Financial Hardship and Obesity:
The Link between Weight and Household Debt

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Abstract: There is a substantial correlation between household debt and health. Individuals with less healthy lifestyles are more likely to hold debt, yet there is little evidence as to whether this is merely a correlation or if financial hardship actually causes obesity. In this paper, we use data from the National Survey of Adolescent Health to test whether financial hardship affects body weight. We divide our sample into two groups: men and women, explore two different types of financial hardship: holding credit card debt and having trouble paying bills, and three outcomes: overweight, obese and Body Mass Index (BMI). We use a variety of econometric techniques: Ordinary Least Squares, Propensity Score Matching, sibling Fixed Effects, and Instrumental Variables to investigate the relationship that exists between financial hardship and body weight. In addition, we conduct several robustness checks. Although our OLS and PSM results indicate a correlation between financial hardship and body weight these results appear to be largely driven by unobservables. Our IV and sibling FE results suggest that there is no causal relationship between credit card debt and overweight or obesity for either men or women. However, we find suggestive evidence that having trouble paying bills may be a cause of obesity for women.

Keywords: Obesity, financial hardship, body mass index, overweight

JEL codes: I10, I12,

Highlights:

- This paper investigates the effect of financial hardship on body weight
- We use several econometric methods to ascertain if there is a causal effect of financial hardship on body weight
- OLS and PSM results indicate a strong correlation between body weight and financial hardship which appears to be driven by unobservables.
- Sibling FE and IV results indicate little evidence of a causal relationship with the exception of women who have trouble paying their bills who are more likely to be obese.

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Can you afford to be fat? There's a link between weight gain and financial drain. So get ready for some belt tightening because in order to trim your waist you need to trim your debt. ~Dr. Oz

If you had credit card debt…the next thing I found about them was they were overweight, it was like this burden, created this excess that wanted to make them eat and eat and eat. So when you're not doing well with your money it shows up in your health. ~ Suze Orman[1]

There is a substantial correlation between household debt and health. Individuals with less healthy lifestyles are more likely to hold debt (Grafova, 2007). However, unlike what discussions in the popular media may imply, a causal link between debt and health has not been firmly established. Economic theory suggests that a causal relationship between debt and health outcomes could run in either direction or both debt and health could be caused by unobserved common factors such as risk aversion, self-control (impulsiveness) and time preferences (Grafova, 2007).

In this paper, we use data from the National Survey of Adolescent Health (Add Health) to test whether financial hardship affects body weight. We divide our sample into two groups: men and women, explore two different types of financial hardship: holding credit card debt and having trouble paying bills, and three health (body weight)[2] outcomes: overweight, obese and Body Mass Index (BMI). We use a variety of econometric techniques: Ordinary Least Squares (OLS), Propensity Score Matching (PSM), sibling Fixed Effects (FE), and Instrumental Variables (IV) to investigate the relationship that exists between financial hardship and body weight.

Overall, our results indicate that while there is a correlation between financial hardship and body weight there does not appear to be a causal relationship with the exception of women who have trouble paying their bills for whom there is some evidence that they are more likely to be obese. In particular, our OLS results do not indicate any correlation between having credit card debt and body weight after controlling for a wide array of covariates except for men with credit card debt who seem to have a higher probability of being overweight. The correlation appears more dramatic when considering having trouble paying bills as the financial hardship

[1] http://www.doctoroz.com/videos/suze-orman-lose-weight-get-rich-pt-1

[2] Throughout the paper, we refer to our two treatments (having credit card debt and having trouble paying bills) as financial hardship and our three outcomes (BMI, overweight/obese and obese) as body weight.

measure. We find that women tend to have a higher BMI, and are more likely to be overweight/obese and obese when they have trouble paying bills. The results for men differ. There does not appear to be any correlation between having trouble paying bills and both BMI and obesity and the correlation is negative between having trouble paying bills and the probability of being overweight/obese for men. Using PSM, which matches on observables and makes explicit the comparison group, we find very similar results to the OLS. Using sibling FE allows for controlling for family specific unobservables and we find there is no causal relationship between financial hardship and body weight. Using IV, we focus on having trouble paying bills and find that the negative correlation between having trouble paying bills and overweight/obese for men does not seem to causal and is mostly likely due to some unobservables we have not been able to account for in our models. For women who have trouble paying bills the effect on obesity may be stronger than what find under OLS. Finally, we also conduct several sensitivity analyses which suggest that unobservables potentially play a large role in this relationship.

Previous Research on Debt and Health Outcomes

Theoretically, there are competing explanations that may explain the relationship between financial hardship and body weight. A direct causal relationship running from financial hardship to body weight is possible if those in debt must cut back on food expenditures and thus rely on more calorie dense foods hence gaining weight (Averett, 2012). Along similar lines, indebtedness can cause substantial stress and this may manifest itself in excess caloric intake (Wardle et al., 2012). Finally, those in debt may also suffer from food insecurity and behavioral biology indicates that those who are food insecure may develop eating habits that lead to being overweight (Smith, Stoddard and Barnes, 2009). Consistent with these three explanations, we would expect a positive relationship between being indebted and being obese. On the other hand, the “new consumerism” as postulated by Schor (1998) may lead even wealthier individuals to consume beyond their financial means. Under this explanation, individuals who accrue debt may not necessarily gain weight (since appearances may matter more to this group and they can afford to join a gym) indicating that a negative relationship between financial hardship and body weight may exist. Finally, a third factor such as impulsivity might cause an individual to become indebted and also overweight because there is some evidence that both over eating and over spending can be impulsive behaviors (e.g. Beardon and Haws, 2012; Hermans et al., 2012).

Many studies have examined socio-economic status (indicated by education, occupation, wealth and income) and its relationship to health and health behaviors but determining a direction of causality can be elusive.[3] Recently, several papers have specifically examined the link between health and debt (Drentea and Lavrakas, 2000; Lyons and Yilmazer, 2005; Grafova, 2007; Smith, Stoddard and Barnes, 2007; Keese and Schmitz, 2010; Lau and Leung, 2011). These papers investigate the relationship between debt and health using a variety of econometric techniques.

Drentea and Lavrakas (2000) test whether credit card debt and stress regarding debt are associated with health using a 1997 representative survey of adults in Ohio. They investigate several questions; 1) how is credit card debt and stress related to debt correlated with health, 2) is the effect stronger than income on health measures, 3) if an effect exists is it stronger for blacks than whites? The health outcomes they use include own health, body mass index (BMI), smoking, and drinking. The debt indicators they use include debt/income ratio, carrying an unpaid balance, amount of credit line used, charging on more than two cards, and a constructed debt stress index. Using OLS hierarchical regression analysis, Drentea and Lavrakas find that having a higher debt/income ratio is associated with worse health either measured or self-reported. They find little evidence that credit card debt is more important than income in explaining health outcomes and behaviors. Finally, there is no evidence to support that credit card debt or stress due to debt can explain the correlation between race and health outcomes.

Lyons and Yilmazer (2005) use data from the Survey of Consumer Finances (SCF) to examine the relationship between financial strain (measured at the household level) and the self-reported health of the head of household. The issue of endogeneity is addressed by using Instrumental Variables (IV) and a representative sample of the US population. They define financial strain as one of the following: 1) delinquent on any loan payment for two months or more, 2) high leverage, 3) little cash on hand. The measure of health used is self-reported health. Lyons and Yilmazer use two-stage probit models to account for the possibility that financial strain can be both the cause and the consequence of poor health. They do not find evidence that

[3] See Deaton (2002) for a discussion of the issues.

any of the three financial strain measures considered leads to poor health; therefore in their sample it is unlikely that the causality runs from financial strain to worse health.

Grafova (2007) specifically examines how households' non-collateralized debts are correlated with health behaviors (obese, overweight, smoker). She finds that there is not a causal relationship between debt (credit card and student loans) once controlling for covariates and medical expenditures using a family fixed effects model. The data are from the Panel Study of Income Dynamics (PSID) and she examines married working age couples to get at the household nature of debt. She does find a higher correlation; men who are overweight or obese and women who smoke or are obese are more likely to live in households with non-collateralized debt. However, her results are smaller in magnitude and no longer statistically significant when she controls for fixed effects. It is unclear if this lack of significance is due to having controlled for family level unobservables through the use of family (husband/wife) fixed effects or if it is because the fixed effects estimates are less precisely estimated (the standard errors are two to three times larger for the fixed effects estimates). Grafova hypothesizes that household level unobservables affect both health and debt and therefore explain the observed correlation. Yet, it is also likely that the unobservables are individual specific (i.e. impulsivity) rather than household specific, and her estimates do not account for individual level unobserved heterogeneity.

Smith, Stoddard and Barnes (2009) examine the relationship between economic insecurity measured by changes in the probability of becoming unemployed, drops in real household annual income, and variations in an individual's volatility of income and weight gain using the 1979 National Longitudinal Survey of Youth (NLSY79). Their study focuses on men and they report that an increase in any of their economic insecurity measures is positively correlated with weight gain. Using an IV approach with state-level variables such as the state-level minimum wage and median income level, Smith, Stoddard and Barnes (2009) conclude that their earlier OLS results are confirmed by the IV approach and support that economic insecurity may lead to weight gain. In addition, they examine whether a larger social safety net can offset the negative consequences of economic insecurity on weight gain and find that it does. Their paper differs from ours in that we are examining a specific type of debt rather than generalized economic insecurity.

Keese and Schmitz (2010) use German panel data to analyze the effect of debt on health outcomes. They use three different estimation methods to get at the causal relationship: fixed effects, subsample of the continually employed, and lagged debt variables. The measures of debt that they examine focus on the ability to repay debts; therefore they use the ratio of consumer credit repayments to household net income, ratio of home loan repayments to household income and a binary variable which indicates a household is over-indebted. Over-indebted households have net income after accounting for loan repayments less than the social assistance level. The health measures examined are a self-reported health satisfaction, a mental health score and obesity. The results from their estimations show that the indebted are more likely to have lower health satisfaction, lower mental health and be overweight.

