Obesity and Household Financial Distress*

Katherine Guthrie
katherine.guthrie@mason.wm.edu
College of William and Mary

Jan Sokolowsky†
sokolowsky.jan@gmail.com

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Abstract

Obesity provides a potentially informative signal about individuals' choices and preferences. Using NLSY survey data, we estimate that debt delinquency is 20 percent higher among the obese than the non-obese after controlling for an extensive set of financial and economic credit risk factors. The economic significance of obesity for delinquencies is comparable to that of job displacements. Obesity is particularly informative about delinquencies among those with low credit risk. In terms of channels, we find that the conditional obesity effect is partially mediated through health, but is not attributable to individuals' attitudes, time and risk preferences, or cognitive skills.

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†Corresponding author: 100 Archer's Court, Williamsburg, VA 23185. Phone: (757) 208 0409.

1. Motivation

Due to the growing prevalence of obesity in the population, obesity is increasingly being considered as a factor in economic interchange. Airlines and movie theaters require large people to purchase two seats; the obese tend to earn lower wages; and legal cases provide anecdotal evidence of consideration of body weight in hiring and promotion decisions (e.g., Kirkland (2008), Bhattacharya and Bundorf (2009), and Lundborg, Nystedt, and Rooth (2009)). To justify the use of obesity as the basis for differential treatment, businesses often point to the additional costs imposed by serving or employing the obese.[1]

To date, the role of obesity in credit markets has not yet been explored. The rate of personal bankruptcies has more than quadrupled between 1980 and 2005, culminating in the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA), one of the most significant legislative changes to impact households' financial decisions in recent U.S. history. 5.4 million more households have filed for bankruptcy between 2006 and 2010. At the end of 2008, household debt amounted to over $11 trillion in mortgages and $2.6 trillion in consumer credit. Commercial banks, which held $879 billion of consumer credit, incurred a net loss of about $30 billion in 2008 alone.[2]

The purpose of our research is to shed light on the magnitude and nature of the relationship between obesity and credit risk. Obesity is a known health risk factor and carries a social stigma. Its presence, despite being preventable, thus provides a potentially informative signal from individuals' past choices about their preferences, future choices, or risk exposure.

[1] The weight gain in the U.S. population during the 1990s cost the airlines an estimated 350 million gallons of additional jet fuel in 2000 (Dannenberg, Burton, and Jackson (2004)). A Duke University Medical Center analysis found that obese workers filed twice the number of workers' compensation claims, had seven times higher medical costs from those claims and lost 13 times more days of work from work injury or work illness than did non-obese workers (Østbye, Dement, and Krause (2007)). According to Thompson, Edelsberg, Kinsey, and Oster (1998), already in 1994 the cost of obesity to U.S. businesses amounted to $2.4 billion for paid sick leave, $2.6 billion for life and disability insurance, and $7.7 billion for health insurance. See Hammond and Levine (2010) for a recent and thorough review of the economic consequences of obesity.

[2] Our estimates are based on data released by the American Bankruptcy Institute and the Federal Reserve.

We first establish that obesity does in fact have predictive power for consumer delinquencies and bankruptcies. Second, we investigate the channels through which obesity affects credit risk.

Our empirical analysis primarily utilizes 2004 and 2008 survey data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79), which is a nationally representative sample of the U.S. population born between 1957 and 1964. We estimate that the obese have a 3.8 percentage point higher likelihood of becoming delinquent over the following four years (this constitutes a 20.5% increase relative to the sample delinquency rate of 18.5%), after controlling for credit-risk-relevant factors that are observable to lenders and permissible under federal regulations, such as respondents' income and net wealth, debt capacity, credit histories, and income instability.[3] Taking into account the frequency with which unemployment spells, marriage dissolutions, and disability shocks occur, the total incidence of obesity on delinquencies is on par with that of unemployment spells, triple the effect of marriage dissolutions, and twice as important as disability shocks.

The possibility remains that obesity simply proxies for omitted credit-risk-relevant variables that are available to lenders. To mitigate this concern, we show that the result is robust to including geographic fixed effects down to the county level. In addition, in a subsample of respondents who have applied for credit, we show that obesity is conditionally uncorrelated with lenders' credit decisions, but has strong predictive power for subsequent delinquencies. We conjecture that obesity does not proxy for information that is used by lenders, but is unobservable to us. The obesity effect on delinquencies is also not driven by observable borrower characteristics that are prohibited under the Equal Credit Opportunity Act (ECOA), such as ethnicity, gender, marital status, religious affiliation, and age.[4]

[3]Delinquency is defined as having completely missed a payment or been at least 2 months late in paying any bills in the previous 5 years.

[4]Propensity scoring is highly effective at making the obese and non-obese comparable along observable characteristics, reveals common support over nearly the entire range of the propensity score, and yields similar estimates.

We document significant cross-sectional heterogeneity in the ability of obesity to predict delinquencies. Obesity is particularly informative when it is less prevalent, e.g., among respondents who are white, rich, and of low credit risk. These findings are consistent with obesity being more informative (i) about individuals' choices than their socioeconomic environments; (ii) among individuals with higher human capital and correspondingly greater ability and incentive to prioritize medical expenditures over other financial obligations; and (iii) when its informativeness is not subsumed by past financial distress.

Does obesity affect delinquencies through a causal channel or does it proxy for omitted borrower characteristics? We find that the residual obesity effect — i.e., the part that is not already captured by observable and permissible credit risk characteristics — is partially mediated through health. Including measures of physical well-being reduces the obesity effect by about a third. Based on our explorations of the NLSY data, we conjecture that discretionary health expenditures on health maintenance are the driving force behind the health channel, rather than health shocks and/or associated productivity loss. Also, the obesity effect is concentrated among the obese who are dissatisfied with their excess weight. Controlling for weight loss goals absorbs 24% of the obesity effect, most of which is incremental to the health mechanism. This observation hints at obesity capturing self-control problems, though it could also reflect adverse consequences of weight loss regimens.

In addition, we are able to rule out heterogeneity in individuals' preferences (time and risk), decision-making ability (IQ, parents' socioeconomic status, sibling fixed effects), and attitudes (trust and locus of control) as drivers of the obesity effect. Many of these characteristics help predict delinquencies. Their inclusion, however, does not account for any significant fraction of the obesity effect, in part due to the fact that these characteristics are also reflected in other observable economic variables such as education, income, wealth, and indebtedness.

Credit markets are characterized by asymmetric information between borrowers and lenders. In identifying obesity as an incrementally informative and difficult-to-manipulate signal of credit quality, our work adds to the literature that studies observable borrower choices and characteristics as a source of soft information about default risk. For example, default risk can be inferred from mortgage broker fees, spending on luxury goods, online endorsements by friends, self-reported maximum interest rates one is willing to pay for loans, as well as physical appearance.[5] The evidence on the market's ability to price the various risks is mixed. Other studies explore the underlying factors that give rise to heterogeneity in financial behaviors or outcomes, such as borrowers' preferences, attitudes, and abilities.[6] Since these factors are not observable by lenders, they do little to help resolve asymmetric information problems, but they provide a deeper economic understanding of the observed heterogeneity in defaults and inform public policy (e.g., on financial literacy or discrimination).

2. Data & Methodology

The goal of this paper is to assess whether obesity captures credit-risk-relevant information that is otherwise unobservable to or nonverifiable by the lender at the time of extending the loan. We do not argue for a causal relationship between obesity and future delinquencies — for our purposes, it suffices to see if obesity remains informative about future delinquencies after controlling for information typically found on credit applications. Ideally, we would

[5] See Berndt, Hollifield, and Sandås (2012), Vissing-Jørgensen (2011), Lin, Prabhala, and Viswanathan (2013), Iyer, Khwaja, Luttmer, and Shue (2014), and Duarte, Siegel, and Young (2012), Ravina (2012), Pope and Sydnor (2011). Some of these studies relate excess weight, assessed from borrowers' photos posted on Prosper, to credit market outcomes. However, the propensity to be classified as overweight or obese is implausibly low (12-27% in the Prosper studies vs. 68% in the adult U.S. population according to CDC (2014), which is based on measured weight and height).

[6] E.g., Johnson, Atlas, and Payne (2014), Jiang and Lim (2013), Guiso, Sapienza, and Zingales (2013), Gerardi, Goette, and Meier (2010), Cronqvist and Siegel (2014), Grinblatt, Keloharju, and Linnainmaa (2011), and Gathergood (2012).

like to add borrowers' obesity status to the credit risk model actually used by lenders. Unfortunately, the ideal data is currently not available to us; it would require the cooperation of a lender in collecting borrowers' weight and height without influencing the loan decision and tracking loan performance over several years.

We use individuals' survey responses from the 1979 youth cohort of the National Longitudinal Survey of Youth (NLSY79), which is administered by the Bureau of Labor Statistics. The NLSY79 is a nationally representative survey that began in 1979, covering 12,686 individuals born between 1957 and 1964. We primarily utilize data from the 2004–2008 biennial interviews, which still cover about 60% of the original sample.[7] Definitions of the main variables used in the analysis are collected in Table 1; definitions of the numerous channel variables are relegated to Table A.8.

Designed to follow life-time experiences of a representative cross-sectional sample of the population, the primary focus of the NLSY79 has been on labor market outcomes. The 2004 and 2008 interviews, however, include questions on respondents' loan delinquency status. Respondents are asked whether they have been delinquent on any bill payment over the last five years, as well as prior bankruptcies and credit card usage. 18.5% of the respondents admit to having been delinquent, 3.9% to having declared bankruptcy, and 9.4% to having maxed out their credit cards. Combined with detailed data on respondents' body mass index (BMI), income, wealth, debt, employment status, education, family background, the NLSY79 allows us to use borrowers' 2004 obesity status to predict financial distress by 2008, while controlling for numerous factors that affect both.[8]

[7]The annualized attrition rate in the NLSY79, adjusted for the discontinuation of the two subsamples, is only 1%. The drop in participation is primarily driven by the discontinuation of the military subsample (1,079 participants) after the 1984 interview and the discontinuation of the subsample of economically disadvantaged, non-black/non-Hispanic respondents (1,643 participants) after the 1990 interview. The loss of these two subsamples does not affect the representativeness of the survey of this age cohort in the U.S. population, because those two subgroups were intentionally oversampled.

[8]We estimate probit models. Probit, logit, and linear probability model results do not materially differ from each other.

We construct an estimate of each respondent's BMI from respondents' self-reported weight (as reported in the 2004 survey) and height (average of self-reported heights in the 1985, 2006, and 2008 surveys). Following the convention set forth by the World Health Organization (WHO), we classify a respondent as obese if his/her BMI is 30 or greater. Figure 1 displays the distribution of BMI in the U.S. population in their early 40s and its classification. 32% of the cohort are of normal weight, 39% are overweight, and 28% are classified as obese.

[Insert Figure 1 here.]

In contrast to the millions of observations typically available to credit risk modelers, our sample consists of only 6,995 observations.[9] The relative infrequency of bankruptcies impairs the statistical power of our analysis. Using delinquencies instead of bankruptcies improves the statistical power, as they occur more frequently. Also, the enactment of BAPCPA in 2005 caused a spike in personal bankruptcy rates in 2005 and temporarily depressed bankruptcy filings over the following years.

Do delinquencies capture serious financial distress or do they merely reflect inconsequential delays in payments (e.g., failure to update credit card details for subscriptions or late payments due to being on vacation)? We tabulate delinquencies vs. bankruptcies in Table 2. In the 2008 survey, 9.2% of delinquent respondents declared bankruptcy between 2004 and 2008. In the 2004 survey, 11.8% of delinquent respondents filed for bankruptcy between 2000 and 2004. For comparison, the bankruptcy rates among the non-delinquent respondents were 2.7% in 2008 and 2.5% in 2004. That is, delinquency almost quadruples bankruptcy

[9] There are 7,661 respondents in the 2004 survey, 7,156 of which have information on future delinquency. Missing BMI eliminates another 161 respondents. Our results are robust to using those respondents' BMI from earlier or later years, as well as to using BMI from the 2000 survey for all respondents.

risk, supporting the view that delinquencies are indeed a valid indicator of serious financial distress.[10]

[Insert Table 2 here.]

As is standard in credit risk modeling (BGFRS 2007), we create a number of attributes for each credit-risk-relevant variable, which are referred to as characteristic. Attributes are dummies indicating whether an observation falls into a particular range of the underlying characteristic. Jointly, the attributes cover the range of each characteristic (missing observations are assigned their own attribute).[11] The obvious constraint to the number of attributes is the size of the sample available to the credit risk modeler. Being limited in this regard, we simply create five attributes corresponding to the quintiles of continuously measured characteristics (or their logarithmic transformation) and an additional attribute for missing responses. For each characteristic, we check whether our main result is robust to various alternative specifications of attributes.[12]

DiNardo, Garlick, and Stange (2010) criticize the underlying monotonicity assumption behind the obesity-outcome relationship and the parsimonious specifications of control variables typically employed in academic research on obesity for failing to capture important non-linearities and heterogeneity. While we keep our main analysis simple by comparing outcomes between the obese and non-obese, we also carefully examine the effect of weight on delinquency over the entire range of BMI (semiparametrically and for finer BMI categories). Moreover, our research design mitigates these concerns through the use of attributes, as well as robustness tests in which we stratify our sample by race and gender.

[10] In undisclosed results, we find that delinquencies are also associated with a high probability of declining wealth. Both relationships are robust to including all the variables introduced in Tables 3 and 5.

[11] Dropping observations with missing data on any other benchmark control variable would reduce the sample by about one third and yield a larger estimate of the obesity effect.

[12] Some credit risk modelers reduce the arbitrariness in determining the number and spacing of attributes by iteratively parsing the characteristic to maximize a pre-specified objective function (e.g., maximizing adjusted R^2) subject to pre-specified constraints (e.g., monotonicity requirements). This process is not entirely non-arbitrary, as it still depends on the order in which characteristics are parsed and how the parsing proceeds.

The NLSY79 data are obtained from a complex survey design, so participants do not represent a random sample of the population. Initially, they were geographically clustered to minimize interviewers' travel times between participants and subject to self-selection, because only those respondents who chose to complete the initial interview became NLSY79 cohort members. To obtain estimates that are representative of the U.S. population born between 1957 and 1964, we use the sample weights provided in the NLSY (which also adjust for non-interviews) in all of our analyses.[13]

The usual disclaimer about surveys applies to our research as well. The answers to the interview questions are self-reported, and may reflect biases (e.g., underreporting of one's weight) or mistakes (e.g., a misunderstanding of the interview question). In addition, answers to questions that gauge respondents' time and risk preferences in some cases reflect beliefs, not actual economic choices. Appendix A.2. contains a discussion of measurement error in our key variables, and Appendix A.3. addresses potential attrition and selection bias. Furthermore, our measure of credit risk has two drawbacks. First, we do not have detailed information on loan contract terms, which may differ between the obese and non-obese. Stricter credit conditions for the obese would increase their risk of falling behind on their payments. Without data on the comparability of contract terms between the obese and non-obese, our analysis does not permit a loan performance evaluation. Second, delinquencies occur at the household level, but BMI is available only for the respondent. Positive assortative matching at the household level mitigates this concern to some extent. Abrevaya and Tang (2010) find that a spouse's BMI is the most significant predictor of BMI after controlling for individual socioeconomic and behavioral characteristics.[14]

[13] As access to the detailed geographical information on respondents' residence is restricted, we instead cluster standard errors by the intersection of geographic region and whether the respondent lives in an urban or rural location, SMSA. This approach yields more conservative estimates of standard errors.

