)
College degree			-0.028 (0.021)			-0.033 (0.025)
Advanced degree			-0.028** (0.013)			-0.040*** (0.013)
1yr < job tenure ≤ 2yr				0.016 (0.017)		0.015 (0.018)
2yr < job tenure ≤ 3yr				0.016 (0.022)		0.018 (0.026)
3yr < job tenure				-0.009 (0.010)		0.000 (0.013)
Self-employed					0.065*** (0.021)	0.040 (0.027)
Unemployed					0.027 (0.019)	0.028 (0.019)
Out of labor force					0.015 (0.010)	0.001 (0.012)
Industry dummies	yes	no	no	no	no	yes
Occupation dummies	yes	no	no	no	no	yes
Controls from Table A.1	yes	yes	yes	yes	yes	yes
Controls from Table A.2	yes	yes	yes	yes	yes	yes
# of observations	6,995	6,995	6,995	6,995	6,995	6,995
Pseudo-R <sup>2</sup>	0.156	0.148	0.146	0.146	0.149	0.162

Table A.4: Marginal Effects of Excess Weight on Financial Distress

**Description:** The table displays marginal effects of obesity on subsequent financial distress, estimated from credit risk probit models. The dependent variables are dummies indicating delinquency (columns 1 and 4), bankruptcy (columns 2 and 5), or maxing out a credit card (columns 3 and 6). In all specifications of panel A, we include the set of controls used in column 2 of Table 4. In panel A, the measures of financial distress are obtained from the 2008 survey and the explanatory variables from the 2004 survey. In panel B, the financial distress measures are taken from the 2004 survey, and the explanatory variables from 2000. Note that the regressions in panel B control for fewer credit history variables, as they are not available in the 2000 survey (we only have information on prior bankruptcies). Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

Panel A: 2004 Obesity → 2008 Financial Distress						
	Coarse Obesity Classification			Finer Classification of BMI		
	Delinquent (n=1,482) (1)	Bankrupt (n=275) (2)	Maxed out (n=784) (3)	Delinquent (n=1,482) (4)	Bankrupt (n=275) (5)	Maxed out (n=784) (6)
Obese	0.038*** (0.012)	0.009 (0.006)	0.028** (0.014)			
Underweight				-0.064** (0.029)	0.036 (0.043)	0.016 (0.040)
Overweight				0.028* (0.017)	0.000 (0.005)	0.018** (0.007)
Obese I				0.040*** (0.015)	0.013 (0.008)	0.032* (0.017)
Obese II/III				0.075*** (0.016)	0.004 (0.008)	0.052** (0.021)
BM controls	yes	yes	yes	yes	yes	yes
# of obs	6,995	6,787	6,853	6,995	6,787	6,853
Pseudo-R <sup>2</sup>	0.162	0.193	0.093	0.165	0.194	0.095

Panel B: 2000 Obesity → 2004 Financial Distress				
	Coarse Obesity Classification		Finer Classification of BMI	
	Delinquent (n=1,440) (1)	Bankrupt (n=315) (2)	Delinquent (n=1,440) (4)	Bankrupt (n=315) (5)
Obese	0.062*** (0.009)	0.019*** (0.006)		
Underweight			0.066 (0.054)	0.025 (0.018)
Overweight			-0.005 (0.007)	0.004 (0.006)
Obese I			0.055*** (0.018)	0.022*** (0.006)
Obese II/III			0.071*** (0.020)	0.018* (0.010)
BM controls	yes	yes	yes	yes
# of obs	6,958	7,019	6,958	7,019
Pseudo-R <sup>2</sup>	0.081	0.171	0.082	0.172

Table A.5: Marginal Effect of Obesity on Delinquency After Propensity Scoring

**Description:** The table displays estimates of the marginal effect of obesity on delinquency after propensity scoring. In columns 1 and 3 we include the propensity scores as a control in the regression of 2008 delinquencies on 2004 obesity. In columns 2 and 4 we use the propensity scores to reweigh the observations. In either case, restricting the sample to the common support has no impact on the obesity coefficient. Note that  $R^2$  is much lower than in the comparable specifications in column 2 of Table 4 and column 6 of Table 6, because the propensity score discards the information contained in those covariates that explains variation in delinquencies, but is not correlated with obesity. Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

	Score estimated from covariates in Table 4, column 2		Score estimated from covariates in Table 6, column 6	
	control (1)	reweigh (2)	control (3)	reweigh (4)
Obese	0.041*** (0.013)	0.040*** (0.014)	0.037*** (0.013)	0.037*** (0.014)
BM controls	yes	yes	yes	yes
Other controls	no	no	yes	yes
# of obs	6,995	6,995	6,995	6,995
Pseudo- $R^2$	0.045	0.002	0.046	0.001
Observed prob	0.185	0.185	0.185	0.185
Predicted prob	0.185	0.188	0.185	0.187