Recently, Lau and Leung (2011) use data from the U.S. Health and Retirement Survey to examine the effect of mortgage debt on several indicators of health including self-assessed health and obesity. Their OLS estimates suggest that there is a positive effect of mortgage debt on the probability of being obese for individuals over 50 years of age. To identify the causal effect of debt on obesity they employ two strategies. The first is an IV approach using the state level FMHPI (Freddie Mac Housing Price Index) as their instrument of mortgage debt. The second identification approach is a difference-in-differences approach where they use the decline in housing price by state over the 2004-2008 timeframe. States with housing price declines of 20 percent or more are the “treated” states. In both cases, they find a positive and significant effect of mortgage debt on obesity. However, their use of 20 percent to define treatment is arbitrary and they provide no tests of robustness for this choice.

The previous empirical literature does not reach a consensus on whether obesity causes debt accumulation, debt causes obesity or if both obesity and debt are caused by common unobserved factors such as impulsivity. We complement and extend this literature in several important ways. First, we use data on a younger cohort, individuals from the AddHealth data who were in high school in the mid-1990s. This is a group that has come of age during the obesity epidemic and most previous research has been based on samples of older adults, thus the AddHealth provides new information on the link between financial hardship and body weight for younger individuals. In addition, as people age they tend to gain weight and they also are more likely to have experienced other health shocks that contribute to obesity. Focusing on a younger cohort helps disentangle the effect of age and health on this relationship. Second, we use a variety of empirical methods to determine if there is a causal effect. Specifically, in addition to estimating OLS models using the rich set of controls that the AddHealth data provide, we use matching estimators, sibling fixed effects and instrumental variables. Our results indicate that having credit card debt is not likely to influence body weight but there is suggestive evidence that having trouble paying bills causes women to be more likely to be obese with no effect on men's body weight.

Econometric Methods

Our goal is to ascertain the causal impact of debt on obesity. However, since we have observational data and we lack a credible natural experiment, we have to be particularly cognizant of unobservables which may bias our estimates. The ideal empirical method would be to randomly assign individuals to financial hardship and then measure their body weight. In the absence of such an experiment, we have to rely on other methods. In OLS, biased estimates of the effect of the treatment (credit card debt and trouble paying bills) on being overweight or obese are obtained if we fail to include all the characteristics that affect both financial hardship and body weight. In our case, we are particularly worried about being able to control for individual specific unobservables such as impulsivity which may influence both body weight and financial hardship. In other words, if those with financial hardship differ in unobserved ways from those who are not, between-group comparisons may reflect those differences rather than the impact of financial hardship *per se*. In addition, even if all the correct control variables are included, the linear specification of OLS could be incorrect (Reynolds and DesJardins, 2009). Finally, we are also concerned about the potential for reverse causality. It is plausible that upon gaining body weight one could spend more money as a coping mechanism and thus end up in financial hardship.

To address these endogeneity concerns, we employ several empirical methods. The richness of the AddHealth data allows us to estimate OLS models that control for a wide array of covariates including a measure of impulsivity. However, if there is insufficient common support on observables across those with and without financial hardship then cross section OLS estimates may be biased due to selection on observables. We address this potential selection problem via PSM. PSM allows us to effectively create a counterfactual for individuals in the treatment group using individuals from the control group who are most similar in terms of observable characteristics. Specifically, each observation in the treatment group is matched with one or more observations in the control group. Under certain assumptions, the average difference in outcomes can then be attributed to the presence of financial hardship (Rosenbaum & Rubin, 1983). In particular, PSM relies on the "conditional independence assumption": all factors related to receiving a treatment are observed and measured (Black and Smith, 2004). Such methods address selection on observables but do not fully deal with the selection problem because unobserved characteristics are likely to influence both financial hardship and body weight.[4]

Thus, even if there is common support among those with and without financial hardship, if there are unobservables that are correlated with both financial hardship and body weight, then the OLS and PSM estimators will yield biased estimates of the effect of financial hardship on body weight. We address selection on unobservables in two ways by using sibling fixed effects and instrumental variables.

The AddHealth data contains siblings so we can estimate sibling fixed effects models which allow us to control for any family specific unobservables that could be influencing financial hardship and body weight.[5] However, a family fixed effects model does not allow us to control for potential reverse causality.

One way to address this reverse causality is to use IV models. This method relies upon having credible instruments. In our case a credible instrument would be one that is correlated with financial hardship but not with body weight. We use several instruments that we argue meet the criteria[6]. In wave I, when the adolescents were in high school, their parents were interviewed. From the parent questionnaire there is a binary variable that equals 1 if the parent reported that they had enough money to pay their bills. Because this was asked when the adolescent was in high school and because we control for many measures of parental socio-economic status in our models, we believe this is legitimately excluded from the body weight equation. From the young adult questionnaire we add two other instruments: a variable equal to one if the respondent currently lives with their parents and a variable equal to one if they receive

[4] Following Anderson (2012) we use several different matching methods including nearest neighbor, *k*- nearest neighbors, nearest neighbor within caliper, kernel, local linear regression, and radius.

[5] Although the more salient unobservable heterogeneity may be individual specific, the AddHealth did not ask the debt questions in multiple waves precluding such an analysis. Grafova (2007) uses family fixed effects in her investigation of the effect of household debt on health behaviors.

[6] We present the standard tests of instrument validity in our results section.

any money from their parents or have had them pay for anything significant during the past year. Both of these should be predictive of financial hardship but have no effect on body weight except through their effect on financial hardship.

Data

As noted above, we use data from the AddHealth, a school-based longitudinal study of a nationally representative sample of adolescents in grades 7 to 12 in the United States which started during the 1994-5 school year.[7] We use data from Wave I when the individuals were first interviewed and were aged 11 to 21 years and from Wave III which was fielded between July 2001 and April 2002 when respondents were 18 to 28 years old. These data are particularly well-suited for our analysis as we have information on financial hardship and body weight as well as a rich array of covariates.

Outcome Variables

Our outcome variables are all measured at wave III. We use self-reported height and weight to calculate the individual's BMI. BMI is not an optimal measure of obesity because it is unable to distinguish between lean body mass and body fat (Burkhauser and Cawley, 2008 and Johansson et al., 2009). However, it is the only measure in our data and widely used in social science research. We create an obesity indicator for those with a BMI greater than or equal to 30 to denote obese and another greater than or equal to 25 to denote overweight or obese and we also use the BMI itself as an outcome although we recognize that changes in BMI that do not move an individual into the overweight category are not necessarily health risks.

Treatment variable (Measures of financial hardship)

We examine two measures of financial hardship: whether the respondent reports having any credit card debt or having had trouble paying bills in the past month. Because these types of financial hardship can arise for various reasons and their impact on body weight is likely to be quite different, we chose to examine them separately. Specifically, respondents are asked" Do you *[if the respondent is married, add: "or your {HUSBAND/WIFE}"]* have any credit card debt?" which we use to create our credit card debt variable. Also, we create a binary variable

[7] More details on this dataset are available at http://www.cpc.unc.edu/projects/addhealth/design/designfacts.

equal to 1 if the respondent reported having trouble paying various bills including telephone, gas and electric. Appendix table 1 details the construction of this variable.

Covariates

In our models, we include a rich array of control variables that potentially influence both the probability of financial hardship and body weight. Of particular importance, we control for the respondent's BMI from Wave I. This lagged BMI allows us to account for historical factors such as dietary habits, fitness levels and family environment that are difficult to account for otherwise. From Wave I, we also control for family socioeconomic status including parental education and father's employment status, and whether the family was on welfare. From Wave I we control for mother's obesity to capture any genetic predisposition to obesity as well as whether the mother breastfed the respondent given that there is some evidence the breastfeeding is protective against obesity. We also control for whether their mother was a binge drinker. We include controls from Wave I intended to capture the respondent's rate of time preference including whether the respondent drank or smoke in high school, whether they had ever stolen anything, whether they thought they were smarter than others, usual hours of work in the summer, the adolescent's high school GPA and whether the adolescent believed it was likely they were going to go to college. We also include several contemporaneous variables from Wave III; the respondent's current age, race, marital status, income, a measure of religiosity,[8] whether they have gambled for money including casino games, horse racing, bingo and sporting events, whether they have played the lottery, if they volunteer or have a savings account[9]. In addition, in the models where the treatment is having trouble paying bills, we include an indicator for whether the individual has a credit card.[10]

Of particular note, we include a measure of impulsiveness. The AddHealth contains three possible measures that potentially capture a tendency to act impulsively. We use a contemporaneous measure from wave III when respondents were asked: "Do you agree or

[8] Respondents are asked how religious they are and can respond not at all, slightly, moderately or very.
[9] See Caliendo and Kopeinig (2005) for an excellent discussion of the selection of variables for the propensity score.
[10] In wave I, 20,745 individuals completed the in-home interview. We drop 5,602 who were not interviewed in both waves I and III. In addition, we drop individuals who had missing data on key variables for our analysis including height, weight, trouble paying bills and credit card debt. This leaves us with a final sample size of 5,985 men and 6,515 women.

disagree that when making a decision, you go with your "gut feeling" and don't think much about the consequences of each alternative?"[11]

Empirical Results

Our results are presented in tables 1 through 9. In table 1, we present sample means for our outcome variables by gender and our two measures of financial hardship: having credit card debt and having trouble paying bills. Both men and women who are in credit card debt have higher BMIs and are more likely to be overweight or obese. Specifically, for women, 20.1 percent of women in credit card debt are obese while only 17.8 percent of those not in credit card debt are obese and these unadjusted means are statistically different from each other.

Turning to our second measure of financial hardship, having trouble paying bills, the patterns observed above for women are remarkably similar. However, we see that men who do *not* report trouble paying their bills are significantly more likely to be overweight yet the difference in BMI across these two groups is not statistically significant.

Table 2 presents the cross tabulation of our two financial hardship measures. As we suspected, these two measures of financial hardship do not overlap entirely. For men, about 42 percent of respondents have both credit card debt *and* trouble paying their bills. For women, the percentage is closer to 50 percent. About 37 (43) percent of men (women) who do not have trouble paying their bills report some credit card debt while 57 (49) percent of men (women) who had no credit card debt reported trouble paying their bills. Finally, 62 (57) percent of men (women) did not report either type of debt. Thus, while there is overlap, it is by no means complete.