[14] Using MEPS data (specifically, longitudinal panel 9 covering years 2004 and 2005), we also find that conditional on observing a non-obese respondent of the same age as the NLSY cohort, the probability of another household member being obese is 28%. Conditional on observing an obese respondent, the probability is 53%.

3. Obesity Is a Delinquency Risk Factor

As is evident from Table 3, the obese are about 50% more likely to experience financial distress than the non-obese. For example, 16.2% of the non-obese and 24.4% of the obese respondents admit to delinquency in the 2008 survey.[15] However, the observable characteristics of the obese also represent a systematically higher credit risk than those of the non-obese. The obese have lower income and wealth, and are more highly leveraged. Their credit histories are substantially worse: they are more likely to have been delinquent, bankrupt, and denied credit in the past. We also find that obesity is more prevalent among Hispanics and blacks, and that it is negatively correlated with respondents' educational attainment. The only mitigating factors are that the obese tend to have more stable incomes (measured as the standard deviation in total net family income over years 1996 to 2004 relative to its mean) and are less likely to be self-employed. The biggest challenge we face is to differentiate the effect of obesity from the effect of other risk factors.[16]

[Insert Table 3 here.]

3.1. Permissible and Observable Credit Risk Factors — Benchmark Model

Column 1 of Table 4 provides our point of departure. Without any control variables, the marginal effect of obesity on delinquency risk is 8.1 percentage points, with a standard error of 1.3 percentage points. To arrive at our benchmark result in column 2, we control for all

[15] Figures A.1 and A.2 in the Appendix provide a graphical representation of the unconditional delinquency and bankruptcy rates across the weight categories. The overweight have a 17.5% delinquency rate, 3 percentage points higher than respondents of normal weight. The differential is 8 percentage points for the obese (class I) and 14 percentage points for the severely obese (classes II/III). The results are almost identical if we restrict the sample to the 5,301 respondents who were indebted in 2004, through mortgages, home loans, car loans, student loans, credit card debt, or debt owed to other businesses, people or institutions (such as doctors, lawyers, and hospitals). Delinquency need not be restricted to borrowers, because even respondents without debt as of 2004 may have borrowed subsequently.

[16] *Unemployment* identifies unemployment spells since the last interview (it does not mean currently unemployed). As it pertains to a longer time period, the number is larger than the unemployment rate in 2004.

credit-risk-relevant factors available in the NLSY that are permissible by law and observable by lenders, including income and wealth, debt-to-income and debt-to-asset ratios, prior credit histories, as well as income risk and labor market indicators. The benchmark model reflects our preferred specification that balances flexibility and simplicity. It includes 16 characteristics with a total of 96 attributes (continuous characteristics are split into quintile attributes; missing observations for each characteristic are assigned their own attribute). As expected, the relationship between obesity and delinquency is partially attributable to the correlation between obesity and credit-risk-relevant factors. Nevertheless, the average marginal effect of obesity on delinquency remains economically large at 3.8 percentage points (20.5% of the total delinquency rate) and precisely estimated (a standard error of only 1.2 percentage points).[17]

[Insert Table 4 here.]

The estimated marginal effects of the controls on delinquency are reported in three additional tables in the Appendix; here we provide only a brief summary of the main findings. The first set of controls includes income, wealth, and debt, which capture borrowers' credit capacity and have also been linked to obesity in numerous prior studies.[18] As expected, being in a higher income or wealth quintile is strongly associated with a reduced risk of delinquency (see Table A.1). Also, delinquencies tend to rise with the debt-to-asset ratio. However, we find that the current debt-to-income ratio is not related to future delinquencies, which is consistent with the results of Foote, Gerardi, Goette, and Willen (2009).

[17]Accounting for the complex survey design (using information on primary sampling units and strata from the restricted geocode file, as well as the 2004 sampling weights) lowers the standard error on *obese* in the benchmark regression to 0.011.

[18]For example, Lundborg, Nystedt, and Rooth (2009) document an 18% earnings penalty for obesity among 450,000 Swedish men; Zagorsky (2004) finds that Americans with BMIs in the normal range have about twice the net worth of the obese; and Münster, Rüger, Ochsmann, Letzel, and Toschke (2009) show that obesity is more prevalent among the over-indebted in Germany.

The second set of controls captures respondents' credit histories. They reveal information about borrowers' types that would otherwise remain hidden from lenders. While bad luck can inflict the best risk types (e.g., a major local employer relocates or a car accident leaves a worker disabled), bad types will on average have worse credit histories than good types. If, as we posit, obesity is related to credit risk, we would expect obesity and future delinquencies to be correlated with the incidence of prior bankruptcies and delinquencies. Both the 2004 and 2008 interviews ask respondents about bankruptcies and delinquencies, which allows us to condition on past derogatories when predicting 2008 delinquency status. As expected, we find that credit risk is serially correlated, i.e., prior delinquencies and bankruptcies positively predict future delinquencies (see Table A.2). This finding is consistent with the view (i) that individual fixed effects are important credit risk factors or (ii) that financial distress can have long-lasting repercussions (e.g., analogous to a poverty trap). On average, having been delinquent or bankrupt translates into a 26.0 or 7.3 percentage point higher likelihood of becoming delinquent again.

In addition, in 2004 NLSY participants were asked whether they had applied for a loan in the last 5 years or since the last bankruptcy; and whether the application was denied or approved. An application for a loan indicates a borrowers' need or desire to borrow (e.g., due to liquidity constraints or for consumption smoothing). More importantly, credit denials also reflect lenders' assessments of the applicants' credit risk. The fact that a household applied for and was granted credit does not help predict future delinquencies, either positively or negatively. However, delinquencies are estimated to be 16.3 percentage points higher when credit was denied, and 11.0 percentage points higher for credit applications withheld because of a low chance of approval.

The third set of controls pertains to income risk. Credit applications routinely ask potential borrowers about their current employment situation and how long they have been with the employer, which can be used to assess how likely it is that a potential borrower will continue to earn his/her current income. Using the standard deviation in income 1996–2004 divided by its mean as our primary measure of income instability, we find that respondents in the highest quintile of income instability are 6.3 percentage points more likely to become delinquent than respondents in the lowest quintile (see Table A.3).[19] The estimated effects of respondents' job tenure and recent unemployment spells are not statistically distinguishable from zero. We further control for education, self-employment status, as well as respondents' occupations and industries, which Drewianka (2010) has shown to affect earnings stability in the cross-section using data from the PSID. Not surprisingly, greater educational attainment translates into a lower delinquency rate, e.g., an advanced degree by 2.8 percentage points, whereas self-employment manifests itself in a more than 6.5 percentage point greater expected delinquency rate.[20]

Replacing current income (taken from the 2004 survey) with a measure of permanent income (average income over years 1996–2004) improves the contribution of the debt-to-income ratio for predicting delinquencies, but has no discernable impact on the income gradient or the obesity effect (column 3). The estimate of the obesity effect on delinquencies is also highly robust to increasing the flexibility of the specification. The marginal effect remains 0.038 when we create deciles instead of quintiles for the continuous characteristics (column 4) and is 0.036 when we include dummies for each $5,000 increment in income, $10,000 increment in wealth, and 5% increment in the debt-income and debt-asset ratios, as well as earnings instability (column 5).[21]

[19]The results are similar if we measure income risk as the standard deviation in the growth rate of net family income.

[20]Measuring unemployment at the household level rather than the respondent level would be more appropriate. Unfortunately, the NLSY only has information on whether a spouse was employed during the last year (which does not match up with the unemployment indicator for the respondents' unemployment spells since the last interview). Untabulated results show that controlling for spousal unemployment has no impact on the obesity effect or the respondent's unemployment effect.

[21]In this specification, we lose about 24% of the sample, because certain attributes perfectly predict delinquency (the benchmark estimate over this subsample yields a point estimate on obesity of 0.036). Untabulated tests show that the obesity effect is also robust to polynomial specifications (including logarithmic transformations, which cause

In column 6, we add county fixed effects (and cluster standard errors by county) to address the concern that the relationship between obesity and delinquency is driven by unobserved local economic shocks, especially since it is plausible that vulnerability to such shocks correlates with local obesity rates. The marginal effect of obesity on delinquency increases to 0.047, while its statistical precision remains almost unchanged (a standard error of 0.014). Due to sparse coverage, some counties lack variation in delinquency and consequently drop out of the estimation, lowering the sample size to 5,826 respondents. To ensure that the change in the obesity effect is not an artifact of sample selection, we re-estimate the benchmark model from column 2 on the sample used in column 6. Comparing columns 6 and 7 reveals that the obesity effect is not attributable to differences in local conditions.[22,23]

Gronniger (2006) argues that variation in BMI within a broad category need not have a monotonic effect on outcomes like mortality. As such, the optimal level of BMI may not belong to the BMI category with the best average outcome. To gain a better understanding of the relationship between BMI and delinquency across the full range of BMIs, we estimate the relationship between BMI and delinquency semiparametrically.

[Insert Fig. 2 here.]

Figure 2 plots the predicted probability of delinquency for a typical individual at any given level of BMI. The upper panel shows the relationship between delinquency risk and

a loss of up to 2,799 observations due to earnings, leverage, and coverage ratios of zero, or negative wealth), to the inclusion of longer income and wealth histories, and to various interactions between income, wealth, and indebtedness.

[22]Because respondents' place of residence is available only through the restricted NLSY Geocode file, we continue our analysis without geographic fixed effects for easier replicability.

[23]In Appendix A.1.1., we document robustness in three additional dimensions. First, our results extend to alternative measures of financial distress, namely bankruptcies and maxed-out credit cards. Second, we show that credit risk tends to rise across the BMI categories, i.e., the result is not driven by our simplification of comparing delinquency rates between the obese and non-obese. Third, we obtain similar results utilizing the survey waves from before the financial crisis. In Appendix A.1.2., we use the covariates from the benchmark model to obtain a propensity score of obesity to make the two groups comparable along their observable characteristics. We find that propensity scoring further strengthens our estimate of the effect of obesity on delinquency.

BMI without controlling for any covariates; the lower panel shows the relationship after purging the effect of all benchmark controls. All covariates other than BMI are collapsed into a delinquency propensity score, which is treated parametrically; the plot is scaled up to the delinquency rate at the average propensity score. We find that the delinquency risk increases over most of the BMI spectrum and most drastically between BMIs of 30 and 37. The evidence suggests that our main result is not qualitatively sensitive to the categorization of excess weight.[24]

3.2. Does Obesity Proxy for Omitted Credit Risk Factors?

The possibility remains that we are missing some important information that is available to lenders, like data on the number of credit accounts, credit limits, and utilization. Those measures may also be correlated with obesity, for the same reasons that we expect obesity to proxy for credit risk in the first place. This raises the question whether the obesity effect that we have documented so far is attributable to omitted variable bias.

We have already incorporated lenders' information contained in credit decisions on loan applications into our control variables. Here, we investigate its properties in more detail. First, we test whether obesity also predicts credit denials. If obesity does in fact predict denials after controlling for the other credit risk factors, then it might proxy for omitted variables that are available to the lender. In a second step, one could then test whether the informational overlap between obesity and denial is the same as the overlap between obesity and delinquency.

Column 1 of Table 5 shows the results of the first test. The sample is restricted to respondents who in the 2004 survey said they had applied for credit. The credit decision (*Denial*) is now the dependent variable (equal to one if the loan application was rejected). We include the full set of observable and permissible credit risk factors as controls, with the

[24]Unlike BMI, height is not systematically related to delinquencies.

exception of the credit decision itself. The coefficient on obesity is 2.5 percentage points, with a standard error of 2.0 percentage points (a p-value of over 20%). We cannot reject the hypothesis that obesity is not reflected in credit decision.

[Insert Table 5 here.]

When we regress delinquency on obesity (and the controls), the coefficient on obesity is large and significant (4.8 percentage points in column 2). Controlling for the credit decision (column 3) and conditioning on credit approval (column 4) does not take away from the obesity effect on delinquency. The results indicate that the credit decisions contain no informational overlap with obesity.[25]

The test, however, is subject to an important caveat: it does not account for the potential pricing of credit risk. Credit issuance decisions are not merely based on credit risk, but weigh risk against expected return. Unfortunately, our data does not include information on credit pricing. Nevertheless, the test can remain informative to the extent that credit pricing does not completely offset credit risk. E.g., wealth, earnings instability, and credit histories strongly predict credit denials in the same direction as they predict delinquencies, which suggests that differential pricing does not render these factors irrelevant in credit issuance decisions. We conjecture that the same holds for obesity.

The statistical fit of our model — a Pseudo-R^2s of about 16% in the benchmark model — matches or surpasses that of other credit risk models in the literature (though the numbers are not directly comparable due to differences in samples, measurements, and methodologies). Gross and Souleles (2002), for example, obtain Pseudo-R^2s of about 14% in dynamic probit regressions explaining delinquencies and 13% explaining bankruptcies after controlling for account age, credit utilization, internal and external credit scores, and

[25] NLSY respondents also report whether they chose not to apply for credit because they believed that their loan request would be denied. In unreported regressions we find that the obese are 1.4 percentage points less likely to apply for credit conditional on baseline controls, but the point estimate is neither economically large nor statistically different from zero (the standard error is 32.9 percentage points).

local economic conditions (many of their variables were collected by the credit card issuers themselves). Vissing-Jørgensen obtains Pseudo-R^2s of about 10% in predicting loss rates with information on account age, loan amounts, down payments, interest rates, loan terms, credit limits, repayment histories, credit scores, demographics, and store fixed effects. Using the area under the receiver-operator-curve as their measure of screening power (AUC), Iyer, Khwaja, Luttmer, and Shue (2014) obtain a value of 0.714 for the econometrician's in-sample delinquency prediction model with access to all coded data in Prosper (including standard financial variables, credit scores, soft information, and interest rates charged). The corresponding AUC value of our benchmark model is 0.754. The relatively decent fit of our model in explaining delinquencies suggests a limited scope for omitted variable bias driving the obesity effect.

3.3. Personal and Demographic Characteristics that Are Prohibited by Law

One important concern about using obesity in assessing credit risk is that it merely proxies for factors that are known to be correlated with credit risk, but are by law prohibited from being used in credit decisions.[26] For example, it is well-known that obesity and default rates are higher among blacks and Hispanics (e.g., CDC (2009), Martin and Hill (2000), and Pope and Sydnor (2011)). In Table 6, we individually introduce indicator variables for ethnicity, gender, marital status, religious affiliation, and age as control variables (in addition to all the controls used in the benchmark regression).