Table A.6: Additional Evidence on Cross-sectional Heterogeneity in the Informativeness of Obesity

**Description:** The table displays estimates of the marginal effect of obesity on delinquency across income and wealth quintiles (panel A) and conditional on credit history and across holdings of secured and unsecured debt (panel B). All specifications control include quintile attributes of the obesity propensity score. We run separate regressions for good and poor credit histories. Poor credit history encompasses any of the adverse histories (delinquency, bankruptcy, or credit denial) as well as the cases in which respondents expected to be denied. For debt types, we interact obesity with debt type. Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

Panel A: Interactions with Income and Wealth						
Average marginal effect of obesity over the quintiles of ...						
	Income			Wealth		
	marginal effect (1)	range w/in Q (\$ thsd.) (2)	% obese w/in Q (3)	marginal effect (4)	range w/in Q (\$ thsd.) (5)	% obese w/in Q (6)
Obese						
× Q1	0.041 (0.029)	0–29	34.0	0.035 (0.026)	-926–8	34.7
× Q2	0.044 (0.028)	29–53	29.2	0.016 (0.022)	9–67	32.2
× Q3	-0.005 (0.028)	53–76	32.1	0.032** (0.016)	67–167	31.1
× Q4	0.073*** (0.026)	76–111	25.0	-0.010 (0.027)	167–354	24.1
× Q5	0.118*** (0.037)	111–443	18.0	0.182*** (0.053)	354–2720	16.8
BM controls	yes			yes		
# of obs	6,995			6,995		
Pseudo-R <sup>2</sup>	0.060			0.078		

Panel B: Effect of Obesity by Credit History and Debt Type			
	Credit history		Debt type
	Good (1)	Poor (2)	(3)
Obese	0.045*** (0.013)	0.027 (0.030)	
Obese			
× no debt (19.9%)			0.033 (0.027)
× secured debt only (52.9%)			0.035** (0.014)
× unsecured debt only (7.1%)			-0.013 (0.049)
× sec & unsec debt (20.1%)			0.075*** (0.025)
BM controls	yes	yes	yes
# of observations	4,675	2,264	6,995
Pseudo-R <sup>2</sup>	0.016	0.008	0.069

Table A.7: Selection Bias is Negligible

**Description:** The table displays estimates of the marginal effect of obesity on delinquency. Heteroskedasticity-robust standard errors, clustered by residence typology (region and urban/rural) are in parentheses. \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

	Delinquency
Obese	0.038*** (0.012)
BMI missing	0.084** (0.039)
BM controls	yes
# of obs	7,156
Pseudo-R <sup>2</sup>	0.162

Table A.8: **Description of Channel Variables**

Variable	Description	Survey year
Health status	Self-assessment of health at age 40. “In general, would you say your health is {excellent, very good, good, fair, poor}?” Sample stats: excellent 21%, very good 38%, good 28%, fair 11%, poor 2%. Excluded category: excellent health.	1998–2006
$\Delta$ in health	Better=1 (Worse=1) if health status improves (deteriorates) between assessments at age 40 and age 50. Sample stats: better 8%, steady 20%, worse 17%, not available 55%. Excluded category: no change in health.	1998–2010
Insurance cov	Based on respondents’ insurance coverage (without spouse/children). Continuous: if insured in 2004 and respondent reports no coverage gaps in 2006/2008. With gaps or uninsured: lacks insurance in 2004, or reports gaps/lack in 2006/2008. Set to missing for all respondents for whom any one observation on insurance coverage was missing. Sample stats: continuous coverage 65%, gaps 26%, never insured 7%.	2004–2008
Risk tolerance	Ahn and Light’s (2010) imputed Arrow-Pratt coefficients of relative risk tolerance following the procedure developed by Kimball et al. (2008) based on hypothetical scenario; quintiles. “Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance that it will double your (family) income and a 50-50 chance that it will cut your (family) income by {one half, one third, one fifth}. Would you take the new job?” Excluded category: quintile 1 (lowest risk tolerance).	1993, 2002, 2004
Risk taker	Likert-type self-assessment of willingness to take financial risks; responses grouped 0; 20%, 1–4; 35%, 5; 19%, 6–9; 17%, 10; 3.5%. “How would you rate your willingness to take risks in financial matters? Rate your willingness from 0 to 10, where 0 means ‘unwilling to take any risks’ and 10 means ‘fully prepared to take risks’.” Excluded category: response category 0 (unwilling to take any risks).	2010
Risky share	Fraction of financial assets (value of stocks, mutual funds, bonds, retirement accounts, insurance plans, savings, tax deferred accounts, CDS, trust assets) invested in stocks and mutual funds; based on self-reported actual ownership; quintile 1 includes all respondents with zero equity ownership; Q2–Q5 are quartiles for equity ownership > 0. Excluded category: quintile 1 (zero equity exposure).	2004
Wealth risk	Standard deviation in the growth rate of net wealth over consecutive survey rounds; minimum of 4 observations; based on self-reported actual wealth. Excluded category: quintile 1 (lowest variability in the growth rate of net wealth).	1986–2000
Factor score	Described in DellaVigna and Paserman (2005). 1-factor score extracted from 7 measures that identify respondents’ impatience from their actions: display of impatience during the survey, health habits (smoking and drinking), use of contraceptives, participation in vocational clubs in high school, having insurance coverage and a bank account. Measures are standardized, missing observations for any one measure are replaced with that respondent’s average standard score from his/her available measures. Winsorized.	1980–1985
Survey attitude	“What was the respondent’s attitude toward the interviewer: {friendly/interested; cooperative/not interested; impatient/restless; hostile}.” Dummy = 1 if respondent was categorized as impatient or restless during any of the first six follow-up surveys (11%).	1980–1985