Table 3 presents the sample means for all of our covariates by gender and our two measures of financial hardship. Asterisks indicate when variables are statistically different for those in credit card debt or having trouble paying bills versus those who are not by gender.[12] It appears that those with credit card debt have higher incomes on average than those who have trouble paying their bills.

[11] This measure is quite similar to the one used by Anderson et al. (2012) to measure impulsiveness in Wave I. In addition, in wave III, respondents are asked a series of questions about their propensity to take risks from which we created an index of impulsivity. The "gut feeling" and impulsivity measures are strongly positively correlated.

[12] Not shown in the tables but included in the fully specified OLS models are controls for those missing information on income, parents' education, father's job and mother's breastfeeding and binge drinking behavior.

OLS Models

Tables 4a (credit card debt) and 4b (trouble paying bills) present the results from OLS models of regressing the three body weight outcomes on credit card debt or trouble paying bills. In panel A of each table, we report the results of a simple regression of each body weight outcome on each measure of financial hardship. In table 4a, these unadjusted regressions reveal a strong positive correlation between credit card debt and body weight for both men and women with the exception of obese men where the coefficient is not statistically significant. In table 4b, we see that same strong positive correlation between having trouble paying bill and our body weight outcomes for women but for men, the correlation is negative and significant only for overweight/obese.

Panel B of tables 4a and 4b, adds our measure of impulsiveness to these regressions. Interestingly, when credit card debt is the treatment, we find that adding impulsiveness increases the magnitude of the coefficient on credit card debt indicating that, perhaps surprisingly, our measure of impulsivity and credit card debt are actually negatively correlated. The opposite is true when the treatment is trouble paying bills. In this case, adding our measure of impulsiveness reduces the magnitude of the coefficient on having trouble paying bills. Impulsiveness itself is always a positive and generally a significant predictor body weight, including it in the regressions does not reduce the magnitude or the significance of the coefficients on financial hardship. Clearly, impulsiveness, as we measure it here, is not the key driver of the relationship between financial hardship and body weight.

In panel C, we add the lagged BMI to the models. Lagged body weight is consistently a positive and significant predictor of current body weight and its inclusion tends to render the coefficients on impulsiveness and financial hardship insignificant for credit card debt. For having trouble paying bills, the inclusion of lagged body weight renders impulsiveness insignificant but the coefficients on having trouble paying bills remain statistically significant. For women these coefficients are generally smaller.

In panel D, we include the full set of covariates (the fully specified regressions are in appendices 2a and 2b). The addition of these other controls does further reduce the magnitude of the coefficients on financial hardship but we still see a positive and significant effect of credit card debt on being overweight for men but a negative and significant effect of having trouble paying bills on being overweight for men. For women, these fully specified OLS models reveal no impact of credit card on body weight but a positive and significant effect of having trouble paying bills on body weight.[13] Finally, as mentioned earlier our focus is on weight gain that may potentially lead to health problems; therefore in the remainder of the paper we focus on the body weight outcomes of overweight/obese and obese. Tables 5a and 5b contain those OLS results along with those of our other econometric techniques.

As a robustness check on our OLS estimates, we estimate the treatment effect (i.e. the effect of financial hardship on our body weight outcomes) making several assumptions about the relative correlation between financial hardship and the unobservables. Normally, OLS assumes that the correlation between the treatment variable (financial hardship) and the error is zero. Using the method of Krauth (2011) we relax this assumption. In our case, we assume that the ratio of the correlation of financial hardship with the unobservables to correlation of financial hardship to observables (covariates) lies within some known interval. We use specific interval ranges to bound the relative correlation.[14] In table 6 panel A, we find that for men that the effect of having trouble paying bills on being overweight/obese is overturned when the correlation between having trouble paying bills and the unobservables is two times as large as the correlation between having trouble paying bills and the covariates. For women allowing the correlation between having trouble paying bills and unobservables equal to the correlation between having trouble paying bills and the covariates can overturn the OLS results as shown in panel B and a similar result is found for men with credit card debt in panel C. While we cannot know for certain the level of the correlation between the treatment and the unobservables, this gives us some indication of the sensitivity of our results.

PSM models

As noted above, we are concerned about the endogeneity of financial hardship in our models of body weight. Thus, in tables 5a and 5b, we present the results from PSM (kernel matching only)[15], Sibling FE and IV methods. For both men and women in tables 5a and 5b, the PSM

[13] The coefficients on our control variables are in line with what has been found in other studies. For example, those who are married are heavier, for women body weight is higher for with lower income and education and for both men and women having an obese mother leads to higher body weight.
[14] See table 6 for specific intervals. The upper bound of the range indicates the maximum allowed relative correlation between treatment (financial hardship) and the unobservables relative to the treatment (financial hardship) and the observables (covariates). We only bound the OLS results that are significant.
[15] Appendix tables 3a and 3b contain results from several other matching methods.

results support the findings from OLS.[16] In particular, the effect of credit card debt on overweight is positive and significant for men but credit card debt has no significant impact on overweight or obesity for women. For the treatment, having trouble paying bills, we continue to find that men who have trouble paying their bills are significantly less likely to be overweight or obese yet there is no significant effect on obesity for males. In contrast, women who have trouble paying their bills are 2.5 percentage points more likely to be obese and 2.7 percentage points more likely to be overweight or obese and both these point estimates are statistically significant.

As with our OLS models, we conduct several specification checks of our PSM results. One that is suggested by Dehejia (2005) is to rerun the logit that creates the propensity score to see how sensitive the results are to changes in the specification of the propensity score. When we did this by including higher order terms for all of our continuous covariates we found that in general, our results are not sensitive to these changes in the estimation of the propensity score (these results are available upon request). Specifically, it is nearly always the case that when we report a significant effect in tables 5a and 5b, the statistical significance remains and the point estimates are remarkably close.

Another specification test is the Rosenbaum bounds test. Recall that we can only match on observables and it is possible that unobservables are distributed quite differently across individuals with the same propensity score. This test is used to assess how large the unobservable heterogeneity would have to be to overturn the matching estimator results when those results are statistically significant (Caliendo and Kopeinig, 2005) and is similar in spirit to the Krauth method. In our application, it is likely that any bias from unobservables is upward. In other words, we think any plausible unobservables are going to be correlated either positively or negatively with our outcome (body weight) and our treatment (experiencing financial hardship).

We report the p-value of the Mantel-Haenszel (MH) statistic for the upper bound given our belief that any bias would be upward. These are presented for the kernel matching only.[17] The Rosenbaum bounds test presents the likelihood that two individuals would have different

[16] A number of studies find meaningful differences between OLS and PSM results (Anderson, 2012; Plotnick, 2012; Belfield and Kelly, 2012). However, recent research by Shah et al. (2005) and Stürmer et al. (2006) suggests that it is often the case that the results from PSM are not that different from other multivariate methods (e.g. Caliendo and Lee, forthcoming).

[17] Henry and Yi (2009) note that kernel matching is preferred as it produces the least bias compared to an experimental estimate.

outcomes given the same observable characteristics. Γ represents the odds that two individuals who are observationally equivalent differ in their treatment effect. If $e^{\gamma}=1$ then two individuals have the same probability of being exposed to financial hardship. As Γ rises the odds of two observationally equivalent individuals being in financial hardship increasingly differs. The p-value of the Mantel-Haenszel test statistic shows whether that difference is statistically significant.

The results are in table 7. For men with credit card debt, at $e^{\gamma}=1.2$ the MH statistic becomes insignificant which indicates that if there were a 20 percent difference in unobservables across control and treatment groups the positive and significant (2.8 percentage points more likely to be overweight or obese result in table 5a) would be overturned. However, at $e^{\gamma}=1.35$, the p-value becomes .08. This pattern, where the MH statistic goes from significant to insignificant and back to significant, indicates a significant negative treatment effect; i.e. the relationship between credit card debt and overweight becomes negative (Becker and Caliendo, 2007). In other words, unobservable heterogeneity that is 35 percent different between control and treatment groups could reverse the sign of our effect.

For men who report trouble paying their bills, although the coefficient estimates from the matching are negative and significant we maintain our assumption that the bias would be upward. In this case MH statistics are significant up to $e^{\gamma}=2$ indicating that for any reasonable difference in the unobservables our results are robust. For women who have trouble paying their bills, the coefficient on overweight/obese is positive and significant and the MH statistic becomes insignificant at $e^{\gamma}=1.45$ and then the treatment effect would become negative at $e^{\gamma}=1.7$. For obese women who report having trouble paying their bills, the critical values of e^{γ} are 1.55 and 1.85 indicating that a 55 percent difference in unobservable heterogeneity would make our results insignificant. While this sensitivity analysis indicates how bias from unobservables may alter our inferences it in no way tells us if such bias is present (Aakvik, 2001).

We perform additional robustness checks to examine selection on unobservables based on the work of Altonji et al. (2008). Our results from the PSM hinge on selection being only from observable factors. Similar to the method by Krauth (2011) used above, Altonji et al. (2008) make the argument that researchers can impose different levels of selection on unobservables which are as reasonable as the PSM assumption that there is no selection on unobservables. Using a bivariate probit we can alter the correlation between the unobservables in the body weight and financial hardship variables and examine whether the estimates are similar to those from OLS and PSM.[18] The bivariate probit includes one equation regressing the outcome (overweight/obese) on our covariates and financial hardship measures and the other equation regressing the treatment variables (credit card debt and trouble paying bills) on our covariates. To start, we assume there is no correlation between errors ($\rho=0$) in the two equations of a bivariate probit; assuming $\rho=0$ implies that there are no unobservables that affect both financial hardship and weight. As expected when $\rho=0$, the results in the top panel of table 8 confirm the OLS and PSM results and are similar in size and significance.

Altonji et al. (2008) also suggest that we can use the amount of selection on observables to proxy for the amount of selection on unobservables. By making this assumption we can assess the importance of unobservable characteristics on our estimates of the treatment effect. The estimates in the middle panel of table 8 indicate that when we impose this assumption, our results are overturned (i.e. our coefficient is now negative or insignificant) with the exception of the results for men who have trouble paying bills where the coefficient was negative and significant to begin with, thus suggesting that the result that men who have trouble paying bills are thinner on average is robust.