[Insert Table 6 here.]

[26]ECOA makes it unlawful for lenders to discriminate against credit applicants with protected personal or demographic characteristics. The prohibition is far reaching, from discouraging applications to differential loan pricing. Under the Federal Reserves Regulation B, which implements ECOA, protected characteristics include race, ethnicity, gender, marital status, religion, and to a limited extent age. Furthermore, Regulation FF does not allow lenders to use medical information in credit eligibility or pricing decisions.

Controlling for these prohibited characteristics does not affect our estimate of the obesity coefficient in any meaningful way, though some of the factors are correlated with delinquency. Relative to whites, blacks are more likely to be delinquent by 4.1 percentage points, suggesting that ethnicity proxies for unobserved socioeconomic factors. We also find that women are more likely to be delinquent than men, by about 2.6 percentage points. While those never married, separated, divorced, or widowed are more likely to be delinquent than married borrowers, the effect is relatively small in magnitude (1.3 and 1.4 percentage points) and not statistically significant at conventional levels.[27] Delinquency risk does not differ by religious affiliation, both in respondents' youth (not reported) and adulthood (as surveyed in 2000). While BMIs tend to increase with age up until the mid 50s or early 60s (e.g., Baum and Ruhm (2009), DiNardo, Garlick, and Stange (2010)), the age profile does not play an important role in our study, largely because the NLSY participants' age range is limited (an interquartile range of only 5 years).[28]

3.4. Is Obesity Risk Economically Relevant?

Income or expenditure shocks that interfere with debt payments are called trigger events. The three key trigger events are job displacements, marriage dissolutions (due to separation, divorce, or death of a spouse), and health shocks. One way to assess the economic magnitude of obesity risk is to compare it to the marginal effects of known trigger events. Unlike obesity,

[27]In unreported robustness tests, we also interact ethnicity, gender, and marital status. The estimated obesity effect remains quantitatively similar.

[28]Throughout the paper, using this specification with the expanded set of control variables as an alternative benchmark model does not substantially impact our results, with one exception. The only instance in which the estimates are sensitive to the inclusion of the additional covariates is Table 8, panel A, column 1. Specifically, when the obesity propensity score is based on the larger set of controls, then the obesity effect is about equal across all five quintiles of the obesity propensity score. However, including the additional controls in estimating the credit risk score does not change the estimates in Table 8, panel A, column 4. The interpretation is that the obesity effect varies with the economic rather than the prohibited predictors of obesity.

which is highly persistent, these trigger events represent sudden shocks to respondents' economic and financial well-being.[29]

Table 7 presents the results. Each regression controls for the full set of credit risk characteristics used in the benchmark regression (column 2 in Table 4). Based on the estimates shown in column 4, those who become unemployed between 2004 and 2008 are 6.1 percentage points more likely to become delinquent than those who do not experience unemployment. Similarly, those whose marriages dissolve are 4.6 percentage points more likely to become delinquent. Disability increases the probability of delinquency by 6.5 percentage points. At face value, the relative impact of obesity on delinquency is 62% of the unemployment effect, 83% of the marriage loss effect, and 58% of the disability shock.

[Insert Table 7 here.]

However, as indicated in column 5, obesity occurs more frequently in the population than the three trigger events. In 2004, 27.7% of the population born between 1957 and 1964 was obese, but only 7.4% saw their marriage dissolve over the subsequent four years. After adjusting for the relevance of each credit risk in the population, the incidence of obesity on delinquencies ($= 0.038 \times 0.277 = 1.05\%$) is almost on par with that of unemployment (1.08%), triple the magnitude of the impact of marriage dissolutions (0.34%), and double the impact of disability (0.49%).[30]

By how much would obesity affect interest rates if it were priced? The following back-of-the-envelope calculation provides a ballpark estimate. Assume that lenders are risk-neutral,

[29] We identify health shocks as the onset of job limitations in 2006 or 2008, i.e., we count only those cases in which the respondent did not have health limitations in 2004. To identify disability shocks, researchers typically use the stricter definition of the onset of a job limitation that lasts at least two consecutive survey waves. Our results are quantitatively similar if we employ the stricter definition.

[30] That is, we calculate the contribution of each trigger event to the overall delinquency rate in the population. Denote delinquency as D, obesity as O, and non-obesity as $\overline{O}$. Then $\Pr(D) = \Pr(D|O)\Pr(O) + \Pr(D|\overline{O})\Pr(\overline{O}) = \Pr(D|O)\Pr(O) + \Pr(D|\overline{O})\big(1 - \Pr(O)\big) = \Pr(D|\overline{O}) + \big[\Pr(D|O) - \Pr(D|\overline{O})\big]\Pr(O)$. Multiplying the estimated marginal effect of obesity $\Pr(D|O) - \Pr(D|\overline{O})$ by its prevalence $\Pr(O)$ yields the difference between the observed delinquency rate in the population and the rate that would prevail if all respondents were non-obese.

expect a rate of return of 6%, and incur losses of 20% in the event of a default. Let the probability of a default across all outstanding consumer loans be 5% and the amount of consumer debt owed by the obese be proportional to their prevalence in the population (30%).

First, we calculate the conditional probabilities of default for obese and non-obese borrowers by equating their default probabilities, weighted by their prevalence in the population, to the unconditional default rate:

$$0.3 \times \Pr(D|O) + 0.7 \times \Pr(D|\overline{O}) = 5\%. \tag{1}$$

Based on our benchmark estimate that the obese are 20% more likely to default than the non-obese, we find that $\Pr(D|\overline{O}) = 4.72\%$ and $\Pr(D|O) = 5.66\%$.

Second, for the lenders to earn an expected return of 6%, their required returns on loans that do not default (R_o for the obese and $R_{\overline{o}}$ for the non-obese) must offset the loss they incur on defaults:

$$(1 - 4.72\%) \times R_{\overline{o}} + 4.72\% \times (-20\%) = 6\% \tag{2}$$

$$(1 - 5.66\%) \times R_o + 5.66\% \times (-20\%) = 6\%. \tag{3}$$

Solving for R yields $R_{\overline{o}} = 7.29\%$ and $R_o = 7.56\%$, or an obesity risk premium of $7.56\% - 7.29\% = 0.27\%$.

3.5. Cross-sectional Variation in the Informativeness of Obesity

How does the predictive power of observed obesity vary cross-sectionally? The answer to this question is of interest for many reasons, including substantiating our interpretation of the result, assessing its robustness across subsamples, and finetuning our understanding of when conditioning on obesity is most valuable.

At first glance, if obesity proxies for omitted socioeconomic factors that are related to delinquency (perhaps a lingering concern to some readers), then we would expect it to be most informative in the economic environment that gives rise to both obesity and delinquency (e.g., among those with low income and wealth). On the other hand, there are several plausible reasons to expect obesity to be particularly informative when it is *least* likely.

First, to the extent that obesity contains credit-risk-relevant information, it will be revealed to lenders over time, as higher risk translates into more frequent bad realizations. Therefore, we might find the predictive power of obesity for future delinquencies to be lower for borrowers who already have poor credit histories. Second, obesity is less prevalent among individuals with higher incomes and wealth, but those are precisely the individuals with the greatest ability and willingness to incur high medical expenditures that can lead to financial distress. Third, obesity has greater potential to be incrementally informative if it reflects borrowers' choices rather than their economic circumstances; choices allow for inferences about borrowers' preferences and decision quality, whereas circumstances are readily observable to lenders in the form of economic constraints.

We explore the cross-sectional variation across a number of variables that capture the explanations above: the obesity propensity score, a credit risk score, race, and gender (see Table 8); and income, wealth, credit history, and debt types (secured vs. unsecured) (see Table A.6 in the Appendix).[31]

[Insert Table 8 here.]

[31] Appendix A.1.2. details the estimation of the obesity propensity score. The credit risk score comes from regressing year 2004 delinquencies on year 2000 covariates without an obesity indicator. The estimated coefficients are then multiplied by the 2004 values of the covariates to obtain a forward-looking assessment of credit risk (with the caveat that this credit risk score does not contain information on credit applications or past delinquencies, as those are not available in the 2000 survey). From both scores, we create quintile attributes and interact them with obesity.

As shown in columns 1 and 4 of panel A, obesity has the highest marginal effect on delinquency when obesity is least prevalent and when credit risk is lowest, and the obesity effect is statistically different from zero only in the lowest two quintiles for both scores. The magnitude of the heterogeneity is quite large: the difference in marginal effects between the top and bottom quintiles is $8.0-1.8 = 6.2$ percentage points for the obesity propensity score and $8.7 - 3.3 = 5.4$ percentage points for the credit risk score. The relative magnitude — compared to the average delinquency rate in each quintile — is even larger. For example, the 2008 delinquency rate in the bottom quintile of the obesity propensity score is just 9.4%, whereas it is 31.7% in the top quintile. Also, as shown in the Appendix, the obesity effect is strongest among the top 40% of the income distribution and the top 20% of the wealth distribution. Among respondents without prior bankruptcies, delinquencies, and credit denials, the obese are 4.5 percentage points more likely to become delinquent. Among those with damaged credit history, the marginal effect of obesity is only 2.7 percentage points (not statistically different from zero).[32]

It is also of interest whether the obesity effect holds across various demographic groups. Controlling for gender and ethnicity in Table 6 only ensures that the obesity effect is not driven by differences in obesity and delinquency across gender and race. Here we investigate whether the intensity of the obesity effect varies across these demographic groups. To this end, we stratify the sample and run separate regressions for each subpopulation. The results are shown in panel B. The obesity effect is evident among Hispanic and white and female and male respondents, but not among blacks. One potential reason for not finding an obesity effect among blacks is greater measurement error in BMI (Burkhauser and Cawley (2008)). Ethnicity-specific exposure to various obesity risk factors can also impact its predictive power for financial outcomes.

[32]Bootstrapped estimates of the standard errors — to account for the uncertainty in estimated rather than observed propensity scores — are almost identical to those reported.

4. What Are the Mechanisms Through Which Obesity Affects Delinquencies?

Rational choice theory attributes heterogeneity in choices (and economic outcomes, by extension) to heterogeneity in decision makers' constraints, preferences, information, beliefs, or decision-making ability. Following Persico, Postlewaite, and Silverman (2004), we assess the mechanisms through which obesity affects delinquencies by introducing a number of additional proxies intended to capture various sources of heterogeneity. If the inclusion of these measures leads to a reduction in the obesity coefficient, then we can conclude that the obesity effect is at least partially attributable to that mechanism.[33] Since the benchmark credit risk model already contains numerous variables capturing heterogeneity in constraints and preferences, the subsequent tests for mechanisms are to be interpreted as attempts to explain the *residual* obesity effect, i.e., only the part that does not already operate through differences in observable and permissible credit risk characteristics. Definitions of mechanism variables, their summary statistics and correlations with obesity (unconditional as well as conditional on benchmark controls) are collected in Tables A.8, A.9, and A.10 in the Appendix.

4.1. Constraints

One plausible explanation for a link between obesity and delinquency is that obesity leads to health-related loss of income or expenditures, and these costs impede borrowers' ability to meet their debt obligations. Obesity has been identified as a leading health risk factor: it is associated with increased risks of heart disease, diabetes, cancer, breathing problems,

[33] The share of the obesity effect attributable to the channel equals $1 - (\beta_{oc}/\beta_o)$, where β_{oc} is the coefficient on obesity after including the channel controls in the regression and β_o is the coefficient on obesity in the benchmark model without the channel controls.

arthritis, depression, premature death, among many other health consequences.[34] Finkelstein, Trogdon, Cohen, and Dietz (2009) estimate that medical per-adult-capita spending is $1,429 (or 41.5%) higher for the obese than for people in the normal-BMI range. In an earlier study, Finkelstein, Fiebelkorn, and Wang (2003) found that about 14% of total medical spending attributable to obesity came out-of-pocket, though more recent estimates put the number at about 10%. Taken together, the average additional out-of-pocket medical spending due to obesity amounts to approximately $143–$200 per adult capita. However, the incidence of medical spending is highly skewed, with a large fraction of the population incurring zero medical expenditures in a given year.

Obesity-related costs do not only come in the form of higher out-of-pocket medical expenditures. According to research by Marketdata Enterprises, 71 million dieters spent $43 billion on weight loss products and programs in the U.S. in 2004 (about $600 per person). Obesity-related health issues can also affect loan delinquencies through the loss of income. Numerous studies have shown that the obese miss more days at work or have lower productivity due to illness or injury (e.g., Hammond and Levine (2010), Wolf (2002), and Tucker and Friedman (1998)). We conjecture that a wage-growth penalty or higher likelihood of job separation for the obese resulting from poorer job performance can adversely affect their ability to meet their debt obligations in the future.

Since the NLSY does not provide data on health-related expenditures, we rely on various proxies for health-related costs to assess the validity of the health-cost channel. The most informative proxy turns out to be respondents' self-assessed health status (ranging from *excellent* to *poor*). The first assessment was taken after respondents turned 40 years old, and repeated once they reached 50. That is, we have data on the health status of most

[34] Further information is available at ⟨`http://www.surgeongeneral.gov/topics/obesity`⟩. See DiNardo, Garlick, and Stange (2010) for a contrarian view. Moreover, a number of studies and books attribute harmful effects not to fatness per se, but to its underlying causes and the obsession with battling it (e.g., see Gaesser (1996), Campos (2004), and Oliver (2005)).

respondents as of 2004 and information on changes in health for 3,167 respondents. Columns 1–3 in panel A of Table 9 show the results (here we include the trigger events from Table 7, because they all affect households' resource constraints and thus provide a good comparison for the health channel). Controlling for respondents' self-assessed health status reduces the marginal effect of obesity on the delinquency rate by an economically meaningful amount, from 3.9 to 2.7 percentage points.[35] In contrast, the obesity effect is not subsumed by the change in health status (this finding re-enforces our earlier finding that controlling for the onset of new disabilities does not explain the obesity effect). Including both health status and change in health status reduces the obesity coefficient to 2.5 percentage points, i.e., 36% of the obesity effect appears to be channeled through health.[36]

[Insert panel A of Table 9 here.]

Insufficient medical insurance coverage can exacerbate households' exposure to medical expenditure risk. To see how the obesity effect varies by insurance coverage, we run separate regressions for respondents with and without continuous health insurance coverage as reported in the 2004, 2006, and 2008 surveys (columns 4 and 5). The obesity effect is more pronounced among respondents without any gaps in coverage and non-existent among those with gaps. Undisclosed regressions show that controlling for health suppresses the obesity coefficient among the continuously insured by about 31%. Rather than disprove the health expenditure channel, this finding suggests that the obesity effect captures *discretionary* health spending. Among households exposed to gaps in health insurance coverage, the incidence of unemployment, marital dissolution, or disability is 41.7% and the delinquency

[35] Further tests show that (i) the absorptive capacity of health is not driven by sickness (i.e., the *fair* or *poor* categories), but by not being in splendid health (i.e., not being in *excellent* or *very good* health) and (ii) the average marginal effect of obesity on delinquency is most pronounced in *good* health.

