Estimating the Medical Care Costs of Youth Obesity in the Presence of Proxy Reporting Error*

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Abstract

This paper is the first to use instrumental variables to estimate the causal impact of youth obesity on medical care costs in order to address the endogeneity of weight. It is also the first to correct for bias due to correlation between reporting error in the endogenous regressor and the instrument. Models are estimated using restricted-use data on 11-17 year old children from the 2000-2010 Medical Expenditure Panel Survey, allowing us to instrument for child BMI using the BMI of the child's biological mother. To correct for bias due to parental proxy-reporting error in child BMI, we impute measured BMI from the National Health and Nutrition Examination Survey. we find that, on average, medical expenditures on overweight children are $478.21 more relative to healthy weight children and that medical expenditures on obese children are $1098.23 more relative to healthy weight children. Girls who are overweight cost $628.39 more per year relative to healthy weight girls and and girls who are obese cost $1448.94 more relative to healthy weight girls. These results imply that previous research has underestimated the cost of youth obesity.

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1 Introduction

Over the last 50 years, the prevalence of youth obesity has been increasing. In 1965, under 5% of US children and adolescents aged 2–19 years were obese. As of 2012, the prevalence of youth obesity is an estimated 16.9%, with significantly higher rates of obesity among Hispanic and non-Hispanic black children and adolescents (NCHS 2010; Ogden et al., 2012). Further, about 33% of boys and 30.4% of girls are considered to be overweight or obese.[1] This prevalence of overweight currently exceeds 40% among black and Hispanic adolescents (Ogden et al., 2012). Simply being overweight or obese increases their likelihood of type 2 diabetes, gallbladder disease, sleep apnea, joint problems, and cardiovascular risk factors during childhood and adolescence (Han et al., 2010; Guo and Chumlea, 1999; Dietz and Robinson, 2005; Ogden et al., 2002). In addition to physical consequences, being overweight or obese is also associated with negative self-image, low self-esteem, and behavioral and learning difficulties (Dietz, 1998). Overweight children are more likely to become overweight and obese adults (Biro and Wien, 2010), and children who are overweight are more likely to have coronary heart disease, type 2 diabetes, and other serious health problems (NIH, 1998).

Previous research has assessed the cost of youth obesity. Finkelstein and Trogden (2008) found that, on average, obese children and adolescents incur $220 more in medical spending than normal weight children and that overweight children incur $180 more than normal weight children. Trasande et al. (2009) estimated that childhood obesity was responsible for $237.6 million in hospitalizations in 2005, up from $125.9 million in 2001. They found Medicaid bears most of the cost of obesity related conditions, although private payers cover more obesity treatments. Monheit et al. (2009) estimated separate models by gender and found that adolescent girls who become obese cost $790 more per year than normal weight girls. They found no significant effect for boys. These studies suggest that the short term return-on-investment to youth obesity interventions is small,

[1] Weight status for children is determined by percentile rank in gender-age specific CDC growth charts. Table 1 contains youth BMI percentile cutoffs. Table 2 contains the prevalence rates of obesity from 1963 to 2010 calculated from the National Health and Nutrition Examination Survey.

and the financial benefits of targeted interventions only exceed the costs by incorporating the expected future costs of adult obesity (Finkelstein and Trogden, 2008).

A major limitation of these prior studies is they only estimate the association between obesity and youth medical expenditures, and not the causal effect, as they do not explicitly account for possible endogeneity of weight or measurement error in body weight and height. As a result, these studies likely underestimate the true causal effect. Weight is endogenous because it is correlated with unobserved socio-economic status (SES) or access to care that affect medical spending. Families with lower SES are more likely to be obese and have higher incidence of poor health, have unobservable health problems, or engage in other risky behaviors (Fontaine and Bartlett, 2000). However, due to less access to care, these families may have lower expenditures on medical care (Burkhauser and Cawley, 2008). In data sets drawn from surveys, in which height and weight are reported and not measured, it is plausible to observe random additive or classical measurement error as well as measurement error that is non-classical. For example, a number studies find that individuals tend to under-report their own weight, and that this under-reporting is positively correlated with their own BMI (Gillum and Sempos, 2005; Rowland, 1990). This type of misreporting can invalidate measurement error models only suitable for random additive error (Villanueva, 2001; O'Neill and Sweetman, 2013).

We acknowledge these estimation problems and employ instrumental variables estimation to estimate the marginal effect of increased BMI in children on their medical expenditures. Previous studies have used instrumental variables for adult BMI (Cawley, 2004; Kline and Tobias, 2008; Smith et al., 2009). Cawley and Meyerhoefer (2012) use the MEPS to estimate the impact of obesity on adult medical expenditures. They employ restricted-use biological linkage variables in the MEPS to match parents to their biological children. This allows them to instrument for each adult's BMI using the BMI of their oldest child. We use the BMI of each child's biological parents as an IV for the child's BMI. We correct for measurement error in child and parent BMI by using the National Health and Nutrition Examination Survey (NHANES) as a source of measured BMI data. The NHANES contains both measured and self-reported heights and weights and can be used to correct reported BMI in the MEPS. Validation data are typically used to estimate correction equations which are then used to predict true height and weight using observed measures from the principle sample (Cawley, 2004). Instead of estimating correction equations to predict true BMI in the MEPS, we impute BMI directly from the NHANES on to observations in the MEPS.