Finally, Altonji et al. (2005) and Reynolds (2009) examine how much more selection on unobservables over the selection on observables is needed to overturn the results by examining the ratio of estimated treatment effect to the estimated bias. These results are shown in the bottom panel of table 8. For men with credit card debt, the amount of additional selection needed on unobservables to overturn the results is small. For men who have trouble paying bills, selection on unobservables needs to be more than three times greater than the selection on observables to overturn the result. For women, the additional selection on unobservables needed to overturn the result varies depending on the treatment. The size must be larger for having trouble paying bills versus credit card debt.

Overall, these robustness checks do not rule out that there may be a third factor affecting both financial hardship and weight. However, the result that men with trouble paying their bills are thinner appears to be robust.

Sibling Fixed Effects

[18] For a full explanation of the technical details, see Altonji et al. (2008) and Reynolds (2009).

The sensitivity tests on our OLS and PSM models indicate that unobservables may drive some of our findings. One source of unobserved heterogeneity could family specific. Because the AddHealth surveyed students in their high schools, there are a number of siblings in the sample. We leverage this sample design by estimating sibling FE models which allow us to control for family specific heterogeneity. This is the method employed by Grafova (2007). Controlling for family specific unobservables through the use of sibling FE models (column 3 of table 5a and 5b) renders the coefficient on credit card debt insignificant in all specifications for both men and women and the same is true for having trouble paying bills. It is worth noting that the coefficient on having trouble paying bills for men in the overweight/obese equation approaches statistical significance as does the coefficient for women in the obese equation. However, these models are identified off of those few respondents who had a brother or sister in the sample and only those sibling groups where siblings differed on credit card debt or having trouble paying bills contribute to the identification (about 1/3 of our sibling samples differ on these outcomes). Thus, it is not surprising that the standard errors are large. In addition, results from this method may not remove all unobserved heterogeneity because even siblings are not exactly alike and their differences could be correlated with both financial hardship and body weight. For example, one sister may be more future oriented than the other and as a consequence, may be more likely to be prudent with her money and more likely to watch what she eats. This would bias family fixed effects estimates upward.[19]

Instrumental Variables Results

In column 4 of tables 5a and 5b, we present the IV results. We show both the first stage F-statistic which indicates the strength of our instruments[20] and the p-value from the Sargan test of overidentification. For credit card debt, these instruments prove to be weak in that the first stage F-statistic never meets the cutoff of 10 although we do pass the Sargan test in three of the four models. In contrast, our instruments are strong predictors of having trouble paying bills—first stage F-statistics are all in excess of 40. Sargan tests indicate that our exclusion restrictions are valid with the exception of overweight women. These results indicate that the negative and

[19] We ran our OLS models on the sample of siblings as well. The point estimates on the coefficients on financial hardship were not statistically significant at conventional levels. However, it is not possible to determine if this is because there is no effect of financial hardship on our outcomes for this particular sub-sample or if there is an effect but small sample sizes prevent us from estimating it precisely.

[20] A first stage F statistic of 10 is generally considered to indicate strong instruments. See Murray(2006).

significant coefficient on having trouble paying bills for overweight/obese men is in fact likely due to unobservables that we haven't been able to control for in our earlier specifications. Interestingly, the coefficient on bill trouble for obese women is positive and significant, just as it was in OLS and PSM. The magnitude is about five times larger than for these but the effect size is still plausible in that it implies that having trouble paying bills results in 12.1 percentage point increase in the probability of being obese.[21]

Our IV results hinge on the assumption that our instruments are strictly exogenous. We have conditioned our estimates on the BMI from Wave I, thus bolstering our case that the instruments are exogenous. Although the Sargan test is useful to discern if this is the case, one could still argue that our instruments are not rightly excluded from the second stage. For example, living with one's parents may be related to obesity if the respondent's mother is a good cook. In light of the richness of the AddHealth data and the set of covariates we include in our analyses, we believe that our instruments are exogenous to our outcomes once we fully account for our covariates (Murray, 2006). Yet, because of these concerns, we bound our IV results using the procedure suggested by Nevo and Rosen (2012) and operationalized by Kortelainen and Saarimaa (2012) and Reinhold and Woutersen (2010). This method relies on two critical assumptions. Let z be our instrument and x our potentially endogenous variable, in our case this is having trouble paying bills (we no longer focus on the credit card debt because our instruments were not strong predictors). The usual assumption would be that $\rho(z,u)=0$, where *u* is our unobserved error term. Assuming the correlation between the instrument and the error is not zero, $\rho(z,u)\neq 0$, Nevo and Rosen show that as long as $\rho(x,u)\rho(z_i,u)>0$ for j=1 to 3[22] (i.e. the product of the correlation between the treatment variable (*x*) and the error and the correlation between the instrument and the error term is positive) and $\rho(x,u)>\rho(z_i,u)$ then we can bound our IV estimates.

We present the bounds in table 9. Note that our bounds include zero in the interval indicating that there is no causal effect of having trouble paying bills on obesity for women or overweight/obese for men. However, the coefficient on bill trouble in the obese equation for

[21] One explanation for the IV estimate being larger than the OLS estimate is because OLS is estimating the average treatment effect over the entire sample. However, our instruments may only be changing the behavior of a subgroup of individuals for whom the effect of having trouble paying their bills is larger. In other words, the IV estimates will be larger than OLS estimates because of heterogeneity in the subgroup in our sample for whom the instruments are creating variation in having trouble paying bills.
[22] We have three instruments.

women, while large, is within our bounds suggesting that if we had better instruments we might find a causal effect of trouble paying bills on obesity for women.

Conclusions

In this paper, we have attempted to isolate the effect of financial hardship on obesity. This research question seems particularly urgent given the high levels of obesity in the U.S. and the fact that the average American held about $5000 in credit card debt in 2010 (Connelly, 2010). Given the extent of the obesity epidemic facing the U.S. and its resulting medical costs which have been estimated to be as high as 9.1 percent of total annual U.S. medical expenditures (Finkelstein, Fiebelkorn and Wang, 2003), establishing if there is a causal link between debt and obesity may provide further impetus for policy makers to enact regulations protecting consumers from financial hardship. One such regulation is contained in the Dodd/Frank Wall Street Reform and Consumer Protection Act of 2010 which states among other things that the new consumer advocate will "(p)romote fairness and transparency for mortgages, credit cards and other consumer financial products and services" (Zhen, 2011).

Although the popular press accepts that debt may cause obesity our results do not fully support that conclusion. Although our OLS and PSM results indicate a correlation between financial hardship and body weight, our IV and sibling FE results suggest that there is no causal relationship between credit card debt and overweight or obesity for either men or women. However, we find suggestive evidence that having trouble paying bills may be a cause of obesity for women. Most of the significant coefficients in the OLS and PSM models appear to be driven by unobservables. Future research should focus on identification of the causal effect perhaps through better instruments or identification of the unobservables

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Table 1: Sample Means for Dependent Variables

	Men						
	All Men	No Credit Card Debt	Has Credit Card Debt	Sig.[a]	No Trouble Paying Bills	Trouble Paying Bills	Sig.[a]
BMI	26.025	25.869	26.274	*	26.051	25.963	
(std)	(5.236)	(5.301)	(5.122)		(5.064)	(5.627)	
Overweight or Obese	0.517	0.495	0.551	*	0.531	0.482	*
Obese	0.182	0.177	0.189		0.181	0.184	
N	5,985	3,673	2,312		4,220	1,765	

	Women						
	All Women	No Credit Card Debt	Has Credit Card Debt	Sig.[a]	No Trouble with Bills	Trouble Paying Bills	Sig.[a]
BMI	25.403	25.124	25.736	*	24.902	26.425	*
(std)	(6.216)	(6.210)	(6.209)		(5.834)	(6.818)	
Overweight or Obese	0.411	0.391	0.434	*	.375	.482	*
Obese	0.188	0.178	0.201	*	.161	.244	*
N	6,515	3,547	2,968		4374	2141	

[a] indicates significant at 10 percent level or greater

Table 2: Cross tabulations of credit card debt and having trouble paying bills

Key
frequency
row percentage
column percentage

Men

Trouble Paying Bills	Credit Card Debt 0	1	Total
0	2,650 62.80 72.15	1,570 37.2 67.91	4,220 100 70.51
1	1,023 57.96 27.85	742 42.04 32.09	1,765 100 29.49
Total	3,673 61.37 100	2,312 38.63 100	5,985 100 100

Women

Trouble Paying Bills	Credit Card Debt 0	1	Total
0	2,491 56.95 70.23	1,883 43.05 63.44	4,374 100 67.14
1	1,056 49.32 29.77	1,085 50.68 36.56	2,141 100 32.86
Total	3,547 54.44 100	2,968 45.56 100	6,515 100 100