[36] The NLSY also provides (i) physical component summary scores, which summarize NLSY participants' responses to 12 questions about their physical health, (ii) mental component summary scores, (iii) indicators for about 40 different chronic health conditions, and (iv) use of various medications. Variations and combination of these health proxies provide results similar to those reported here. Results are also robust to accounting for the number of years since the health assessment.

rate is 31.7%. In contrast, among households with continuous coverage, trigger event afflict only 17.5% and the delinquency rate is 13.2%. Hence, the lack of insurance is in itself a symptom of financial distress, which can make additional health expenditures unaffordable and render obesity uninformative. Moreover, trigger events and insurance gaps do not afflict households randomly, but are less prevalent among respondents with higher socioeconomic status and human capital, and those least likely to be obese — precisely the groups in which the obesity effect is more pronounced as shown in Section 3.5. Interestingly, we find no indication that insurance coverage ameliorates the effect of obesity in predicting deterioration in health between 2004 and 2008, which further corroborates the discretionary nature of health spending by the obese.

To gain a better understanding of the sources of the obesity effect, columns 6 and 7 show the effect of obesity on the change in total net family income and wealth between 2004 and 2008. The estimates are obtained using robust regressions. The obesity effect appears to work predominantly through a loss of wealth rather than a loss in income. The obese lose roughly $10,000 in wealth relative to the non-obese (or accumulate less). The magnitude is larger than the $7,500 wealth loss experienced by those who become unemployed. At -$1,000, the effect of obesity on income is substantially smaller, both in absolute value and in comparison to the other trigger events.[37]

We conclude that the effect of obesity on delinquencies is at least partially mediated through health outcomes. Discretionary spending on health maintenance among the obese appears to crowd out other financial obligations, pointing to a moral hazard problem (though we do not know the extent to which respondents become delinquent on new vs. existing debt). Our results on the health channel are broadly consistent with the data reported by Himmelstein, Thorne, Warren, and Woolhandler (2009), who find that income shortfalls or

[37]The results are qualitatively similar using OLS, in predicting the likelihood of an income or wealth loss, and also hold for changes between 2000 and 2004.

medical bills due to illness contributed to 62.1% of all bankruptcies in a random sample of bankruptcy filers in the U.S. in 2007. Most of the bankrupt debtors in the sample were well-educated and middle class. Among the medical bankruptcies, 60% of debtors were continuously covered by health insurance in the two years prior to bankruptcy, and out-of-pocket medical expenses averaged $18,000. Common diagnoses included multiple sclerosis, diabetes, injuries, stroke, mental illnesses, and heart disease, all of which are more prevalent and cause more complications among the obese.

The nature of the relationship between health, obesity, and delinquencies raises further issues. If one subscribes to the view that weight is a choice variable, then conditioning loan decisions on obesity would force the obese to internalize the costs of their caloric intake choices. On the other hand, if one believes that weight is not a choice variable, then obesity would merely proxy for health outcomes. In this case, conditioning loan decisions on obesity would penalize borrowers for health outcomes that are beyond their control. The matter is further complicated by the role of external factors that affect the extent to which weight can be a choice variable (e.g., community characteristics and budget constraints can effectively eliminate choices).

4.2. Preferences

Because obesity is the result of excess caloric intake over an extended period of time, it can contain valuable information about individuals' preferences or characteristics underlying their choices. Two particularly plausible candidates are time or risk preferences, as positive associations between BMI and measures of impatience, present-bias, and willingness to take risk have been documented in prior studies.[38]

[38]See Addoum, Korniotis, and Kumar (2013), Courtemanche, Heutel, and McAlvanah (2014), Ikeda, Kang, and Ohtake (2010), Koritzky, Yechiam, Bukay, and Milman (2012), Scharff (2009), and Smith, Bogin, and Bishai (2005).

Our first measure of risk attitude derives from hypothetical gambles asking respondents to trade their current job for a another one with higher expected but risky income. We use Ahn and Light (2010)'s imputed Arrow-Pratt coefficients of relative risk tolerance following the procedure developed by Kimball, Sahm, and Shapiro (2008). Our second measure uses respondents' Likert-type self-assessment about their willingness to take financial risks (responses range from 0 (no risk) to 10 (lots of risk)). We condense the categories by combining original responses 1–4 and 6–9. Our third measure of risk preferences captures respondents' actual willingness to take financial risks as observed by their portfolios' risky asset share (defined as the fraction of financial assets invested in stocks and mutual funds). The fourth measure captures the variability in wealth, which we estimate as the standard deviation in the growth rate of net wealth over consecutive survey rounds 1986–2000.[39]

The results on the effect of risk preferences are displayed in columns 1–4 in panel B of Table 9. Respondents with low risk tolerance, those willing to take financial risks, and those with the most volatile growth rates in wealth are more likely to experience financial distress. Yet, because these risk preferences are only weakly and inconsistently related to BMI, especially after the inclusion of the benchmark controls, they fail to capture any meaningful fraction of the residual obesity-delinquency effect.

[Insert panels B and C of Table 9 here.]

Our first impatience measure is the DellaVigna and Paserman (2005) factor score, which aggregates information from seven behaviors indicative of impatience as assessed in the 1980–1985 survey rounds.[40] Second, we use NLSY interviewers' assessments of the respondent as

[39]We also tried the following alternatives, without success: (i) using respondents' original risk tolerance categories to the job gamble questions or averaging them over time; (ii) using the original 0–10 Likert categories or combining any 2 or 3 adjacent categories; (iii) including real estate wealth as a financial asset in the calculation of risky asset shares; (iv) using respondents' willingness to pay to avoid a hypothetical gamble or their hypothetical portfolio choice with social security funds to stocks and bonds as alternative proxies for risk preferences.

[40]The indicators include interviewers's assessments of respondents' impatience during the survey, health habits (smoking and drinking), use of contraceptives, participation in vocational clubs in high school, as well as having insurance coverage and a bank account.

impatient or restless in any of the first five surveys as an indicator of impatience, as done by Cadena and Keys (2014). Third, we follow Courtemanche, Heutel, and McAlvanah (2014) in estimating respondents' underlying time preference parameters — an annual discount factor, as well as the quasi-hyperbolic discounting parameters capturing present-bias and impatience — from hypothetical survey questions administered in 2006. This last set of measures is particularly promising, because the authors establish a strong relationship between discount rates and BMI. Its drawback is the potential for reverse causality, as respondents in financial distress are more likely to place greater value on receiving money sooner rather than later.

Columns 5–8 in panel B of Table 9 show the results of including the time preference proxies in the credit risk model. All measures of (im)patience are strong predictors of delinquency, above and beyond what is revealed through other economic outcomes. This finding is particularly remarkable, as the first two measures predate delinquency in our sample by about 20 years. However, including the various proxies for (im)patience has no discernable impact on the obesity effect: the estimate decreases by only about 0.001 relative to a base value of about 0.040.[41] As shown in Table A.10, our first two proxies for impatience do not predict obesity, even unconditionally. While the discount factors are related to obesity unconditionally, additional analysis shows that the magnitude of the effects is quite modest — the time preference parameters explain only 0.3% of the variation in obesity, and moving from the 25th to the 75th percentile in the discount factor distributions increases the likelihood of being obese by only 2 and 3 percentage points. Moreover, most of the information about obesity inherent in discount factors is captured by our benchmark credit risk factors.

None of our further attempts to estimate relationships among obesity, time and risk preferences, and delinquency — including controlling for demographic factors and separate

[41]Because the continuous time preference estimates provide a very good empirical fit, we simply drop observations with missing information on time preferences rather than assigning them a unique category. The values in square brackets in the table provide the point estimate of the benchmark obesity coefficient obtained from the relevant subsamples.

estimations by ethnicity and gender — yield additional insights. We conclude that time and risk preferences do not explain the residual obesity effect.

4.3. Decision-Making Ability and Attitudes

Lundborg, Nystedt, and Rooth (2009) fully attribute the negative relationship between obesity and earnings among 450,000 Swedish men to differences in cognitive and non-cognitive skills and fitness between the obese and non-obese. They conclude that employers utilize obesity to statistically discriminate against employees of lower expected productivity. Furthermore, Agarwal and Mazumder (2013) document a strong association between cognitive skills and the quality of household financial decision-making among members of the U.S. military. The NLSY contains information on respondents' early educational attainment/innate ability in the form of scores on the Armed Forces Qualifying Test (AFQT). As shown in Table 9, panel C, column 1, controlling for quintile attributes of the age-adjusted AFQT scores does not affect the relationship between obesity and delinquencies. Delinquency risk, however, does decrease with higher AFQT scores. For example, those with AFQT scores in the top quintile are 3 percentage points less likely to be delinquent than those in the bottom quintile (p-value of 1.3%).

It is possible that parental influence, environmental as well as genetic, manifests itself in a higher propensity for obesity and financial distress in adulthood. Baum and Ruhm (2009), for example, show that socioeconomic status during childhood is strongly related to adults' BMIs, and Cronqvist and Siegel (2014) provide compelling evidence that genetic factors — as determinants of time and risk preferences and decision-making ability — affect individuals' financial choices. In column 2, we control for parental socioeconomic status, measured as mothers' educational achievement and fathers' presence in the household when respondents were 14 years old. Remarkably, these parental influences have economically and statistically significant incremental predictive power for delinquencies more than 30 years later: respondents whose mother did not complete high school are about 1.8 percentage points more likely to become delinquent, and the absence of the father translates into a 1.9 percentage point increase in delinquency risk. Yet, parental socioeconomic status absorbs almost none of the obesity effect (at 3.7 percentage points it remains close to its benchmark value of 3.8 percentage points).[42]

A design feature of the NLSY allows us to utilize within-sibling variation in estimating the obesity-delinquency relationship. After eligible households were identified for the NLSY, all household members born between 1957 and 1964 were asked to participate in the survey. About half of all NLSY respondents come from households with multiple respondents, and we find substantial variation in obesity outcomes even among siblings. Of the 6,995 respondents, 3,453 have siblings in our sample. Respondents with siblings originate from 1,499 unique households, 596 of which have at least one obese and one non-obese respondent. The results, obtained from a linear probability model with sibling fixed effects, are displayed in column 3. Despite that the sibling fixed effects absorb a large fraction of genetic (siblings share 50% of their DNA on average) and childhood environmental heterogeneity, the point estimate of the marginal effect of obesity on delinquencies remains large at 3.9 percentage points (albeit with moderately lower statistical precision at a standard error of 2.3 percentage points). In fact, the coefficient becomes larger after the inclusion of sibling fixed effect; the benchmark obesity estimate without sibling fixed effects in this subsample is 3.0 percentage points.

NLSY participants are also asked about whether they are trying to lose or gain weight, which may be indicative of respondents' lack of self-control. First, trying to lose weight implies that people prefer to weigh less than they do — an indication of their inability to prevent the accumulation of excess weight (60% of the obese and 34% of the non-obese were trying to lose weight in 2002). Second, we judge self-control by whether respondents who

[42]Neither controlling for fathers' education/occupational prestige nor for respondents' youth height as an alternative proxy for cognitive ability (Case and Paxson (2008)) materially impacts the results.

aim to lose or maintain their weight achieve their goal (60% of respondents fail to lose weight when trying to lose weight and 46% fail to maintain their weight when trying to maintain it, and the failure rates are higher among the obese than the non-obese). To mitigate concerns about financial distress leading to weight gain and failure to achieve weight loss goals between 2004 and 2008, we only utilize information about respondents' weight goals from the 2002 survey and weight change between 2002 and 2004.

Including an indicator variable for weight goals — to lose, gain, or maintain weight, or for not having a goal — reduces the obesity effect from 3.8 percentage points to 2.9 percentage points (column 4). The decrease in the obesity coefficient is driven by the *weight loss* category, i.e., about 24% of the benchmark obesity effect is mediated through respondents' subjective dissatisfaction with their BMI. Untabulated results show that the information content of weight goals for the obesity effect is largely orthogonal to health and health changes. Controlling for goals, health at age 40, and health changes lowers the obesity coefficient to 0.017 (with a standard error of 0.014), for a combined absorption of 55% of the obesity effect. In contrast, failure to achieve the desired weight change between 2002 and 2004 has a very limited effect on the obesity coefficient (column 5). While it does help predict delinquencies, it has less predictive power than the weight goals. Taken together, weight goals are more informative about obesity and delinquency than the accomplishment of dieting goals in the short run. Note that these results are not only consistent with a lack-of-willpower interpretation, but also with costly dieting.[43]

Finally, we investigate if the obesity effect captures credit-risk-relevant beliefs and attitudes. Because the obese and non-obese are easily distinguishable in social interactions and obesity carries a social stigma, their experiences are likely to manifest themselves in

[43] Our findings are qualitatively robust to alternative definitions of lack of willpower. To define failure, we tried combinations of different benchmarks (e.g., lose weight vs. lose or maintain weight) and more or less stringent assessments of achievement (e.g., whether a weight change of 5 lbs is considered a gain/loss or no change), as well as tests conditional on weight goals. Controlling for measures of overconsumption as proposed by Zhu (2011) also does not lower the obesity coefficient.

systematically different beliefs and attitudes, such as trust and trustworthiness. In our sample, 31% of non-obese vs. 38% of obese participants report to trust other people 'never' or only 'once in a while'. There are numerous pathways from trust and trustworthiness to financial outcomes, e.g., through people's willingness to take social risks, the revelation of respondents' private information about their own trustworthiness by extrapolation from themselves to others, or adherence to good and bad financial advice. The link between trust and household financial decisions and outcomes is borne out in the data (e.g., see Guiso, Sapienza, and Zingales (2008), Duarte, Siegel, and Young (2012), and Jiang and Lim (2013)).

Moreover, individuals with an external locus of control — those who believe that life outcomes tend to be determined by external circumstances rather than through self-motivation and self-determination — might be less proactive in matters of personal health and finance. Indeed, an external locus of control is associated with poor eating and exercise behaviors and BMI (Fan and Jin (2014)) and lower saving rates and wealth accumulation (Cobb-Clark, Kassenboehmer, and Sinning (2014)).

Columns 6 and 7 show our results controlling for trust and locus of control. Trust has predictive power for delinquencies in our credit risk model, but the Rotter score does not. Relatively distrustful respondents are 6.0 percentage points more likely to be delinquent than those who say they can trust others *always* or *most of the time*.[44] These potential channels, too, fail to absorb much of the obesity coefficient. Though both attitude measures are unconditionally associated with obesity, the association weakens considerably after controlling for the benchmark credit risk factors.

[44]The trust effect might reflect reverse causality, as the trust question was asked only in the 2008 survey. The Rotter score, a measure of locus of control developed in the psychology literature, comes from the 1979 survey.