Discount factor	Described in Courtemanche et al. (2014); based on hypothetical scenario. $DF = \$1,000/(\$1,000 + \$X_{year})$ . “Suppose you have won a prize of \$1,000 which you can claim immediately. However, you can choose to wait {one month, one year} to claim the prize. If you do wait, you will receive more than \$1,000. What is the smallest amount of money in addition to the \$1,000 you would have to receive one month from now to convince you to wait rather than claim the prize now?” Winsorized.	2006
$\beta, \delta$ -factors	Described in Courtemanche et al. (2014); based on hypothetical scenario. Most respondents reveal a greater discount factor for the one-year delay than for the one-month delay, which is consistent with present-biased preferences. Back out $\beta$ and $\delta$ from $\beta\delta = \$1,000/(\$1,000 + \$X_{year})$ and $\beta\delta^{12} = \$1,000/(\$1,000 + \$X_{month})$ . Winsorized.	2006
AFQT score	Quintiles of the residuals from a regression of AFQT scores on age dummies (summary stats in the following table reflects the percentile rank in the sample distribution). Excluded category: quintile 1 (lowest IQ scores).	1981
M education	Mother’s educational attainment. 1: did not finish high school (41%); 2: finished high school (37%); 3: at least some college (16%). Excluded category: did not finish high school.	1979
F presence	Father present at home when respondent was 14 years old. 70% present, 30% absent.	1979
Weight goals	“Are you now trying to lose weight, gain weight, stay about the same, or are you not trying to do anything about your weight?” Lose 42%, gain 3%, 27% maintain, 23% no goal. Excluded category: stay about the same.	2002
Fail weight goals	Dummy = 1 for respondents who are trying to (i) lose weight in 2002, but do not lose weight between 2002 and 2004 and (ii) stay about the same, but gain weight. Sample stats: 38% fail, 30% succeed, 32% did not have weight loss/maintenance goal. Excluded category: goal achieved.	2002, 2004
Trust	“Generally speaking, how often can you trust other people?” {High trust: always or most of the time; Medium trust: about half the time; Low trust: once in a while or never}. Sample stats: high trust 37%, medium trust 29%, low trust 33%. Excluded category: high trust.	2008
Locus of control	Rotter score: Respondents are shown 4 pairs of statements along the lines of “What happens to me is my own doing” vs. “Sometimes I feel that I don’t have enough control over the direction my life is taking”. They first select which one is closest to their opinion, then evaluate whether it is much closer or slightly closer to their opinion. Range 4 to 16.	1979

Table A.9: Summary Statistics (Potential Mechanisms), By Obesity

**Description:** This table captures that the obese and non-obese systematically differ in their constraints, preferences, and attitudes. The summary statistics are based on the measures underlying the variables used in Table 9 (i.e., they do not refer to the quintiles). \*\*\* denote statistically significant differences in means between the obese and non-obese at the 1% significance level. Observations are weighted using NLSY 2004 sampling weights.