Table 3: Sample Means by Gender and Debt Status

	Men							Women						
	All Men	Has trouble paying bills			Has credit card debt			All Women	Has trouble paying bills			Has credit card debt		
Variable		Yes	No	sig?[a]	Yes	No	sig?[a]		Yes	No	sig?[a]	Yes	No	sig?[a]
Wave I variables														
Age in years	22.073	22.196	22.0216	*	22.4442	21.8394	*	21.8761	21.9594	21.8354	*	22.1934	21.6107	*
	(1.7371)	(1.693)	(1.7529)		(1.5684)	(1.7967)		(1.7495)	(1.7195)	(1.7627)		(1.619)	(1.8096)	
Married	.1515	.1609	.1476		.2042	.1184	*	.2206	.2555	.2035	*	.2652	.1833	*
Income is between $1 and $7	.1482	.1598	.1434		.1202	.1658	*	.2098	.2139	.2078		.1769	.2374	*
Income is between $8 and $3,900	.1642	.1637	.1645	*	.1337	.1835	*	.1986	.1952	.2003		.1715	.2213	*
Income is between $4,000 and $11,700	.1766	.1909	.1706	*	.1466	.1955	*	.1972	.2172	.1875	*	.1917	.2019	
Income is between $12,000 and $20,100	.2179	.2408	.2083	*	.2431	.202	*	.2066	.22	.2	*	.2419	.1771	*
Income is between $20,352 and $500,909	.2496	.2091	.2666		.3253	.202	*	.1521	.1196	.168	*	.1924	.1184	*
Gambled for $	.6501	.6635	.6445		.7145	.6096	*	.5283	.5297	.5277		.6061	.4632	*
Has a savings account	.6316	.5331	.6727	*	.6704	.6071	*	.655	.5441	.7092	*	.6705	.642	*
Purchased a lottery ticket	.6438	.6742	.631	*	.7184	.5968	*	.5919	.624	.5761	*	.6685	.5278	*
Religious	1.3054	1.2425	1.3318	*	1.2794	1.3218	*	1.4685	1.4176	1.4934	*	1.4592	1.4762	
Black	.2027	.2204	.1953	*	.1773	.2186	*	.2339	.2662	.2181	*	.2389	.2298	
Other race	.1226	.1099	.128	*	.1133	.1285	*	.1038	.0883	.1113	*	.1065	.1015	
Hispanic	.1559	.1428	.1614	*	.1856	.1372	*	.1409	.1425	.1401		.1577	.1269	*
Wave III variables														
BMI wave I	22.8226	22.8721	22.8019		23.013	22.7027	*	22.2602	22.8823	21.9556	*	22.5676	22.0029	*
	(4.4565)	(4.5648)	(4.4107)		(4.3427)	(4.5231)		(4.4224)	(4.7247)	(4.234)		(4.4043)	(4.4217)	

Drank in past 30 days	.1123	.1212	.1085		.1185	.1084		.07	.0803	.0649	*	.0681	.0716	
Thinks smart compared to others	.5714	.5411	.5841	*	.609	.5478	*	.5625	.5241	.5814	*	.596	.5345	*
Likely to go to college	.4992	.4204	.5322	*	.5095	.4928		.6281	.532	.6751	*	.6533	.607	*
Usual hours of work in summer	16.7858	17.5915	16.4488	*	19.5017	15.0762	*	13.3962	13.8893	13.1548	*	15.4693	11.6614	*
	(18.2949)	(18.5463)	(18.1804)		(18.4164)	(18.0117)		(16.0522)	(16.4791)	(15.8354)		(16.8134)	(15.1726)	
Dad is not working	.0379	.0487	.0334	*	.0389	.0373		.0353	.0458	.0302	*	.032	.0381	
Dad's job is other than management/prof.	.5305	.502	.5424	*	.5329	.529		.5008	.4647	.5185	*	.5142	.4897	*
Smoked in high school	.1906	.255	.1637	*	.1972	.1865		.188	.255	.1552	*	.191	.1855	
Parent had some college	.2017	.2079	.1991		.2245	.1873	*	.2153	.2214	.2124		.2449	.1906	*
Parent is high school graduate	.2775	.2997	.2682	*	.2612	.2878	*	.2769	.3143	.2586	*	.2716	.2814	
Parent's education is less than High school	.0911	.1014	.0867	*	.0878	.0931		.1065	.1308	.0947	*	.0947	.1164	*
Parent received welfare	.0909	.132	.0737	*	.0753	.1007	*	.0995	.1387	.0802	*	.0805	.1153	*
Parent smoked	.2267	.2669	.21	*	.2219	.2298		.2398	.2971	.2117	*	.2369	.2422	
Mother is obese	.1532	.1575	.1514		.1579	.1503		.1558	.1714	.1481	*	.1651	.148	*
Mother was a binge drinker	.1031	.115	.0981	*	.099	.1056		.101	.1163	.0935	*	.1024	.0998	
Mother breastfed	.3733	.3473	.3841	*	.375	.3722		.3655	.341	.3775	*	.3679	.3634	
High school GPA	2.6833	2.5632	2.7335	*	2.7178	2.6615	*	2.9023	2.7529	2.9754	*	2.9208	2.8867	*
	(.7724)	(.7674)	(.7691)		(.7462)	(.7878)		(.7506)	(.7436)	(.7433)		(.7112)	(.7818)	
Stolen from a store	.2765	.3303	.254	*	.2989	.2625	*	.2104	.2522	.19	*	.2156	.2061	
Observations	5985	1765	4220		2312	3673		6515	2141	4374		2968	3547	

Standard deviations in parentheses

Note: Income is total personal income before taxes measured in $.

[a] indicates significant at the 10% level or greater.

Table 4a: OLS Credit Card Debt

		Women			Men		
	VARIABLES	BMI	Overweight/ Obese	Obese	BMI	Overweight/ Obese	Obese
Panel A	Has credit card debt	0.611***	0.043***	0.023**	0.405***	0.056***	0.012
		(0.154)	(0.012)	(0.010)	(0.138)	(0.013)	(0.010)
	Constant	25.124***	0.391***	0.178***	25.869***	0.495***	0.177***
		(0.104)	(0.008)	(0.006)	(0.087)	(0.008)	(0.006)
	R-squared	0.002	0.002	0.001	0.001	0.003	0.000
Panel B	Has credit card debt	0.653***	0.045***	0.025***	0.416***	0.056***	0.013
		(0.154)	(0.012)	(0.010)	(0.138)	(0.013)	(0.010)
	Impulsive	0.953***	0.050***	0.049***	0.248*	0.009	0.024**
		(0.176)	(0.013)	(0.011)	(0.145)	(0.013)	(0.011)
	Constant	24.823***	0.375***	0.162***	25.777***	0.492***	0.168***
		(0.111)	(0.009)	(0.007)	(0.100)	(0.010)	(0.007)
	R-squared	0.007	0.004	0.004	0.002	0.003	0.001
Panel C	Has credit card debt	0.012	0.007	-0.007	0.131	0.037***	-0.004
		(0.099)	(0.010)	(0.008)	(0.089)	(0.011)	(0.008)
	Impulsive	0.215*	0.006	0.012	0.068	-0.003	0.014*
		(0.113)	(0.011)	(0.009)	(0.094)	(0.011)	(0.008)
	BMI_1994	1.078***	0.065***	0.055***	0.892***	0.061***	0.053***
		(0.016)	(0.001)	(0.001)	(0.014)	(0.001)	(0.001)
	Constant	1.339***	-1.037***	-1.027***	5.595***	-0.888***	-1.027***
		(0.328)	(0.026)	(0.019)	(0.305)	(0.028)	(0.020)
	R-squared	0.590	0.340	0.382	0.577	0.298	0.373
Panel D	Full set of control variables	See appendix 3 for full details					
	Has credit card debt	-0.018	-0.002	-0.003	0.135	0.028**	0.004
		(0.100)	(0.010)	(0.008)	(0.091)	(0.011)	(0.008)
	Impulsive	0.151	-0.008	0.007	0.071	-0.004	0.012
		(0.114)	(0.011)	(0.009)	(0.095)	(0.012)	(0.008)
	BMI_1994	1.051***	0.062***	0.053***	0.886***	0.060***	0.053***
		(0.016)	(0.001)	(0.001)	(0.015)	(0.001)	(0.001)
	R-squared	0.609	0.370	0.397	0.590	0.311	0.386
	Observations	6,515	6,515	6,515	5,985	5,985	5,985

Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 4b: OLS Trouble Paying Bills

	VARIABLES	Women BMI	Women Overweight/ Obese	Women Obese	Men BMI	Men Overweight/ Obese	Men Obese
Panel A	Has trouble paying bills	1.523***	0.106***	0.083***	-0.088	-0.049***	0.004
		(0.172)	(0.013)	(0.011)	(0.155)	(0.014)	(0.011)
	Constant	24.902***	0.376***	0.161***	26.051***	0.531***	0.181***
		(0.088)	(0.007)	(0.006)	(0.078)	(0.008)	(0.006)
	R-squared	0.013	0.010	0.010	0.000	0.002	0.000
Panel B	Has trouble paying bills	1.468***	0.103***	0.080***	-0.093	-0.049***	0.003
		(0.172)	(0.013)	(0.011)	(0.155)	(0.014)	(0.011)
	Impulsive	0.813***	0.041***	0.042***	0.231	0.007	0.024**
		(0.176)	(0.013)	(0.011)	(0.144)	(0.013)	(0.011)
	Constant	24.680***	0.365***	0.150***	25.971***	0.528***	0.172***
		(0.097)	(0.008)	(0.006)	(0.090)	(0.009)	(0.007)
	R-squared	0.017	0.012	0.012	0.001	0.002	0.001
Panel C	Has trouble paying bills	0.517***	0.046***	0.032***	-0.152	-0.053***	-0.000
		(0.111)	(0.011)	(0.009)	(0.101)	(0.012)	(0.009)
	Impulsive	0.180	0.003	0.010	0.066	-0.004	0.014*
		(0.114)	(0.011)	(0.009)	(0.094)	(0.011)	(0.008)
	BMI_1994	1.073***	0.064***	0.054***	0.892***	0.061***	0.053***
		(0.016)	(0.001)	(0.001)	(0.014)	(0.001)	(0.001)
	Constant	1.298***	-1.039***	-1.032***	5.678***	-0.862***	-1.028***
		(0.329)	(0.026)	(0.019)	(0.310)	(0.028)	(0.020)
	R-squared	0.592	0.342	0.383	0.577	0.299	0.373
Panel D	Full set of control variables			See appendix 3 for full details			
	Has trouble paying bills	0.374***	0.024**	0.024***	-0.064	-0.043***	0.000
		(0.112)	(0.011)	(0.009)	(0.103)	(0.012)	(0.009)
	Impulsive	0.130	-0.011	0.006	0.078	-0.002	0.011
		(0.114)	(0.011)	(0.009)	(0.096)	(0.012)	(0.008)
	BMI_1994	1.049***	0.061***	0.053***	0.886***	0.060***	0.053***
		(0.016)	(0.001)	(0.001)	(0.015)	(0.001)	(0.001)
	R-squared	0.609	0.371	0.397	0.590	0.313	0.386
	Observations	6,515	6,515	6,515	5,985	5,985	5,985

Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 5a: Comparison of results for having credit card debt (full set of covariates)

			(1)	(2)	(3)	(4)
			OLS	PSM: Kernel Matching	FE	IV
Women	Overweight/obese	Has credit card debt	-0.002	0.005	0.0215	0.5138
			(0.010)	(0.013)	(0.0469)	(0.3459)
		R-squared	0.370			
		Sargan test of overid				0.013
		F-test on 1^{st} stage				2.66
		Observations	6,515	6,515	282	5,469
		On common support		6,515		
	Obese	Has credit card debt	-0.003	0.001	-0.0462	0.4729*
			(0.008)	(0.010)	(0.0351)	(0.2831)
		R-squared	0.397			
		Sargan test of overid				0.991
		F-test on 1^{st} stage				2.66
		Observations	6,515	6,515	282	5,469
		On common support		6,515		
Men	Overweight/obese	Has credit card debt	0.028**	0.033**	-0.0187	-0.0633
			(0.011)	(0.015)	(0.0593)	(0.239)
		R-squared	0.311			
		Sargan test of overid				0.391
		F-test on 1^{st} stage				4.64
		Observations	5,985	5,985	191	5,081
		On common support		5,981		
	Obese	Has credit card debt	0.004	0.005	0.0357	-0.0668
			(0.008)	(0.012)	(0.0446)	(0.1735)
		R-squared	0.386			
		Sargan test of overid				0.193
		F-test on 1^{st} stage				4.65
		Observations	5,985	5,985	191	5,081
		On common support		5,981		

Table 5b: Comparison of results for having trouble paying bills (full set of covariates)

			(1)	(2)	(3)	(4)
			OLS	PSM: Kernel Matching	FE	IV
Women	Overweight/obese	Has trouble paying bills	0.024**	0.027*	0.0260	0.196**
			(0.011)	(0.015)	(0.0506)	(0.0798)
		R-squared	0.371			
		Sargan test of overid				0.013
		F-test on 1st stage				41.46
		Observations	6,515	6,515	233	5,469
		On common support		6,513		
	Obese	Has trouble paying bills	0.024***	0.025**	0.0565	0.121*
			(0.009)	(0.013)	(0.0377)	(0.0617)
		R-squared	0.397			
		Sargan test of overid				0.791
		F-test on 1st stage				41.47
		Observations	6,515	6,515	233	5,469
		On common support		6,513		
Men	Overweight/obese	Has trouble paying bills	-0.043***	-0.041***	-0.0587	-0.0202
			(0.012)	(0.016)	(0.0480)	(0.0661)
		R-squared	0.313			
		Sargan test of overid				0.392
		F-test on 1st stage				68.56
		Observations	5,985	5,985	277	5,081
		On common support		5,983		
	Obese	Has trouble paying bills	0.000	0.004	0.00832	-0.0187
			(0.009)	(0.012)	(0.0362)	(0.0480)
		R-squared	0.386			
		Sargan test of overid				0.189
		F-test on 1st stage				68.56
		Observations	5,985	5,985	277	5,081
		On common support		5,983		

Table 6: Bounds on the OLS estimates given relative correlation restrictions

Panel A: Bounds on has trouble paying bills by weight outcome (Men)

Relative correlation restriction	Overweight/Obese
0.00	-0.043*** (-0.06652, -0.01948)
[0.00, 1.00]	[-.0451, -.0388] (-.0687 , -.00137)
[0.00, 2.00]	[-.0451, -.03151] (-.0687, .0332)
[0.00, 3.00]	[-.0451, -.0231] (-.0687, .0760)
[0.00, 5.00]	$[-\infty, \infty]$ $(-\infty, \infty)$
Other parameter estimates:	
Lambda hat star	4.878
Theta hat star	-.139
Lambda hat (0)	5.14

Panel B: Bounds on has trouble paying bills by weight outcome (Women)

Relative correlation restriction	Overweight/Obese	Obese
0.00	0.024** (0.00244, 0.04556)	0.024*** (0.00636, 0.04164)
[0.00, 1.00]	[-.104, .023] (-.139, .044)	[-.0623, .0238] (-.0895, .0408)
[0.00, 3.00]	[-.505, .023] (-.661, .044)	[-.321, .0238] (-.429 .0408)
[0.00, 5.00]	$[-\infty, \infty]$ $(-\infty, \infty)$	$[-\infty, \infty]$ $(-\infty, \infty)$
Other parameter estimates:		
Lambda hat star	3.66	3.66
Theta hat star	1.21	.871
Lambda hat (0)	.195	.294

Panel C: Bounds on has credit card debt by weight outcome (Men)

Relative correlation restriction	Overweight/Obese
0.00	0.028** (0.00644, .0496)
[0.00, 1.00]	[-.023, .0282] (-.060, .051)
[0.00, 3.00]	[-.181, .0282] (-.307, .051)
[0.00, 5.00]	$[-\infty, \infty]$ $(-\infty, \infty)$
Other parameter estimates:	
Lambda hat star	3.61
Theta hat star	.420
Lambda hat (0)	.583

Intervals in square brackets are the bounds themselves and the intervals in the parentheses are the 95% conservative confidence intervals.
Krauth's procedure limits the number of covariates so the bounds are estimated with the limited set of covariates. However, our OLS estimates indicated when the relative correlation equals zero are of similar size and significance.

Table 7: Rosenbaum Bounds Sensitivity Test

	Overweight/Obese			Obese
e^{γ}	Men Credit Card Debt P-values	Women Trouble paying bills P-values	Men Trouble paying bills P-values	Women Trouble paying bills P-values
γ=1	0.000015	3.30E-16	0.000267	8.90E-16
γ =1.05	0.000567	4.10E-13	7.70E-06	3.20E-13
γ =1.10	0.008622	1.70E-10	1.30E-07	5.00E-11
γ =1.15	0.060929	2.60E-08	1.50E-09	3.80E-09
γ =1.20	0.227138	1.70E-06	1.10E-11	1.60E-07
γ =1.25	0.507065	0.000053	6.20E-14	3.70E-06
γ =1.30	0.241857	0.000838	2.20E-16	0.000053
γ =1.35	0.079483	0.007458	0	0.000492
γ =1.40	0.018257	0.039844	0	0.003125
γ =1.45	0.00298	0.136825	0	0.014125
γ =1.50	0.000354	0.323008	0	0.047268
γ =1.55	0.000031	0.45944	0	0.121515
γ =1.60	2.10E-06	0.24295	0	0.248530
γ =1.65	1.10E-07	0.101405	0	0.418429
γ =1.70	4.70E-09	0.033386	0	0.425380
γ =1.75	1.60E-10	0.008733	0	0.263044
γ =1.80	4.60E-12	0.001836	0	0.142911
γ =1.85	1.10E-13	0.000314	0	0.068256
γ =1.90	2.30E-15	0.000044	0	0.028757
γ =1.95	0	5.20E-06	0	0.010743
γ =2	0	5.20E-07	0	0.003579

These results assess the sensitivity of the kernel matching because this is the matching method most often recommended in the literature (Henry and Yi, 2009)

Table 8: Sensitivity of Treatment effects to unobservable characteristics

	Women		Men	
	Credit Card Debt	Trouble Paying Bills	Credit Card Debt	Trouble Paying Bills
	Estimates under assumption that correlation between unobservables is zero			
ATT Overweight/Obese	-0.003	0.021**	0.032***	-0.039***
	(.009)	(.010)	(.011)	(.012)
ATT Obese	0.000	0.021***		-0.003
	(.008)	(.008)		(.009)
	Estimates assuming selection on observables equals selection on unobservables			
ATT Overweight/Obese	-0.034***	-0.029***	0.012	-0.037***
	(.010)	(.010)	(0.011)	(.012)
ρ	0.0773	0.126	0.0451	-0.0047
ATT Obese	-0.019**	-0.015**		-0.005
	(.008)	(.008)		(.009)
ρ	0.0779	0.142		0.008
	Estimated relative selection assuming no effect of treatment			
ATT/bias Overweight/Obese	0.085	0.152	0.073	-0.016
ATT/bias Obese	0.044	0.099		0.005
Observations	6,515	6,515	5,985	5,985

Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Estimates shown are marginal effects.

Table 9: Bounds on the IV estimates (Nevo and Rosen procedure)

Men overweight/obese bill trouble

Instrument	Lower bound	Upper bound
Parent reported that they had enough money to pay their bills	-1.613	0.8348
Currently lives with their parents	-0.1173	0.1055
Currently receives support from parents	-0.1253	0.0949

Women obese bill trouble

Instrument	Lower bound	Upper bound
Parent reported that they had enough money to pay their bills	-0.3423	0.9976
Currently lives with their parents	-0.0171	0.1997
Currently receives support from parents	-0.0935	0.5914

Appendix Table 1. Creation of Having Trouble Paying Bills Variable

In Wave III, respondents are asked:

- In the past 12 months, was there a time when {YOU WERE/YOUR HOUSEHOLD WAS} without telephone service for any reason?
- In the past 12 months, was there a time when {YOU WERE/YOUR HOUSEHOLD WAS} didn't pay the full amount of the rent or mortgage because you didn't have enough money?
- In the past 12 months, was there a time when {YOU WERE/YOUR HOUSEHOLD WAS} evicted from your house or apartment for not paying the rent or mortgage?
- In the past 12 months, was there a time when {YOU WERE/YOUR HOUSEHOLD} didn't pay the full amount of a gas, electricity, or oil bill because you didn't have enough money?
- In the past 12 months, was there a time when {YOU WERE/YOUR HOUSEHOLD WAS} had the service turned off by the gas or electric company, or the oil company wouldn't deliver, because payments were not made?
- In the past 12 months, was there a time when {YOU/SOMEONE IN YOUR HOUSEHOLD} needed to see a doctor or go to the hospital, but didn't go because {YOU/THEY} could not afford it?
- In the past 12 months, was there a time when {YOU/SOMEONE IN YOUR HOUSEHOLD} needed to see a dentist, but didn't go because {YOU/THEY} could not afford it?

Respondents who answer a yes to one or more of the above, are coded has having had trouble paying their bills.