5. Conclusion & Discussion

Our empirical findings highlight the potential for distortions in household credit markets. Failure to price obesity risk would constitute an unintended redistribution of wealth from the non-obese to the obese, with possible adverse consequences for the allocation of capital and personal investment in health. Without data on the pricing of obesity risk, however, our results are merely suggestive of cross-subsidization. Gaining a deeper understanding of the economic drivers behind the obesity effect also remains an important area for future research. On the one hand, if obesity is informative about the inherent type of the borrower, then a rise in the obesity rate would have no effect on total defaults, but could prove beneficial for more accurate credit risk models. On the other hand, if obesity increases cash flow risk, then its increased prevalence could be a contributing factor to the high default rates in consumer credit markets.

By shedding light on the potential economic value of statistical discrimination of obesity in the credit market, our results inform the discussions on the desirability of providing legal or regulatory protection to the obese. While U.S. federal regulations (ECOA) currently restrict the use of medical information in the provision of credit, it is not clear whether obesity would be considered a medical condition per se. Health insurance markets — similar to credit markets in their actuarial nature, but with a richer history of attempting to price obesity risk — are subject to continually evolving regulations expanding or limiting the set of permissible risk classifications in an effort to balance concerns for financial and social equity. Until the enactment of the Patient Protection and Affordable Care Act in 2010, the use of weight or BMI in underwriting of individuals' medical insurance policies was not restricted by any federal regulation. Group health plans offered as employment benefits, on the other hand, are subject to Title VII of the Civil Rights Act and the Health Insurance Portability and Accountability Act (HIPAA), which mandate equal treatment of all employees and prohibit conditioning medical insurance on health status. Exceptions added to HIPAA in 2006 opened the door to differential pricing between the obese and non-obese in employers' group health plans. Numerous large employers responded by offering wellness programs to their employees with monetary incentives for healthier lifestyles. The State Employees' Insurance Board of Alabama, for example, approved a policy under which obese employees will have to pay an additional $25 per month in health insurance beginning in 2011 if they do not make sufficient progress toward lowering their BMI.

Despite the similarity between race and obesity in predicting credit risk, they are treated differently under U.S. law (Kirkland (2008)). In both cases, the empirical results establish statistical stereotypes that are based on the logic of actuarial personhood. Whose personhood is to be protected from statistical discrimination is up to the law. Unlike being black, obesity is not an immutable trait. The obese have neither been the target of government attempts to subordinate them nor been denied access to public life and opportunity. Thus, Kirkland concludes, "As long as being fat is like being a smoker, it will never be like being black." Incidentally, smoking has a similar effect on delinquency risk as obesity in our sample (an average marginal effect of 3.7 percentage points). It also appears to operate through health, and is associated with income and wealth loss. The smoking effect is somewhat sensitive to controlling for the impatience factor score of DellaVigna and Paserman (2005), which subsumes information on youth smoking behavior.[45]

[45]Even without explicit legal restrictions, the actuarialization of obesity can conflict with the protections afforded under antidiscrimination law. For credit score models to comply with antidiscrimination rules, the characteristics included in the model must have sufficient business rationale, yet not disproportionately affect protected populations. While the obesity effect is not driven by the disproportionate prevalence of obesity among blacks, the use of obesity in credit modeling may still have a disparate (and even unjustified) impact on them.

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Figure 1: Distribution and Categorization of BMI

We compute body mass index (BMI) from NLSY respondents' self-reported height and weight. As our measure of adult height, we use the average of the heights reported in 1985, 2006, and 2008. The weight measure comes from the 2004 survey. The classification of BMIs into under/normal/overweight and obese categories reflects 2004 WHO standards. Data source: NLSY79.

Interpretation: 28% of the NLSY participants in our sample are obese, which is representative of the U.S. adult population in their 40s as of 2004.

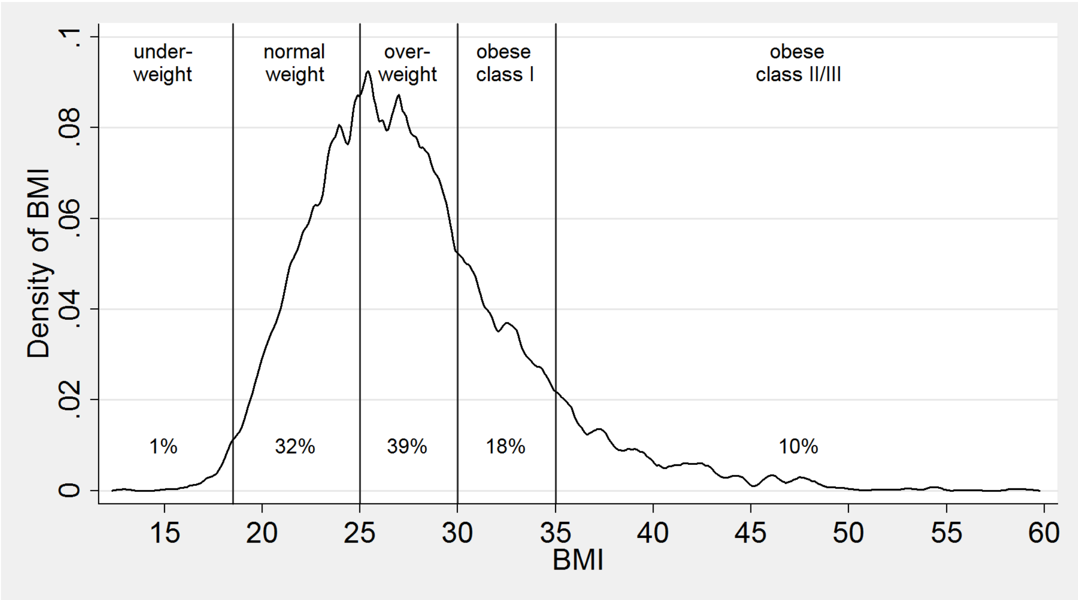

Figure 2: Average Rate of Delinquency Across BMIs — Local Linear Estimates

The plots show the predicted delinquency rate for an average individual at any given BMI, obtained from local regressions. Delinquency refers to missed payments or payments that were late by at least two months over the last five years, as reported by participants in the 2008 NLSY survey. We calculate BMI using the average of individuals' self-reported heights in the 1985, 2006, and 2008 surveys and their self-reported weight in the 2004 survey. The upper panel is based on nonparametric estimates of the relationship between delinquency and BMI without accounting for any control variables. The lower panel is based on semiparametric estimates; all benchmark covariates other than BMI are collapsed into a delinquency propensity score, which is then treated parametrically. Dashed lines represent 95% confidence intervals. Kernel bandwidth = 2, pilot bandwidth = 3. Data source: NLSY79.

Interpretation: In the cross-section, delinquency risk rises with respondents' BMI over most of the BMI range, even after controlling for differences in observable and permissible credit risk factors.

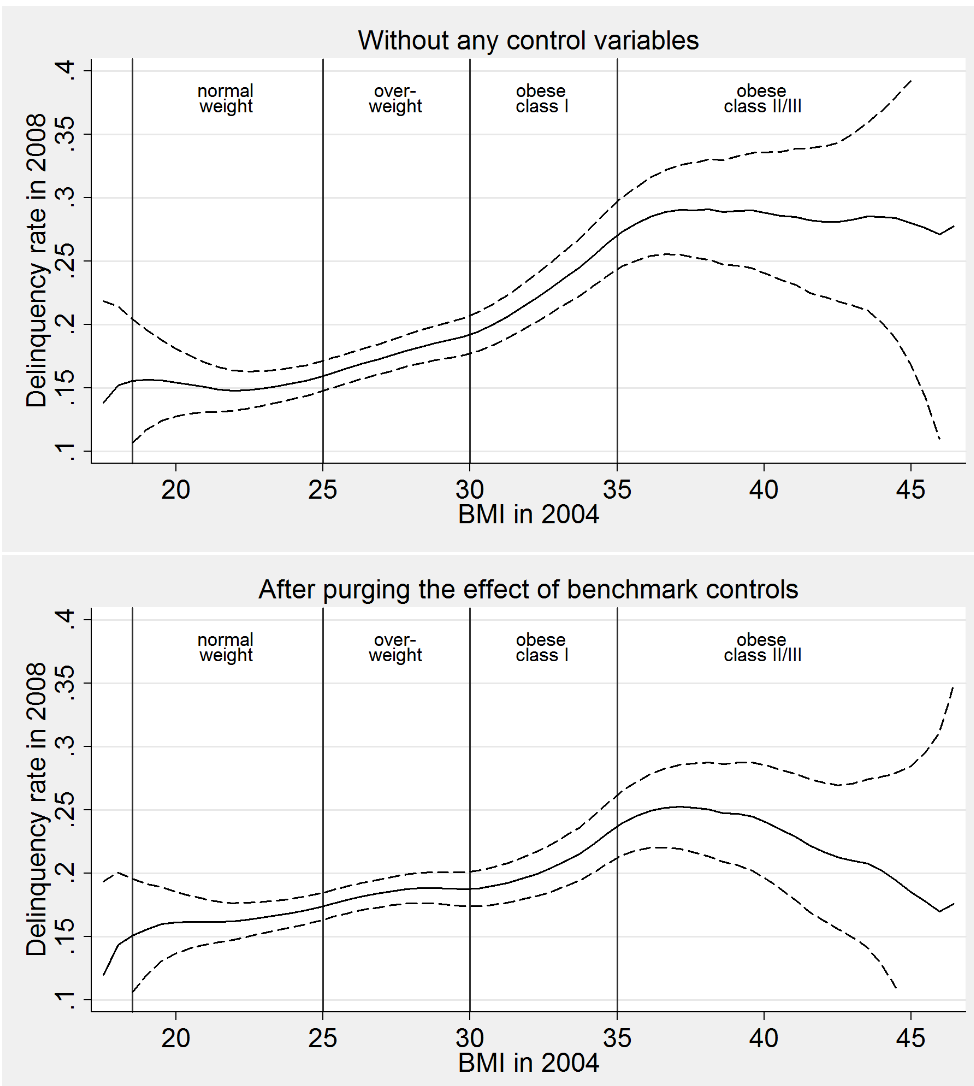

Table 1: **Definitions of Main Variables (Source: NLSY79)**

Variable	Description	Survey year
Obese	Indicator variable for body mass index (BMI) $\geq$ 30. BMI is the ratio of respondents' self-reported weight (converted to kilograms) and height (converted to meters) squared. Weight comes from the 2004 survey; for height, we use the average of the self-reported heights from 1985, 2006, and 2008 (we discard the observations from 1981 and 1982, because respondents may not yet have reached their adult heights at that time).	1985, 2004, 2006, 2008
Delinquent	Indicator variable for yes/no answer to survey question "In the last 5 years, have you completely missed a payment or been at least 2 months late in paying any of your bills?". For most of our credit risk analyses, we use delinquency from the 2008 survey as the dependent variable, and delinquency from the 2004 survey as a control variable.	2004, 2008
Bankrupt	Respondents were asked if they had ever declared bankruptcy, and if so when. First, we combine respondents' answers from the 2004 and 2008 surveys to obtain a cleaner measure of bankruptcies ever experienced (in the 2008 survey quite a few respondents admit to pre-2004 bankruptcies that they did not report in 2004). Next, we construct a measure of bankruptcy flows by counting only bankruptcies that happen 2000–2004 for the control variable, and 2004–2008 for when we use bankruptcy as the dependent variable. We chose 5-year windows to make the bankruptcy flow measure comparable to the delinquency measure.	2000, 2004, 2008
Maxed-out credit card	Indicator variable for households with one or more maxed-out credit cards. Based on the survey question "On how many credit cards do you {or spouse/partner} owe the maximum amount allowed by the credit card company?"	2004, 2008
Recent credit decision	NLSY participants were asked if they or their spouses had applied for credit within the previous 5 years or since their last bankruptcy, whether they were turned down or had been granted less credit than they had applied for, and whether they had not apply because they thought they might be turned down. From respondents' answers, we create four mutually exclusive categories: 1=not applied; 2=applied & accepted; 3=applied & denied; 4=not applied b/c hopeless.	2004
Denied	Only defined for the subsample of respondents who indicated that they had applied for credit in the 2004 survey: 0=applied & accepted (corresponds to category 2 in *Recent credit decision*); 1=applied & denied (corresponds to category 3 in *Recent credit decision*).	2004
Income and wealth	Total net family income in the past calendar year; quintiles. Alternative measure: average income 1996–2004 as a proxy for permanent income. Total net family wealth at time of survey; quintiles.	2004
Income instability	Standard deviation in income 1996–2004, divided by its mean; quintiles. Alternative measure: standard deviation in the biennial growth rate of net family income 1986–2004 (minimum of 4 observations).	1996–2004
Debt/income ratio	All debts (credit cards, student loans, business loans, mortgages, home equity loans, tax liabilities, car loans, debt to businesses, debt to other people), scaled by total net family income; quintiles.	2004
Debt/asset ratio	All debts, scaled by all assets (checking/saving account, money market funds, CDs, bonds, stocks, mutual funds, business assets, retirement accounts, insurance plans, tax-advantaged accounts, real estate, cars, collectibles, loans made to others); quintiles.	2004
Education	Highest degree ever received. Grouped into 0=nothing; 1=high school; 2=some college; 3=college; 4=advanced/professional. Using number of years of schooling (highest grade completed) from the 2004 survey yields almost identical results.	2008

Job tenure	Total tenure in primary job, reported in weeks as of interview date. Grouped into years: 1=less than one year; 2=less than two years, but more than one; 3=less than three years, but more than two; 4=three or more years.	2004
Industry and occupation dummies	Based on 4-digit 2000 Census codes; follow the classification in the NLSY codebook. Most represented industries are health care, manufacturing, retail trade, educational services, and construction. Most represented occupations in the NLSY are jobs in administration, management, and sales, as well as drivers and machine operators.	2004
Marital status	Marital status as of interview date: 0=never married; 1=married; 2=separated, divorced, or widowed.	2004
Religion	Respondents' religious affiliation: 1=Protestant (incl. Baptist, Episcopalian, Methodist, Lutheran, Presbyterian), 2=Catholic, 3=other (Jewish, other), 4=none. Survey also asks which religion respondents were raised in, spouses' religious affiliation, and frequency of religious attendance.	2000
Unemployment	Indicator variable for unemployment spells since last interview date, as reported in the 2006 or 2008 surveys.	2006, 2008
Marital dissolution	Based on the survey questions that inquire directly about changes in relationship status since the last interview date. The indicator variable equals one if respondent reports separation, divorce, or widowhood in the 2006 or 2008 surveys.	2006, 2008
Disability	Captures health problems that prevent respondent from working a job, or limit the kind or amount of work respondent can do. To capture disability shocks, the indicator variable only counts cases in which the respondent reports health-related job limitations in 2006 or 2008, but did not report any job limitations in 2004.	2004–2008

Table 2: Delinquencies Are an Indicator of Serious Financial Distress

This table shows that delinquent households are about four times more likely to have declared bankruptcy over the same time period. Delinquent respondents are those who have completely missed a payment or been at least 2 months late in paying any bills in the 5 years preceding the interview date. To match the delinquency measure, we construct a bankruptcy flow measure that captures only bankruptcies over the 5 years preceding the interview. Source: NLSY79.