	Non-obese			Obese			$\Delta$
	mean	st dev	obs	mean	st dev	obs	
Health status	2.149	0.952	4,792	2.601	0.982	2,189	***
$\Delta$ health	0.198	0.709	2,143	0.212	0.726	1,024	
Insurance gap	0.331	0.579	4,658	0.357	0.583	2,138	
Risk tolerance	0.399	0.469	4,803	0.396	0.494	2,192	
Risk taker	3.675	2.549	4,495	3.516	2.662	2,083	**
Risky share	0.209	0.280	3,772	0.197	0.288	1,702	
Wealth risk	1.023	0.642	3,311	1.096	0.664	1,357	***
Impatience factor score	-0.244	1.292	4,691	-0.208	1.313	2,126	
Impatience attitude	0.096	0.295	4,669	0.104	0.305	2,137	
Discount factor	0.597	0.258	4,458	0.564	0.270	2,020	***
$\beta$	0.799	0.212	4,404	0.777	0.221	1,999	***
$\delta$	0.754	0.314	4,404	0.736	0.342	1,999	*
AFQT ranking	0.604	0.275	4,606	0.542	0.287	2,113	***
Mother education	1.935	0.724	4,520	1.767	0.718	2,055	***
Father presence	0.781	0.414	4,795	0.754	0.431	2,191	**
Trying to lose weight	0.344	0.475	4,803	0.590	0.492	2,192	***
Failing to lose/keep weight	0.338	0.473	4,803	0.478	0.500	2,192	***
Trust	1.795	0.822	4,765	1.912	0.838	2,170	***
Rotter score	8.465	2.386	4,763	8.779	2.412	2,164	***



Table A.10: Unconditional and Conditional Relationship between Obesity and Potential Mechanisms

**Description:** This table shows regression coefficients and standard errors from linear probability models, relating obesity to each mechanism variable listed in the left column, both without and with the benchmark controls. Only the regressions containing  $\Delta$  health contain another variable from this list, namely *Health status*; and  $\beta$  and  $\delta$  are estimated jointly. Standard errors are heteroskedasticity-robust and clustered by residence typology (region and urban/rural). \*\*\*, \*\*, and \* denote significant differences from zero at the 1%, 5%, and 10% significance levels. Observations are weighted using NLSY 2004 sampling weights.

	Without benchmark controls		With benchmark controls	
	LPM est	Std error	LPM est	Std error
Health status: very good	0.108***	0.015	0.090***	0.014
Health status: good	0.207***	0.014	0.168***	0.015
Health status: fair	0.318***	0.021	0.276***	0.028
Health status: poor	0.251***	0.036	0.212***	0.047
$\Delta$ health: better health	-0.060*	0.032	-0.052	0.030
$\Delta$ health: worse health	0.069***	0.015	0.057***	0.015
$\Delta$ health: health 50 not available	-0.011	0.010	-0.017	0.009
Insurance: gap	0.035**	0.013	-0.026*	0.013
Insurance: no coverage	0.001	0.024	-0.067**	0.024
Risk tolerance: Q2	-0.009	0.018	-0.006	0.019
Risk tolerance: Q3	-0.032	0.031	-0.022	0.032
Risk tolerance: Q4	-0.034	0.031	-0.020	0.031
Risk tolerance: Q5	-0.038	0.027	-0.022	0.028
Risk taker: Q2	-0.023	0.017	0.005	0.017
Risk taker: Q3	-0.037*	0.020	0.011	0.023
Risk taker: Q4	-0.047**	0.019	0.019	0.023
Risk taker: Q5	0.057*	0.028	0.076**	0.034
Risky share: Q2	-0.028	0.016	0.042*	0.020
Risky share: Q3	-0.052**	0.022	0.027	0.023
Risky share: Q4	-0.050*	0.027	0.022	0.024
Risky share: Q5	-0.035	0.024	0.025	0.022
Wealth risk: Q2	0.052**	0.021	0.042*	0.023
Wealth risk: Q3	0.004	0.023	-0.005	0.024
Wealth risk: Q4	0.048**	0.024	0.025	0.024
Wealth risk: Q5	0.083***	0.015	0.049**	0.021
DP impatience factor score	0.004	0.006	-0.013	0.008
CK impatience attitude	0.017	0.012	0.010	0.016
Discount factor	-0.096***	0.029	-0.051	0.033
$\beta$	-0.102***	0.031	-0.041	0.033
$\delta$	-0.040	0.023	-0.023	0.024
AFQT: Q2	-0.040**	0.015	-0.035*	0.017
AFQT: Q3	-0.067***	0.019	-0.032	0.022
AFQT: Q4	-0.090***	0.015	-0.041*	0.023
AFQT: Q5	-0.124***	0.021	-0.033	0.025
Mother's educ: HS	-0.083***	0.012	-0.057***	0.014
Mother's educ: HS+	-0.123***	0.013	-0.063***	0.015
Father's presence	-0.030**	0.012	0.003	0.014
Goal: lose weight	0.244***	0.011	0.234***	0.014
Goal: gain weight	-0.110***	0.020	-0.160***	0.023
Goal: none	0.085***	0.017	0.062***	0.017
Failed goal (wgt $\uparrow$ )	0.122***	0.021	0.116***	0.021
Trust: medium	0.034**	0.013	0.009	0.017
Trust: low	0.068***	0.012	0.025*	0.014
Rotter score	0.002**	0.001	0.000	0.001