After correcting for proxy-reporting error, we find that medical expenditures are significantly higher for girls aged 11-17 who are overweight and obese relative to those for girls who are healthy weight. Our estimates are larger in magnitude than those from previous studies that do not use instrumental variables. This suggests that endogeneity of weight and measurement error have a large role in biasing non-IV estimates of the impact of obesity on child medical expenditures. Further, previous studies have likely underestimated the cost of youth obesity and in turn, the cost effectiveness of interventions that target youth obesity before they reach adulthood.

2 Identification Strategy

2.1 Instrumental Variables

We estimate the effect of BMI on medical expenditures using the IV-GLM procedure described in Carroll et al. (2006). In order for IV estimation to produce consistent estimates, the instrument must be sufficiently correlated with the endogenous or mismeasured variable. Our first stage partial F-statistics range from 144.25 - 325.40, well in excess of the rule-of-thumb F-stat = 10 for all of our specifications (Stock et al., 2002). More difficult to establish for IV is that the instrument is independent of the error in the structural model.[2] Independence is violated if parent BMI is correlated with environmental factors that are unobservable, but affect the child's BMI. This cannot be directly tested in our data, however, there is a substantial literature validating the genetic relationship between weight of biological relatives which finds almost no support for shared

[2]Independence is a stronger assumption than for linear IV, but is required for IV-GLM (Carroll et al., 2006).

environmental effects on BMI (Lindeboom et al., 2010; Haberstick et al., 2010; Wardle et al., 2008; Grilo and Pogue-Geile, 1991).

Prior economic research has employed genetic variation in weight to generate instrumental variables. Cawley (2004) uses the BMI of a sibling to instrument for adult BMI in estimating the impact of obesity on wages. Cawley and Meyerhoefer (2012) use the BMI of children to instrument for the BMI of their biological parents in order to estimate the impact of obesity on adult medical expenditures. Kline and Tobias (2008) use the BMI of parents to instrument for the BMI of their children and estimate the impact of BMI on wages in Britain. They find nonlinearities in the impact of BMI on wages that differ by gender.

2.2 Proxy-Reporting Error

Proxy-reporting of child BMI by their parents can generate correlation between the parent's BMI and the reporting error in their child's BMI. Prior research has documented a negative correlation between adult's self-reported weight and measurement error in their own weight in the form of under-reporting (Shiely et al., 2013; Gorber et al., 2007; Villanueva, 2001). A number of small studies have tried to determine the manner in which parents report their children's weight and height. Studies of parental reporting of adolescent BMI show slight over-reporting of height and under-reporting of BMI (Brettschneider et al., 2012; O'Connor and Gugenheim, 2011; Goodman et al.; Reed and Price, 1998). For example, O'Connor and Gugenheim (2011) surveyed parents of children 2 to 17 years old at an outpatient orthopedic clinic, asking them to report their child's height and weight prior to having them measured. They found that mean weight error in parental reports increased with child age and with age-specific child BMI z-score. Parents tended to under-report their child's weight, leading to 21 percent of children measured as obese being misclassified in parental reports.

Parental under-reporting of their children's weight may be intentional if parents know the true weight of their child, but choose to misreport it, possibly due to stigma associated with obesity (Puhl and Heuer, 2010). Another possibility is that parents are unaware of their child's true height and weight, and respond with the most recent measurements they recall or inaccurate measurements. This may cause random measurement error, but may result in under-reports as children's height and weight tend to rise over time regardless of obesity status. In either case, the consequence of under-reporting is a negative correlation between the child's BMI and the proxy-reporting error in child BMI. This negative correlation, combined with positive correlation between parent and child BMI may imply negative correlation between parent BMI and the reporting error in child BMI, regardless of the reason parents misreport their children's weight.[3] If parent BMI is correlated with the measurement error in child BMI, then using parent BMI as an IV for child BMI may not result in consistent estimates of the impact of child obesity on medical expenditures.

Systematic misreporting of a covariate is a kind of omitted variables problem that is most easily analyzed using simple linear regression. Like random-additive error, under-reporting will lead to bias OLS coefficients. Unlike random-additive measurement error, under-reporting correlated with the IV can cause IV estimates to overestimate the marginal effect of changes in child BMI. This can be demonstrated using the probability limit of the beta coefficient in a simple linear IV model.