Interpretation: Delinquencies do not merely capture forgotten bills; they are indicative of serious financial distress.

	Bankruptcy rate	
Survey year	2004	2008
	(1)	(2)
Non-delinquent	2.51	2.67
Delinquent	11.78	9.17
Population average	4.20	3.87

Table 3: Summary Statistics, By Obesity

The top and bottom 1 percent of debt-to-income and debt-to-asset ratios have been winsorized. *** 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. Source: NLSY79.

Interpretation: The obese and non-obese differ systematically in their observable credit-risk-relevant, socioeconomic, and demographic characteristics.

	Non-obese			Obese			
	mean	st dev	obs	mean	st dev	obs	Δ
Outcomes: Markers of financial distress (2008)							
Delinquent	0.162	0.369	4,803	0.244	0.429	2,192	***
Bankrupt	0.032	0.177	4,794	0.054	0.228	2,189	***
Maxed-out credit card	0.082	0.274	4,752	0.127	0.333	2,169	***
Credit-risk-relevant characteristics (2004)							
Income	86,507	84,700	4,197	64,556	52,184	1,932	***
Wealth	306,941	549,979	4,695	170,916	340,079	2,148	***
Debt/income ratio	1.517	2.090	4,075	1.403	2.040	1,896	*
Debt/asset ratio	0.494	1.194	4,417	0.686	1.715	2,025	***
Past delinquency	0.159	0.366	4,771	0.244	0.430	2,182	***
Past bankruptcy	0.032	0.177	4,793	0.068	0.251	2,188	***
Limited credit access	0.147	0.354	4,775	0.218	0.413	2,184	***
Income instability	0.395	0.330	4,555	0.364	0.303	2,094	***
> High school educ	0.318	0.466	4,752	0.205	0.404	2,168	***
Self-employed	0.104	0.306	4,803	0.076	0.266	2,192	***
Job tenure	7.743	6.854	4,149	7.939	6.953	1,856	
Unemployed	0.128	0.335	4,546	0.127	0.333	2,056	
Out of labor force	0.274	0.446	4,591	0.270	0.444	2,091	
Sociodemographic characteristics (2004)							
White	0.821	0.383	4,803	0.721	0.449	2,192	***
Male	0.513	0.500	4,803	0.514	0.500	2,192	
Currently married	0.657	0.475	4,803	0.631	0.483	2,192	*
Protestant	0.502	0.500	4,803	0.554	0.497	2,192	***
Age	43.301	2.337	4,803	43.381	2.255	2,192	

Table 4: Marginal Effect of Obesity on Delinquency After Controlling for Credit-Risk-Relevant Variables that Are Observable and Permissible

The first row in the table displays average marginal effects of obesity on subsequent delinquency, estimated from credit risk probit models. Obesity is a dummy variable for NLSY79 respondents with BMI $\geq$ 30 based on self-reported height and weight in 2004, and delinquency is a dummy variable for those respondents with missed or late payments between 2004 and 2008. For example, the obesity estimate in column 2 indicates that obese respondents were on average 3.8 percentage points more likely to report delinquency four years later than non-obese respondents (the delinquency rate in the sample is 20.5%), after controlling for all credit-risk-relevant factors available in the NLSY that are permissible by law and observable by lenders. 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. The values in rows *Income–Occupation dummies* indicate the total number of attributes for each characteristic (i.e., the number of dummies capturing the range of each control variable, most of which come from the 2004 survey). For example, the benchmark specification in column 2 features 5 quintile attributes for continuous characteristics, plus one attribute for missing observations; the bottom quintiles are the omitted categories. Tables A.1, A.2, and A.3 provide average marginal effects of the control variables and show how the marginal effect of obesity changes as we add characteristics one at a time. Gray-shaded cells highlight how the specification in each column differs from that of column 2. In column 3, we replace current income (taken from the 2004 survey) with average income over survey years 1996–2004 (a proxy for permanent income). In columns 4 and 5, we increase the flexibility of the specification by increasing the number of attributes for continuous underlying characteristics. Column 6 includes geographic fixed effects for households' county of residence in 2004 (NLSY respondents' location data is available in the restricted access geocode file from the BLS); column 7 replicates the benchmark estimate for the county-fixed-effects subsample.

Interpretation: Obesity remains an economically and statistically strong predictor of financial distress after flexibly controlling for all credit risk factors that are permissible for credit scoring by law, observable by lenders, and available in the NLSY.

	No controls (1)	**Bench-mark (2)**	Perma-nent inc (3)	Decile attrib (4)	$, % attrib (5)	County FE (6)	County sample (7)
Obese	0.081***	**0.038*** **	0.039***	0.038***	0.036**	0.047***	0.040***
	(0.013)	**(0.012)**	(0.011)	(0.012)	(0.015)	(0.014)	(0.014)
Income	no	**6**	6	11	34	6	6
Wealth	no	**6**	6	11	64	6	6
Debt/income	no	**6**	6	11	89	6	6
Debt/assets	no	**6**	6	11	30	6	6
Delinquent	no	**3**	3	3	3	3	3
Bankrupt	no	**3**	3	3	3	3	3
Recent credit decision	no	**5**	5	5	5	5	5
Income instability	no	**6**	6	11	23	6	6
Education	no	**6**	6	6	6	6	6
Job tenure	no	**5**	5	5	5	5	5
Self-employed	no	**2**	2	2	2	2	2
Unemployed	no	**3**	3	3	3	3	3
Out of labor force	no	**3**	3	3	3	3	3
Industry dummies	no	**20**	20	20	20	20	20
Occupation dummies	no	**30**	30	30	30	30	30
County fixed effects	no	**no**	no	no	no	yes	no
# of observations	6,995	**6,995**	6,995	6,995	5,336	5,826	5,826
Pseudo-R^2	0.009	**0.162**	0.163	0.170	0.212	0.228	0.162

Table 5: Obesity Does Not Enter Credit Decisions, But Predicts Delinquencies

In this table we investigate whether obesity captures information that is available to lenders, but unobservable to us (the researchers). To this end, we constrain the sample to NLSY79 participants who indicated in the 2004 survey that they had recently applied for credit. On this subsample, we regress the binary variable *Denied* (equals one if credit was denied) on all of the observable and permissible covariates of Table 4 column 2 (excluding the credit application indicator). The average marginal effect of obesity on the credit decision is displayed in column 1; it indicates that the obese were 2.5 percentage points more likely to have been denied credit, though the estimate is not statistically distinguishable from zero. Next we regress *Delinquent* on obesity and the controls included in column 1. Column 2 provides the baseline estimate for the effect of obesity on delinquency without controlling for lenders' information captured in *Denied*. We add *Denied* as a control in column 3, and we condition on credit not having been denied in column 4. The coefficients in columns 2–4 indicate that the obese in those subsamples were 4.6–4.8 percentage points more likely to report delinquency 4 years later than the non-obese, and that respondents who were denied credit were 8.7 percentage points more likely to become delinquent (i.e., *Denied* is incrementally informative about future financial distress). Accounting for lenders' decision to deny credit does not significantly impact the obesity effect 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.

Interpretation: There is no significant informational overlap between obesity and lenders' decision to deny credit.

Dependent var:	Credit denied	Delinquent		
		Baseline	Control for Denied	Condition on Denied=0
	(1)	(2)	(3)	(4)
Obese	0.025	0.048***	0.046***	0.048***
	(0.020)	(0.016)	(0.016)	(0.017)
Denied			0.087***	
			(0.016)	
Benchmark controls	yes	yes	yes	yes
# of obs	3,007	3,007	3,007	2,241
Pseudo-R^2	0.259	0.191	0.200	0.163

Table 6: Obesity Is Not Just a Proxy for Protected Personal or Demographic Characteristics

The table displays average marginal effects of obesity on subsequent delinquency, estimated from credit risk probit models. The underlying empirical models are extensions of the benchmark credit risk model as presented in Table 4, column 2. Every specification includes the full set of attributes of the benchmark model; in columns 1–5, we successively introduce new control variables that are potentially correlated with obesity and credit risk, but are prohibited under ECOA (ethnicity, gender, marital status, religion, and age). The excluded base categories are whites, males, the married, respondents age 39, and Protestants. In column 6, we include all of the new controls. The coefficients on obesity show that NLSY participants who were classified as obese in 2004 based on self-reported weight and height were between 3.5 and 3.8 percentage points more likely to report delinquency in the 2008 survey than non-obese participants (these estimates are not materially different from the benchmark estimate of 3.8 percentage points). Similarly, being black is associated with a 3.9–4.1 percentage point higher likelihood of falling behind on payments. 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.

Interpretation: The obesity effect documented in the benchmark model does not merely reflect personal or demographic characteristics whose use in credit decisions is prohibited by law.

	Ethnicity (1)	Gender (2)	Marital status (3)	Religion (4)	Age (5)	All controls (6)
Obese	0.035***	0.038***	0.038***	0.037***	0.037***	0.035***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Hispanic	0.025					0.030
	(0.017)					(0.019)
Black	0.041***					0.039***
	(0.010)					(0.011)
Female		0.026*				0.026*
		(0.015)				(0.015)
Never married			0.013			0.009
			(0.016)			(0.015)
Separated, divorced, widowed			0.014			0.012
			(0.011)			(0.012)
Catholic				-0.009		-0.008
				(0.013)		(0.014)
Other denomination				0.020		0.022
				(0.019)		(0.020)
No religious affiliation				0.004		0.002
				(0.015)		(0.015)
Age dummies	no	no	no	no	yes	yes
Benchmark controls	yes	yes	yes	yes	yes	yes
# of observations	6,995	6,995	6,995	6,995	6,995	6,995
Pseudo-R^2	0.164	0.163	0.162	0.163	0.163	0.167

Table 7: Comparing Obesity Risk to the Impact of Trigger Events on Delinquencies

The table displays average marginal effects of obesity and various trigger events on delinquency rates. For example, the estimate for the effect of *Unemployment* on delinquency in column 1 indicates that NLSY respondents who experienced an unemployment spell between 2004 and 2008 were 6.5 percentage points more likely to become delinquent. That is, the time window for trigger events matches that for delinquencies, which capture late or missed payments over the preceding 5 years as reported in the 2008 survey. As before, *Obese* is based on respondents' self-reported weight in 2004. In all specifications (columns 1–4), we include the set of controls used in column 2 of Table 4. *Unemployment*, *Marital dissolution*, and *Disability* represent negative shocks to the household. They come from the 2006 and 2008 surveys. *Unemployment* and *Marital dissolution* equal one if a respondent experiences the conditions between 2004 and 2008, and zero otherwise. *Disability* only equals one if respondents are not disabled in 2004 *and* claim disability in the 2006 or 2008 surveys to capture the onset of disability. 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. Column 5 displays the relative frequency of occurrence of obesity, unemployment, marital dissolutions, and disability in our NLSY sample. For example, the entries indicate that 27.7% of respondents are obese in 2004 and that 17.7% experience an unemployment spell between 2004 and 2008. Observations are weighted using NLSY 2004 sampling weights to make sure the sample is representative of this age cohort in the U.S. adult population.

Interpretation: In comparison to adverse life events known to trigger financial distress, the impact of obesity on delinquency is economically substantial; its economic importance is further magnified by its more frequent occurrence in the population.

	Estimates				Occurrence
	(1)	(2)	(3)	(4)	(5)
Obese	0.039***	0.038***	0.037***	0.038***	27.7%
	(0.012)	(0.012)	(0.012)	(0.012)	
Unemployment	0.065***			0.061***	17.7%
	(0.016)			(0.016)	
Marital dissolution		0.052***		0.046**	7.4%
		(0.020)		(0.021)	
Disability			0.073***	0.065***	7.5%
			(0.021)	(0.021)	
Benchmark controls	yes	yes	yes	yes	
# of observations	6,995	6,995	6,995	6,995	
Pseudo-R^2	0.167	0.164	0.165	0.171	

Table 8: Cross-sectional Heterogeneity in the Informativeness of Obesity

The table displays estimated average marginal effects of obesity on subsequent delinquency across the quintile attributes of the obesity propensity score and the credit risk score (panel A), and across subsamples stratified by race and gender (panel B). We obtain the obesity propensity score from regressing obesity on all the attributes in the benchmark model of column 2 in Table 4. The credit risk score is the predicted delinquency risk (combining estimated coefficients from the regression of year 2004 delinquencies on year 2000 covariates [excluding obesity] with the covariates' 2004 values). Note that for the credit risk score, data on credit applications and prior delinquencies are not available in 2000, which restricts the credit history controls to just prior bankruptcies. In all specifications, quintile attributes of the obesity propensity score are included (they capture the benchmark controls' correlation with obesity, but discard information about delinquencies that is orthogonal to obesity; thus the lower Pseudo-R^2 compared to the benchmark model). *Range w/in Q* provides the minimum and maximum value of the interacted variable within that particular quintile. *% obese* shows the fraction of the population in each quintile that is obese. For example, the table entries indicate that among respondents, who according to observable and permissible credit risk characteristics are least likely to be obese, the obese are 8.0 percentage points more likely to become delinquent than the non-obese. The predicted likelihood of a respondent being obese according to his/her observable and permissible credit-risk factors ranges between 1% and 17.4% within the bottom quintile of the obesity propensity score, and the actual rate of obesity in this subsample is 12.9%. 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.

Interpretation: Obesity is more informative about subsequent delinquency among respondents who are less likely to be obese in the first place and those in initially favorable economic circumstances.

Panel A: Interactions with Credit Risk Factors

	Average marginal effect of obesity over the quintiles of ...					
	Obesity propensity score			Credit risk score		
	marginal effect	range w/in Q	% obese w/in Q	marginal effect	range w/in Q	% obese w/in Q
	(1)	(2)	(3)	(4)	(5)	(6)
Obese						
× Q1	0.080**	0.010–0.174	12.9	0.087**	0.130–0.191	19.7
	(0.036)			(0.038)		
× Q2	0.060**	0.174–0.242	21.4	0.062***	0.192–0.240	30.0
	(0.026)			(0.021)		
× Q3	0.046	0.242–0.299	25.8	0.025	0.241–0.246	32.7
	(0.029)			(0.017)		
× Q4	0.033	0.299–0.370	34.0	0.018	0.246–0.285	28.4
	(0.036)			(0.023)		
× Q5	0.018	0.370–0.732	44.2	0.033	0.285–0.453	27.5
	(0.028)			(0.036)		
BM controls	yes			yes		
# of obs	6,995			6,995		
Pseudo-R^2	0.046			0.076		

Panel B: Effect of Obesity by Race and Gender

	Race			Gender	
	Hispanic	Black	White	Male	Female
	(1)	(2)	(3)	(4)	(5)
Obese	0.048*	0.006	0.043**	0.034***	0.049**
	(0.027)	(0.014)	(0.018)	(0.010)	(0.019)
BM controls	yes	yes	yes	yes	yes
# of obs	1,326	2,142	3,527	3,394	3,601
Pseudo-R^2	0.026	0.019	0.048	0.030	0.058

Table 9: Which Sources of Choice Heterogeneity Can Explain the Obesity Effect?