Appendix Table 2a: OLS Models of the Effect of Having Credit Card Debt on Body Weight

VARIABLES	Men BMI	Men Overweight/ obese	Men Obese	Women BMI	Women Overweight/ Obese	Women Obese
Wave III Variables						
Has credit card debt	0.135	0.028**	0.004	-0.018	-0.002	-0.003
	(0.091)	(0.011)	(0.008)	(0.100)	(0.010)	(0.008)
Impulsive	0.071	-0.004	0.012	0.151	-0.008	0.007
	(0.095)	(0.012)	(0.008)	(0.114)	(0.011)	(0.009)
BMI_1994	0.886***	0.060***	0.053***	1.051***	0.062***	0.053***
	(0.015)	(0.001)	(0.001)	(0.016)	(0.001)	(0.001)
Volunteer				0.257**	-0.002	0.012
				(0.111)	(0.011)	(0.009)
Age	-0.219***	-0.013***	-0.018***	-0.184***	-0.010***	-0.011***
	(0.032)	(0.004)	(0.003)	(0.034)	(0.003)	(0.003)
Married	0.654***	0.055***	0.037***	1.376***	0.123***	0.064***
	(0.138)	(0.016)	(0.013)	(0.134)	(0.013)	(0.011)
Inc. btw $1 -$7	0.395	0.018	0.032	0.573*	0.038	0.039*
	(0.260)	(0.031)	(0.022)	(0.307)	(0.028)	(0.021)
Inc. btw $8-$3900	0.254	-0.009	0.025	0.827***	0.073**	0.047**
	(0.253)	(0.031)	(0.021)	(0.309)	(0.028)	(0.022)
Inc. btw $4000-$11700	0.066	-0.035	0.031	0.669**	0.048*	0.044**
	(0.253)	(0.031)	(0.021)	(0.309)	(0.028)	(0.022)
Inc. btw $12000-$20100	0.116	-0.023	0.008	0.738**	0.061**	0.043**
	(0.248)	(0.030)	(0.021)	(0.308)	(0.028)	(0.022)
Income missing	0.275	0.017	0.022	0.712**	0.046	0.052**
	(0.247)	(0.030)	(0.021)	(0.314)	(0.029)	(0.022)
Gamble	0.198*	0.021	-0.013	0.151	-0.010	-0.007
	(0.104)	(0.013)	(0.009)	(0.109)	(0.011)	(0.008)
Has savings account	0.078	0.022*	-0.014*	-0.315***	-0.022**	-0.012
	(0.096)	(0.012)	(0.009)	(0.110)	(0.011)	(0.008)
Lottery	0.304***	0.016	0.028***	0.100	0.033***	0.003
	(0.102)	(0.013)	(0.009)	(0.110)	(0.011)	(0.008)
Religious	0.116**	0.016***	0.008*	0.115**	0.007	0.004
	(0.048)	(0.006)	(0.004)	(0.056)	(0.006)	(0.004)
Black	0.244*	-0.011	0.016	0.387***	0.071***	0.001
	(0.132)	(0.016)	(0.012)	(0.148)	(0.014)	(0.011)
Other race	0.234	0.000	0.021	-0.173	-0.021	0.005
	(0.151)	(0.018)	(0.013)	(0.158)	(0.016)	(0.012)
Hispanic	0.366***	0.045***	-0.001	0.120	0.039**	-0.000
	(0.141)	(0.017)	(0.013)	(0.157)	(0.016)	(0.013)
Wave I Variables						
Drank in past 30 days	-0.009	0.021	-0.004	-0.059	0.003	-0.005
	(0.145)	(0.018)	(0.014)	(0.214)	(0.021)	(0.015)
Thinks smart compared to others	0.064	0.007	0.003	0.039	-0.007	0.005
	(0.100)	(0.012)	(0.009)	(0.114)	(0.011)	(0.009)
Likely to go to college	0.066	0.011	0.000	0.066	0.013	-0.005
	(0.099)	(0.012)	(0.009)	(0.118)	(0.012)	(0.009)
Usual summer work hrs	0.005*	0.000	0.000	-0.003	0.000	-0.000

	(0.003)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
Dad unemployed	-0.068	0.016	0.007	0.697**	0.104***	0.026
	(0.265)	(0.032)	(0.024)	(0.314)	(0.030)	(0.025)
Dad job unknown	-0.015	-0.015	0.015	0.064	0.049***	-0.003
	(0.146)	(0.018)	(0.013)	(0.160)	(0.016)	(0.012)
Dad job other than manag/prof	0.187	0.020	0.023**	0.031	0.036***	-0.009
	(0.119)	(0.016)	(0.011)	(0.132)	(0.014)	(0.010)
Smoked in HS	-0.207*	-0.019	0.006	-0.493***	-0.023	-0.029**
	(0.119)	(0.015)	(0.011)	(0.144)	(0.014)	(0.011)
Parent has some college	-0.236*	-0.002	-0.020*	0.013	0.021	-0.003
	(0.123)	(0.015)	(0.011)	(0.135)	(0.014)	(0.011)
Parent educ. HS graduate	-0.017	0.006	-0.013	0.324**	0.055***	0.023**
	(0.122)	(0.015)	(0.011)	(0.140)	(0.014)	(0.011)
Parent educ. less than HS	-0.032	0.040*	-0.008	0.156	0.019	0.021
	(0.193)	(0.023)	(0.017)	(0.205)	(0.020)	(0.016)
Parent educ. unknown	0.142	0.021	0.021	-0.646*	-0.019	-0.005
	(0.300)	(0.035)	(0.026)	(0.373)	(0.034)	(0.027)
Parent on welfare	-0.030	-0.016	-0.027*	0.156	-0.011	0.024
	(0.176)	(0.020)	(0.015)	(0.207)	(0.018)	(0.016)
Parent smoked	-0.076	-0.019	0.006	0.250*	0.020	0.020*
	(0.117)	(0.014)	(0.010)	(0.132)	(0.013)	(0.011)
Mom obese	0.807***	0.032**	0.057***	0.791***	0.048***	0.047***
	(0.139)	(0.015)	(0.013)	(0.159)	(0.015)	(0.013)
Mom binge drank	0.050	0.006	-0.009	-0.006	-0.002	-0.005
	(0.151)	(0.018)	(0.013)	(0.181)	(0.017)	(0.013)
Mom binge not known	-0.285	-0.034	-0.025	-0.201	-0.012	-0.043**
	(0.217)	(0.027)	(0.019)	(0.220)	(0.023)	(0.019)
Mom breast fed	-0.175*	-0.035***	-0.012	-0.054	0.003	-0.010
	(0.100)	(0.012)	(0.009)	(0.111)	(0.011)	(0.009)
Mom breast fed unknown	0.228	0.034	0.027	0.299	0.009	0.058***
	(0.210)	(0.026)	(0.018)	(0.221)	(0.023)	(0.019)
GPA	-0.076	-0.012	-0.004	-0.270***	-0.023***	-0.017***
	(0.066)	(0.008)	(0.006)	(0.084)	(0.008)	(0.006)
Took something from store w/o paying for it	-0.258***	-0.013	-0.011	-0.255**	-0.034***	-0.014
	(0.099)	(0.012)	(0.009)	(0.122)	(0.012)	(0.009)
Constant	9.691***	-0.624***	-0.690***	5.320***	-0.833***	-0.774***
	(0.772)	(0.092)	(0.067)	(0.864)	(0.084)	(0.066)
Observations	5,985	5,985	5,985	6,515	6,515	6,515
R-squared	0.590	0.311	0.386	0.609	0.370	0.397

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Benchmark categories: father's job is managerial/professional, income is unknown, parent's highest level of education is college or more.

Appendix Table 2b: OLS Models of the Effect of Having Trouble Paying Bills on Body Weight

VARIABLES	Men BMI	Men Overweight/ obese	Men Obese	Women BMI	Women Overweight/ Obese	Women Obese
Wave III Variables						
Has trouble paying bills	-0.064	-0.043***	0.000	0.374***	0.024**	0.024***
	(0.103)	(0.012)	(0.009)	(0.112)	(0.011)	(0.009)
Impulsive	0.078	-0.002	0.011	0.130	-0.011	0.006
	(0.096)	(0.012)	(0.008)	(0.114)	(0.011)	(0.009)
BMI_1994	0.886***	0.060***	0.053***	1.049***	0.061***	0.053***
	(0.015)	(0.001)	(0.001)	(0.016)	(0.001)	(0.001)
Has a credit card	0.184*	0.034***	-0.004	-0.167	-0.032***	-0.011
	(0.099)	(0.012)	(0.009)	(0.117)	(0.011)	(0.009)
Volunteer				0.258**	-0.001	0.012
				(0.110)	(0.011)	(0.009)
Age	-0.219***	-0.012***	-0.017***	-0.183***	-0.010***	-0.011***
	(0.032)	(0.004)	(0.003)	(0.034)	(0.003)	(0.003)
Married	0.662***	0.058***	0.038***	1.357***	0.123***	0.063***
	(0.138)	(0.016)	(0.013)	(0.133)	(0.013)	(0.011)
Inc. btw $1 -$7	0.427	0.026	0.032	0.555*	0.036	0.038*
	(0.262)	(0.031)	(0.022)	(0.308)	(0.028)	(0.022)
Inc. btw $8-$3900	0.274	-0.004	0.025	0.814***	0.071**	0.046**
	(0.254)	(0.031)	(0.021)	(0.310)	(0.028)	(0.022)
Inc. btw $4000-$11700	0.095	-0.026	0.031	0.638**	0.045	0.042*
	(0.255)	(0.031)	(0.022)	(0.310)	(0.028)	(0.022)
Inc. btw $12000-$20100	0.144	-0.015	0.008	0.729**	0.061**	0.042*
	(0.249)	(0.030)	(0.021)	(0.309)	(0.028)	(0.022)
Income missing	0.278	0.017	0.023	0.743**	0.050*	0.053**
	(0.247)	(0.030)	(0.021)	(0.315)	(0.029)	(0.022)
Gamble	0.196*	0.021	-0.013	0.161	-0.008	-0.007
	(0.104)	(0.013)	(0.009)	(0.109)	(0.011)	(0.008)
Has savings account	0.044	0.013	-0.013	-0.244**	-0.014	-0.007
	(0.097)	(0.012)	(0.009)	(0.111)	(0.011)	(0.009)
Lottery	0.311***	0.018	0.029***	0.090	0.033***	0.002
	(0.102)	(0.013)	(0.009)	(0.110)	(0.011)	(0.008)
Religious	0.114**	0.015**	0.008*	0.119**	0.007	0.004
	(0.048)	(0.006)	(0.004)	(0.056)	(0.006)	(0.004)
Black	0.263**	-0.006	0.016	0.357**	0.068***	-0.001
	(0.132)	(0.016)	(0.012)	(0.148)	(0.014)	(0.011)
Other race	0.224	-0.002	0.021	-0.162	-0.020	0.005
	(0.152)	(0.018)	(0.013)	(0.157)	(0.016)	(0.012)
Hispanic	0.362**	0.043***	0.000	0.134	0.042***	0.000
	(0.141)	(0.017)	(0.013)	(0.156)	(0.016)	(0.013)
Wave I Variables						
Drank in past 30 days	-0.017	0.019	-0.004	-0.056	0.003	-0.005
	(0.145)	(0.018)	(0.014)	(0.214)	(0.021)	(0.015)

Thinks smart compared to others	0.064	0.007	0.003	0.038	-0.007	0.005
	(0.099)	(0.012)	(0.009)	(0.114)	(0.011)	(0.009)
Likely to go to college	0.052	0.007	0.000	0.099	0.016	-0.003
	(0.099)	(0.012)	(0.009)	(0.119)	(0.012)	(0.009)
Usual summer work hrs	0.004	0.001	0.000	-0.003	0.000	-0.000
	(0.003)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)
Dad unemployed	-0.054	0.020	0.007	0.656**	0.100***	0.023
	(0.265)	(0.032)	(0.024)	(0.315)	(0.030)	(0.025)
Dad job unknown	0.003	-0.011	0.015	0.027	0.046***	-0.006
	(0.146)	(0.018)	(0.013)	(0.160)	(0.016)	(0.012)
Dad job other than manag/prof	0.195	0.021	0.023**	0.019	0.035**	-0.009
	(0.119)	(0.016)	(0.011)	(0.132)	(0.014)	(0.010)
Smoked in HS	-0.194	-0.014	0.006	-0.533***	-0.027*	-0.031***
	(0.119)	(0.015)	(0.011)	(0.144)	(0.014)	(0.011)
Parent has some college	-0.227*	0.000	-0.020*	0.011	0.021	-0.003
	(0.123)	(0.015)	(0.011)	(0.135)	(0.014)	(0.011)
Parent educ. HS graduate	-0.014	0.007	-0.014	0.313**	0.054***	0.022**
	(0.122)	(0.015)	(0.011)	(0.140)	(0.014)	(0.011)
Parent educ. less than HS	-0.023	0.042*	-0.009	0.131	0.015	0.020
	(0.193)	(0.023)	(0.017)	(0.205)	(0.020)	(0.016)
Parent educ. unknown	0.143	0.021	0.021	-0.647*	-0.021	-0.004
	(0.300)	(0.035)	(0.026)	(0.373)	(0.034)	(0.027)
Parent on welfare	-0.024	-0.012	-0.028*	0.124	-0.015	0.022
	(0.176)	(0.020)	(0.015)	(0.207)	(0.018)	(0.016)
Parent smoked	-0.072	-0.017	0.006	0.228*	0.018	0.018*
	(0.117)	(0.014)	(0.010)	(0.132)	(0.013)	(0.011)
Mom obese	0.811***	0.033**	0.057***	0.783***	0.047***	0.046***
	(0.139)	(0.015)	(0.013)	(0.158)	(0.015)	(0.013)
Mom binge drank	0.051	0.006	-0.009	-0.009	-0.003	-0.006
	(0.151)	(0.018)	(0.013)	(0.180)	(0.017)	(0.013)
Mom binge not known	-0.287	-0.035	-0.025	-0.212	-0.013	-0.044**
	(0.217)	(0.027)	(0.019)	(0.221)	(0.023)	(0.019)
Mom breast fed	-0.175*	-0.035***	-0.012	-0.065	0.002	-0.011
	(0.100)	(0.012)	(0.009)	(0.111)	(0.011)	(0.009)
Mom breast fed unknown	0.226	0.033	0.027	0.293	0.008	0.057***
	(0.210)	(0.026)	(0.018)	(0.221)	(0.023)	(0.019)
GPA	-0.090	-0.015*	-0.004	-0.250***	-0.020**	-0.016**
	(0.066)	(0.008)	(0.006)	(0.083)	(0.008)	(0.006)
Took something from store w/o paying for it	-0.254***	-0.010	-0.011	-0.269**	-0.035***	-0.015
	(0.099)	(0.012)	(0.009)	(0.122)	(0.012)	(0.009)
Constant	9.671***	-0.629***	-0.693***	5.261***	-0.836***	-0.777***
	(0.768)	(0.091)	(0.066)	(0.863)	(0.084)	(0.066)
Observations	5,985	5,985	5,985	6,515	6,515	6,515
R-squared	0.590	0.313	0.386	0.609	0.371	0.397

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See notes to Appendix Table 2a.

Appendix Table 3a: Propensity Score Models for Credit Card Debt

Men Credit Card Debt									
VARIABLES	OLS	Nearest Neighbor	*k* nearest neighbor	Within Caliper .001	Within Caliper .0001	Within Caliper .00005	Kernel bw.06	LLR bw .18	Radius caliper .001
BMI	0.134	0.188	0.280	0.189	0.179	0.268	0.176	0.132	0.268*
	(0.091)	(0.192)	(0.171)	(0.207)	(0.236)	(0.294)	(0.150)	(0.140)	(0.146)
Obese	0.004	0.007	0.013	0.008	0.009	0.014	0.005	0.002	0.013
	(0.008)	(0.014)	(0.013)	(0.016)	(0.018)	(0.022)	(0.012)	(0.011)	(0.011)
Overweight/obese	0.028**	0.043**	0.036**	0.041**	0.037	0.038	0.033**	0.031**	0.037**
	(0.011)	(0.019)	(0.017)	(0.020)	(0.023)	(0.028)	(0.015)	(0.013)	(0.015)
On common support		5,981	5,981	5,939	5,277	4,789	5,981	5,981	5,939
Observations	5,985	5,985	5,985	5,985	5,985	5,985	5,985	5,985	5,985

Women Credit Card Debt									
VARIABLES	OLS	Nearest Neighbor	*k* nearest neighbor	Within Caliper .001	Within Caliper .0001	Within Caliper .00005	Kernel bw.06	LLR bw .18	Radius caliper .001
BMI	-0.018	0.219	0.190	0.158	0.205	0.182	0.101	0.070	0.067
	(0.100)	(0.227)	(0.198)	(0.221)	(0.286)	(0.343)	(0.165)	(0.169)	(0.184)
Obese	-0.003	0.007	0.010	0.006	0.002	-0.007	0.001	-0.001	-0.001
	(0.008)	(0.015)	(0.013)	(0.014)	(0.018)	(0.021)	(0.010)	(0.011)	(0.012)
Overweight/obese	-0.002	0.011	0.006	0.009	0.005	0.008	0.005	0.003	0.004
	(0.010)	(0.018)	(0.016)	(0.018)	(0.023)	(0.027)	(0.013)	(0.013)	(0.014)
On common support		6,515	6,515	6,469	5,500	4,822	6,515	6,515	6,469
Observations	6,515	6,515	6,515	6,515	6,515	6,515	6,515	6,515	6,515

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3b: Propensity Score Models for Trouble Paying Bills

Men Trouble Paying Bills									
VARIABLES	OLS	Nearest Neighbor	*k* nearest neighbor	Within Caliper .001	Within Caliper .0001	Within Caliper .00005	Kernel bw.06	LLR bw .18	Radius caliper .001
BMI	-0.065	0.156	-0.044	0.148	0.155	-0.112	-0.045	-0.010	-0.032
	(0.104)	(0.230)	(0.220)	(0.237)	(0.272)	(0.316)	(0.170)	(0.155)	(0.177)
Obese	0.000	0.018	0.004	0.016	0.018	-0.004	0.004	0.006	0.001
	(0.009)	(0.017)	(0.015)	(0.018)	(0.019)	(0.024)	(0.012)	(0.011)	(0.013)
Overweight/obese	-0.043***	-0.029	-0.035*	-0.029	-0.034	-0.051	-0.041***	-0.036**	-0.042***
	(0.012)	(0.022)	(0.020)	(0.023)	(0.027)	(0.031)	(0.016)	(0.015)	(0.016)
On common support		5,983	5,983	5,938	5,531	5,215	5,983	5,983	5,938
Observations	5,985	5,985	5,985	5,985	5,985	5,985	5,985	5,985	5,985

Women Trouble Paying Bills									
VARIABLES	OLS	Nearest Neighbor	*k* nearest neighbor	Within Caliper .001	Within Caliper .0001	Within Caliper .00005	Kernel bw.06	LLR bw .18	Radius caliper .001
BMI	0.374***	0.382	0.586**	0.393	0.096	-0.093	0.458**	0.443**	0.379*
	(0.112)	(0.253)	(0.229)	(0.253)	(0.291)	(0.353)	(0.198)	(0.198)	(0.198)
Obese	0.024***	0.018	0.036**	0.019	0.010	-0.003	0.025**	0.024*	0.022*
	(0.009)	(0.016)	(0.015)	(0.016)	(0.020)	(0.022)	(0.013)	(0.012)	(0.013)
Overweight/obese	0.024**	0.016	0.030*	0.023	-0.009	-0.033	0.027*	0.026*	0.028*
	(0.011)	(0.018)	(0.017)	(0.018)	(0.024)	(0.029)	(0.015)	(0.014)	(0.015)
On common support		6,513	6,513	6,458	5,855	5,436	6,513	6,513	6,458
Observations	6,515	6,515	6,515	6,515	6,515	6,515	6,515	6,515	6,515

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1