To examine potential mechanisms behind the obesity-delinquency relationship, we add proxies for various sources of choice heterogeneity to the benchmark credit risk model. If their inclusion reduces the obesity coefficient, then we can conclude that the obesity effect is at least partially attributable to those mechanisms. In panel A (columns 1–3) we investigate constraints, in panel B risk and time preferences, and panel C decision-making ability and attitudes. Definitions of mechanism variables, their summary statistics and correlations with obesity are collected in Tables A.8–A.10. The panels display marginal effects of obesity on subsequent delinquency, estimated from credit risk probit models (every regression includes the full set of attributes from Table 4, column 2). Values in square brackets are point estimates of the benchmark obesity effect on delinquency risk estimated for the subsample and specification used in that column. For example, the value in the square bracket in column 3 of panel A indicates that obese NLSY respondents were 3.9 percentage points more likely to become delinquent than non-obese respondents, after controlling for the benchmark credit risk factors and accounting for the trigger events. Yet, the average marginal effect of obesity after controlling for self-reported subjective health status and changes in self-reported health at ages 40 and 50 is only 2.5 percentage points. In other words, respondents' subjective health assessments contain information about delinquencies that overlaps with that contained in obesity. In columns 4 and 5 in panel A, we do not add additional controls, but stratify the sample by insurance coverage. In columns 6 and 7 in panel A, the dependent variables are the change in income and wealth (in $) between 2004 and 2008, estimated with outlier-robust regressions. As shown in column 7, obese respondents on average accumulate $9,984 less wealth than non-obese respondents, after controlling for income, initial wealth, and the other benchmark characteristics. 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.

Interpretation: The obesity effect is partially attributable to discretionary spending on health, and may capture self-control problems; it does not seem to reflect differences in time- or risk-preferences, beliefs and attitudes, genetics, or environmental influences during childhood.

Panel A: Constraints — Health Costs

	Health status			By insurance coverage		Source of delinquency	
	Health age 40	Δhealth $40 \rightarrow 50$	Both	Contin-uous	Gaps or none	Dep var: Δinc	Dep var: Δwealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Obese	0.027**	0.038***	0.025*	0.059***	-0.009	-972	-9,984***
	(0.012)	(0.012)	(0.013)	(0.014)	(0.016)	(593)	(2,195)
	[0.039]	[0.039]	[0.039]				
Unemployment	0.060***	0.060***	0.058***	0.054***	0.058**	-4,565***	-7,466***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.025)	(750)	(2,719)
Marital dissolution	0.046**	0.047**	0.047**	0.025	0.071*	-14,549***	-28,400***
	(0.020)	(0.021)	(0.020)	(0.024)	(0.040)	(994)	(3,676)
Disability	0.057***	0.063***	0.049**	0.045*	0.091***	-5,420***	-5,115
	(0.020)	(0.021)	(0.020)	(0.025)	(0.031)	(1,001)	(3,635)
Very good health	0.028**		0.034***				
	(0.012)		(0.012)				
Good health	0.078***		0.092***				
	(0.015)		(0.014)				
Fair health	0.069***		0.091***				
	(0.024)		(0.025)				
Poor health	0.112***		0.147***				
	(0.043)		(0.048)				
Better health		-0.018	-0.038**				
		(0.021)	(0.018)				
Worse health		0.025*	0.046***				
		(0.013)	(0.014)				
Health 50 not available		0.007	0.010				
		(0.011)	(0.011)				
BM controls	yes	yes	yes	yes	yes	yes	yes
# of obs	6,995	6,995	6,995	4,474	2,259	5,564	6,730
Pseudo-R^2	0.178	0.172	0.182	0.168	0.157		

Panel B: Risk and Time Preferences

	Risk preferences			
	Risk tol 1/CRRA Hypothetical (1)	Risk taker Likert Hypothetical (2)	Risky share % stocks Actual (3)	Wealth risk $\sigma(g_{\$})$ Actual (4)
Obese	0.037***	0.037***	0.038***	0.036***
	(0.012)	(0.012)	(0.012)	(0.013)
	[0.038]	[0.038]	[0.038]	[0.038]
Q2	-0.023*	-0.012	-0.010	-0.006
	(0.014)	(0.010)	(0.013)	(0.009)
Q3	-0.030**	-0.011	-0.037*	0.010
	(0.014)	(0.015)	(0.020)	(0.015)
Q4	-0.002	0.015	0.010	0.021
	(0.015)	(0.014)	(0.017)	(0.014)
Q5	-0.037**	0.090***	-0.016	0.042***
	(0.016)	(0.035)	(0.018)	(0.015)
BM controls	yes	yes	yes	yes
# of obs	6,995	6,995	6,995	6,995
Pseudo-R^2	0.164	0.165	0.163	0.165

	Time preferences			
	Impatience DP (2005) Actual (5)	Impatience CK (2010) Actual (6)	Patience CHM (2012) Hypothetical (7)	Patience CHM (2012) Hypothetical (8)
Obese	0.039***	0.039***	0.040***	0.041***
	(0.013)	(0.013)	(0.010)	(0.011)
	[0.037]	[0.040]	[0.041]	[0.042]
Factor score	0.014***			
	(0.005)			
Survey attitude		0.039***		
		(0.009)		
Discount factor			-0.073***	
			(0.008)	
β				-0.058***
				(0.016)
δ				-0.045***
				(0.008)
BM controls	yes	yes	yes	yes
# of obs	6,817	6,806	6,478	6,403
Pseudo-R^2	0.167	0.164	0.168	0.170

Panel C: Decision-Making Ability and Attitudes

	Childhood exposure/genetics				Self-control		Beliefs & attitudes	
	IQ	Parental influence	Sibling FEs		Weight goals	Fail to achieve	Trust	Locus of control
	(1)	(2)	(3)		(4)	(5)	(6)	(7)
Obese	0.037***	0.037***	0.039	Obese	0.029**	0.036***	0.036***	0.036***
	(0.012)	(0.012)	(0.023)		(0.013)	(0.011)	(0.012)	(0.013)
	[0.038]	[0.038]	[0.030]		[0.038]	[0.038]	[0.038]	[0.036]
AFQT Q2	-0.012			Goal: lose weight	0.041***			
	(0.016)				(0.009)			
AFQT Q3	-0.008			Goal: gain weight	0.005			
	(0.014)				(0.024)			
AFQT Q4	-0.025			Goal: none	0.033**			
	(0.021)				(0.015)			
AFQT Q5	-0.030**			Failed goal (wgt $\uparrow$)		0.019**		
	(0.013)					(0.009)		
M educ: HS		-0.017*		Med trust			0.016	
		(0.009)					(0.011)	
M educ: HS+		-0.019		Low trust			0.060***	
		(0.020)					(0.011)	
F present		-0.019**		Rotter score				0.002
		(0.008)						(0.003)
BM controls	yes	yes	yes	BM controls	yes	yes	yes	yes
# of obs	6,995	6,995	3,453	# of obs	6,995	6,995	6,995	6,927
Pseudo-R^2	0.163	0.163	0.147	Pseudo-R^2	0.164	0.163	0.167	0.163

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 test 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 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 5 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 shows 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.[1]

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 differently (e.g., debt-to-income and debt-to-asset ratios) or be excluded from the 2000 credit

[1] 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.

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 that are similar in their observable characteristics (see DiNardo, Fortin, and Lemieux (1996) for an early application and Nichols (2007, 2008) for details on the implementation).[2]

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

[2]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.

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 reweigh 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, Brown, and Mathiowetz (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 τ_{01} is the probability of unreported delinquencies conditional on actually being delinquent (false negatives) and

π_{10} captures false positives (Hausman, Abrevaya, and Scott-Morton (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.[3]

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, Brown, and Mathiowetz (2001) show that the bias factor is

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

where π is the true prevalence of obesity, π_{01} is the probability of false negatives, and π_{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 Figure 1.2.a, average measured BMI in NHANES is about 1.5 units higher than average self-reported BMI in NHIS and BRFSS. Adding the difference to each respondent's reported

[3] Additional bias may arise from inconsistent estimation of the coefficients. Implementing the solution proposed by Hausman, Abrevaya, and Scott-Morton (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⟩.

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%.[4,5,6]

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

[4] 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.

[5] 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 treshold adjustment) and 0.4 (with the threshold adjustment).

[6] 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 datasets (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 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, Brown, and Mathiowetz (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

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.

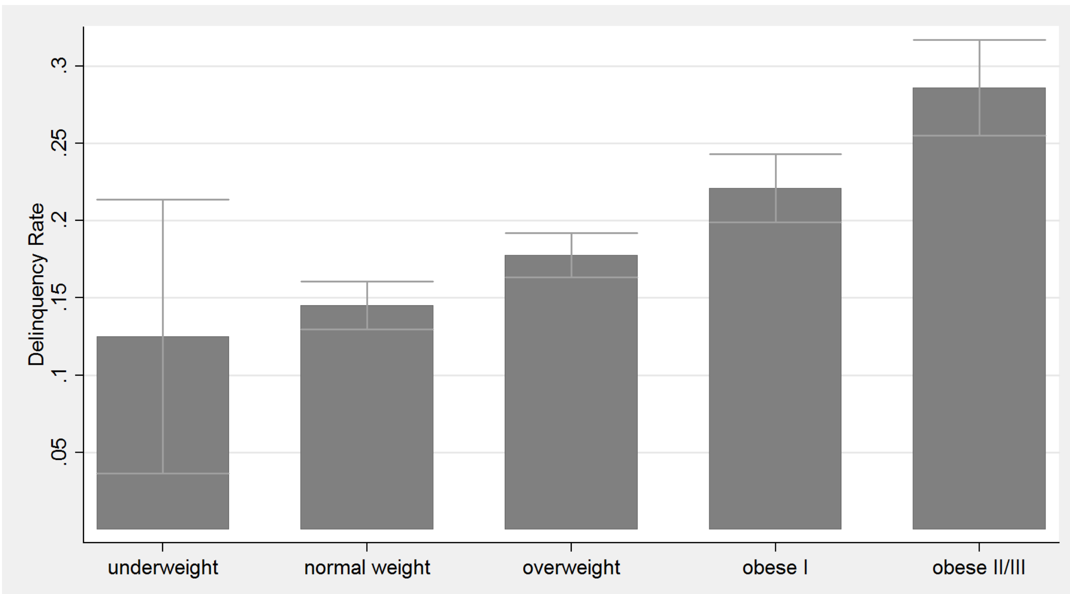

Figure A.2: Bankruptcy Rates Across BMI Categories

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.

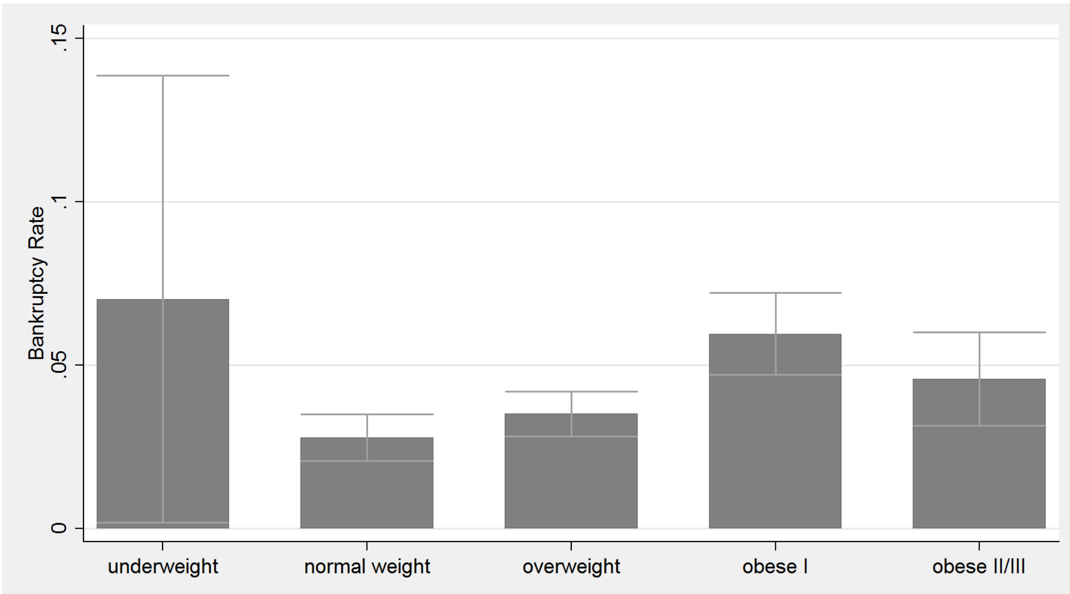

Figure A.3: Economic Environment Before and During the Sample Period

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.

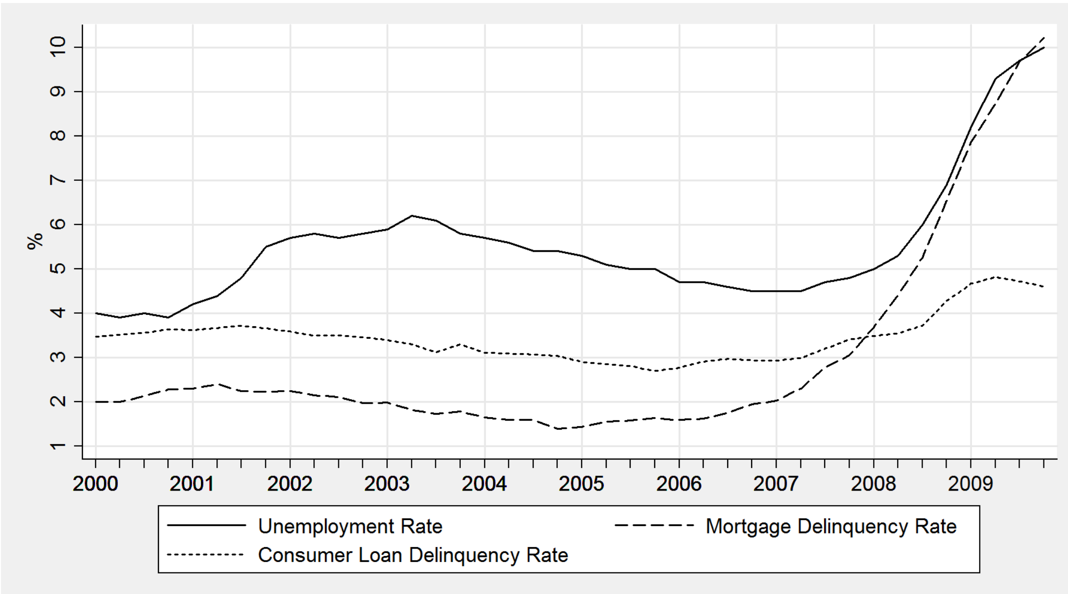

Figure A.4: Comparability of Obesity Propensity Scores Before and After Reweighting

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.

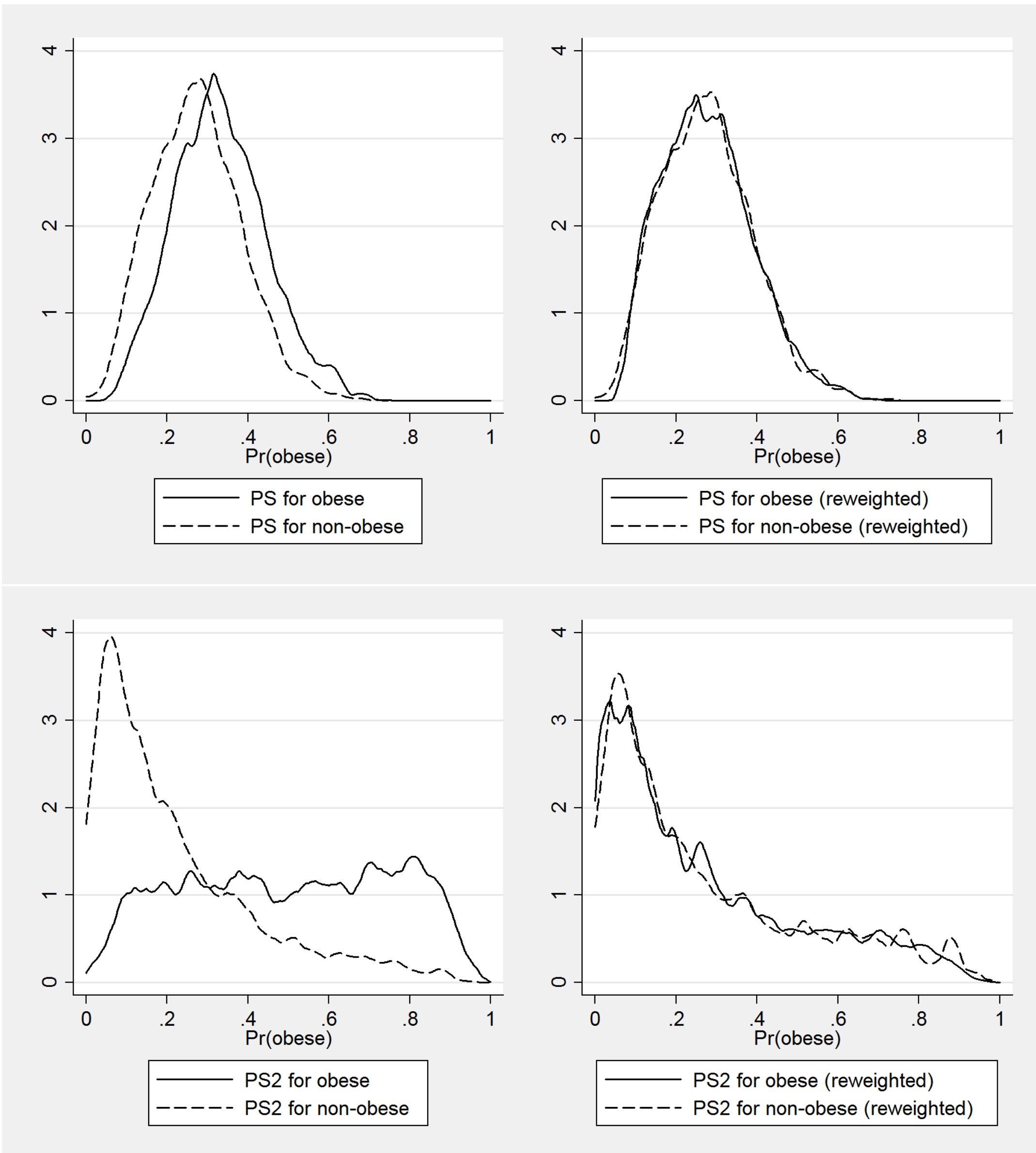

Figure A.5: Comparing the Composition of Nonattrition vs. Attrition Groups

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.

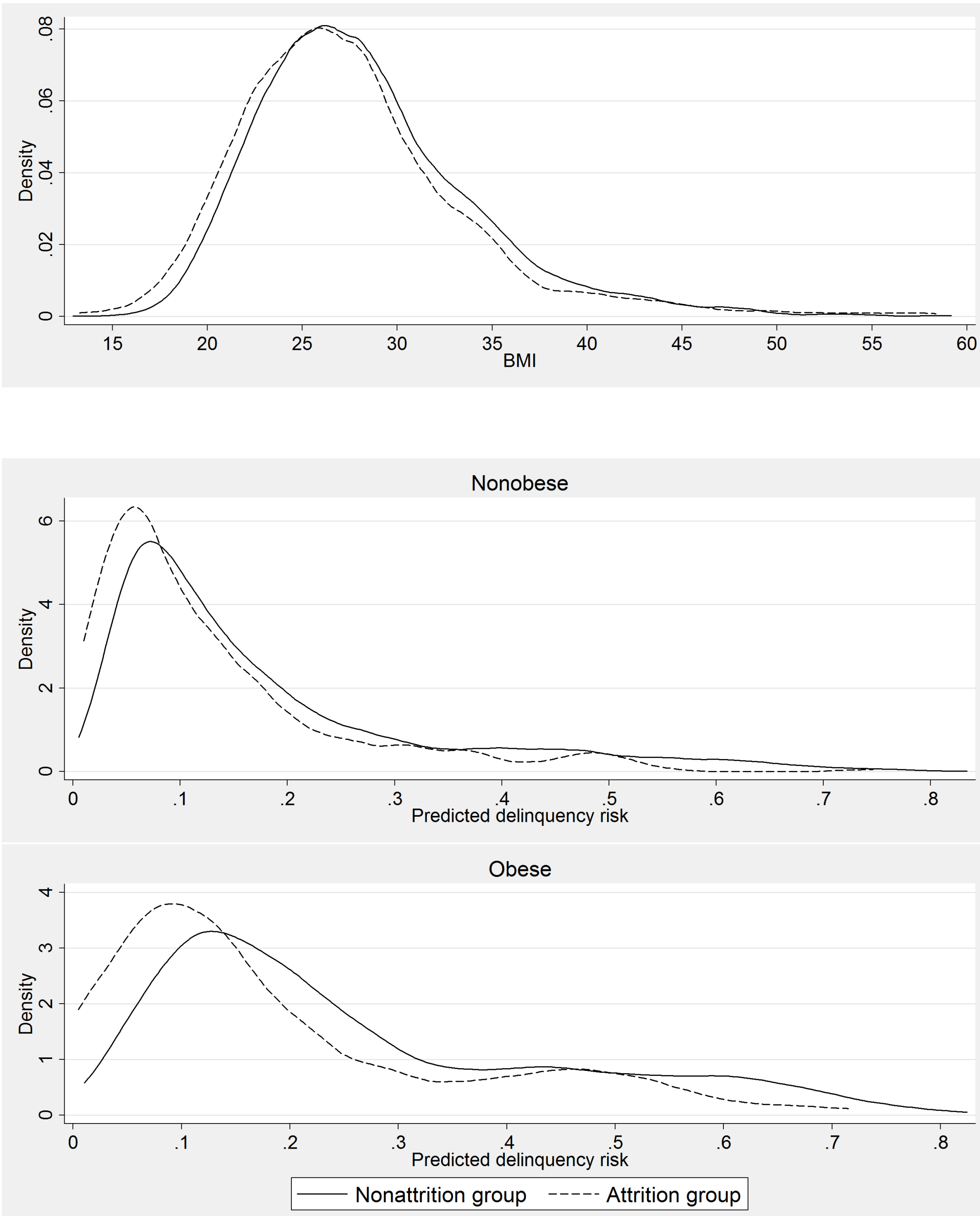

Table A.1: Marginal Effect of Obesity on Delinquency After Controlling for Income, Wealth, and Debt Capacity

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***	0.057***	0.082***	0.070***	0.051***	0.050***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0.016)
Income Q2	-0.068***				-0.055***	
	(0.021)				(0.020)	
Income Q3	-0.110***				-0.064***	
	(0.019)				(0.021)	
Income Q4	-0.150***				-0.083***	
	(0.011)				(0.017)	
Income Q5	-0.204***				-0.117***	
	(0.022)				(0.021)	
Wealth Q2		-0.070***			-0.073***	
		(0.024)			(0.025)	
Wealth Q3		-0.176***			-0.158***	
		(0.018)			(0.023)	
Wealth Q4		-0.196***			-0.165***	
		(0.017)			(0.022)	
Wealth Q5		-0.241***			-0.198***	
		(0.019)			(0.028)	
Debt/income Q2			0.024		0.040	
			(0.020)		(0.027)	
Debt/income Q3			-0.019		0.037	
			(0.017)		(0.028)	
Debt/income Q4			-0.021		0.034	
			(0.017)		(0.029)	
Debt/income Q5			0.027		0.043*	
			(0.026)		(0.025)	
Debt/assets Q2				-0.027	0.037	
				(0.021)	(0.023)	
Debt/assets Q3				-0.022	0.039**	
				(0.014)	(0.018)	
Debt/assets Q4				0.010	0.043*	
				(0.018)	(0.025)	
Debt/assets Q5				0.148***	0.073***	
				(0.017)	(0.022)	
# of observations	6,995	6,995	6,995	6,995	6,995	6,995
Pseudo-R^2	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)

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***	0.049***	0.045***	0.035**
	(0.014)	(0.016)	(0.015)	(0.014)
Delinquent	0.260***			0.232***
	(0.014)			(0.013)
Bankrupt		0.073**		0.006
		(0.031)		(0.024)
Credit approved			-0.014	-0.012
			(0.011)	(0.012)
Credit denied			0.163***	0.091***
			(0.020)	(0.019)
Credit expected to be denied			0.110***	0.043***
			(0.022)	(0.016)
Controls from Table A.1	yes	yes	yes	yes
# of observations	6,995	6,995	6,995	6,995
Pseudo-R^2	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)

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***	0.038***	0.035**	0.036***	0.038***	0.038***
	(0.012)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)
Income instability Q2		0.022*				0.017
		(0.012)				(0.012)
Income instability Q3		0.014				0.008
		(0.014)				(0.014)
Income instability Q4		0.038*				0.030
		(0.020)				(0.019)
Income instability Q5		0.063***				0.048***
		(0.018)				(0.017)
High school degree			-0.013			-0.010
			(0.017)			(0.016)
Some college			-0.008			-0.010
			(0.017)			(0.020)
College degree			-0.028			-0.033
			(0.021)			(0.025)
Advanced degree			-0.028**			-0.040***
			(0.013)			(0.013)
1yr $<$ job tenure $\leq$ 2yr				0.016		0.015
				(0.017)		(0.018)
2yr $<$ job tenure $\leq$ 3yr				0.015		0.018
				(0.022)		(0.026)
3yr $<$ job tenure				-0.009		0.000
				(0.010)		(0.013)
Self-employed					0.065***	0.040
					(0.021)	(0.027)
Unemployed					0.027	0.028
					(0.019)	(0.019)
Out of labor force					0.015	0.001
					(0.010)	(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^2	0.156	0.148	0.146	0.146	0.149	0.162

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

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***	0.009	0.028**			
	(0.012)	(0.006)	(0.014)			
Underweight				-0.064**	0.036	0.016
				(0.029)	(0.043)	(0.040)
Overweight				0.028*	0.000	0.018**
				(0.017)	(0.005)	(0.007)
Obese I				0.040***	0.013	0.032*
				(0.015)	(0.008)	(0.017)
Obese II/III				0.075***	0.004	0.052**
				(0.016)	(0.008)	(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^2	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***	0.019***		
	(0.009)	(0.006)		
Underweight			0.066	0.025
			(0.054)	(0.018)
Overweight			-0.005	0.004
			(0.007)	(0.006)
Obese I			0.055***	0.022***
			(0.018)	(0.006)
Obese II/III			0.071***	0.018*
			(0.020)	(0.010)
BM controls	yes	yes	yes	yes
# of obs	6,958	7,019	6,958	7,019
Pseudo-R^2	0.081	0.171	0.082	0.172

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

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	reweigh	control	reweigh
	(1)	(2)	(3)	(4)
Obese	0.041***	0.040***	0.040***	0.032**
	(0.013)	(0.014)	(0.014)	(0.015)
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	0.017	0.001
Observed prob	0.185	0.185	0.185	0.185
Predicted prob	0.185	0.188	0.185	0.190

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

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	range w/in Q ($ thsd.)	% obese w/in Q	marginal effect	range w/in Q ($ thsd.)	% obese w/in Q
	(1)	(2)	(3)	(4)	(5)	(6)
Obese						
× Q1	0.041	0–29	34.0	0.035	-926–8	34.7
	(0.029)			(0.026)		
× Q2	0.044	29–53	29.2	0.016	9–67	32.2
	(0.028)			(0.022)		
× Q3	-0.005	53–76	32.1	0.032**	67–167	31.1
	(0.028)			(0.016)		
× Q4	0.073***	76–111	25.0	-0.009	167–354	24.1
	(0.026)			(0.027)		
× Q5	0.118***	111–443	18.0	0.182***	354–2720	16.8
	(0.037)			(0.053)		
BM controls	yes			yes		
# of obs	6,995			6,995		
Pseudo-R^2	0.060			0.078		

Panel B: Effect of Obesity by Credit History and Debt Type

	Credit history		Debt type
	Good	Poor	
	(1)	(2)	(3)
Obese	0.045***	0.027	
	(0.013)	(0.030)	
Obese			
× no debt			0.033
(19.9%)			(0.027)
× secured debt only			0.035**
(52.9%)			(0.014)
× unsecured debt only			-0.013
(7.1%)			(0.049)
× sec & unsec debt			0.075***
(20.1%)			(0.025)
BM controls	yes	yes	yes
# of observations	4,675	2,264	6,995
Pseudo-R^2	0.016	0.008	0.069

Table A.7: Selection Bias is Negligible

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^2	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
Δ 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 (2010)'s imputed Arrow-Pratt coefficients of relative risk tolerance following the procedure developed by Kimball, Sahm, and Shapiro (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, Heutel, and McAlvanah (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
β,δ-factors	Described in Courtemanche, Heutel, and McAlvanah (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 β and δ 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

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			
	mean	st dev	obs	mean	st dev	obs	Δ
Health status	2.149	0.952	4,792	2.601	0.982	2,189	***
Δ 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	***
β	0.799	0.212	4,404	0.777	0.221	1,999	***
δ	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

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 Δ health contain another variable from this list, namely *Health status*; and β and δ 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
Δ health: better health	-0.060*	0.032	-0.052	0.030
Δ health: worse health	0.069***	0.015	0.057***	0.015
Δ 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
β	-0.102***	0.031	-0.041	0.033
δ	-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 ↑)	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