Consider a true linear model:

$$Y = \beta X + \epsilon, \tag{1}$$

such that $E(X\epsilon) = 0$. We cannot observe X directly in the data, and instead observe W such that,

$$W = X + u. \tag{2}$$

Thus, the true data X is observed with some additive error term u. If $E(u) = 0$ and $Cov(X, u) = 0$, any variance in u causes an attenuating bias in OLS estimates of β. If $Cov(X, u) \neq 0$, then OLS is still biased towards zero (more significantly if $Cov(X, u) > 0$).

[3]Covariance (and correlation, which is normalized covariance) is not transitive, so this is not a strict implication. (Langford et al., 2001)

We introduce instrument S such that,

$$X = \gamma S + \zeta \tag{3}$$

Where $\gamma \neq 0$ and ζ has mean zero.

IV estimation will consistently estimate β as long as S is uncorrelated with u and ϵ, and is sufficiently correlated with X. We assume $Cov(S, \epsilon) = 0$ and $Cov(S, X) \neq 0$ and focus on the relationship between the IV and the measurement error in X. Typically instruments are also measured with error such that,

$$T = S + v. \tag{4}$$

The probability limit of β_{IV} can be expressed in terms of covariances, as

$$plim\beta_{IV} = \frac{Cov(T, Y)}{Cov(T, W)} = \frac{\beta Cov(T, X)}{Cov(T, W)}. \tag{5}$$

If we assume that $Cov(T, \epsilon) = 0$, only measurement error in W and T can be the source of bias. Changing notation and substituting equations (2) and (4) into equation (5) we can derive,

$$plim\beta_{IV} = \frac{\beta \left\{\sigma_{SX} + \sigma_{Xv}\right\}}{\sigma_{SX} + \sigma_{Xv} + \sigma_{Su} + \sigma_{uv}}. \tag{6}$$

All the covariance terms in the probability limit depend on unobservable relationships. If we restrict $\sigma_{SX} > 0$, we can determine conditions under which $\beta_{IV} > \beta$. The covariance between the true instrument and the measurement error in the endogenous variable W ($Cov(S, W)$) can be positive or negative in sign. When $\sigma_{Su} < 0$, IV estimation will overestimate β. When parent's BMI is the IV, then negative covariance between the true instrument S and the measurement error in W is a possible consequence of proxy-reporting where obese parents are more likely to under-report their children's weight. This can generate negative correlation between child BMI, which is positively correlated with parent BMI, and the additive error in child BMI that is more negative the greater the parent under-reports the child's weight.[4]

We use the IV-GLM proposed by Hardin and Carroll (2003a) to account for the skewness of child medical costs as well as use instrumental variables.[5] Their method is essentially two-stage nonlinear least squares. The first stage is a linear regression of the mismeasured covariates on the set of included and excluded instruments. The second stage is a GLM fit of the outcome on the known covariates and the fitted values of the mismeasured covariate from the first stage[6] (Hardin and Carroll, 2003b). Correlation between S and u enters the IV-GLM procedure in the first stage, resulting in biased predicted values for X. The second stage, conditional on the correct GLM link and variance function, will consistently estimate naive β coefficients treating the biased predicted values for X as correct.

2.3 Corrected Body Mass Index

Prior studies using measured data to correct for measurement error regress BMI on self-reported BMI in a validation sample, and then use the estimated model to predict measured BMI in the main sample, which only contains self reports. (Courtemanche et al., 2014). We follow the arguments of Lee and Sepanski (1995) and impute BMI directly instead of predicting height and weight and using the predictions to calculate BMI. The advantage is we are directly predicting the BMI distribution, and in turn the non-linear relationship between BMI and expenditures.

Instead of using regression equations to predict BMI, we use hotdeck imputation to impute measured BMI values from the NHANES for parents in children in the MEPS.[7] Hotdeck is similar to regression based imputation in that known values from a validation

[4]A powerful instrument ($Cov(S, X) > 0$) and increased under-reporting of heavier children ($Cov(X, u) < 0$) may imply a negative correlation between the true IV and the reporting error in child BMI ($Cov(S, u) < 0$)

[5]For a thorough treatment on non-linear measurement error models, see Chen et al. (2011).

[6]We estimate the IV-GLM in STATA using the **qvf** command in (Hardin et al., 2003). The command fits the GLM using iteratively re-weighted least squares (IRLS). Hardin and Hilbe (2012) detail the steps of the IRLS algorithm.

[7]We appropriate the **hotdeck** command of Mander and Clayton (1999) to implement the imputation.

dataset are used to impute missing values in the principle sample. Unlike regression based imputation, hotdeck stochastically samples from the validation data with replacement and assigns selected values to observations in the principle dataset. Imputation is carried out within matched subsets of both datasets called strata, which are generated using covariates shared in both datasets. The advantage of using hotdeck imputation is we do not impose functional form in the correction equations. Another benefit is we can indirectly observe misreporting behavior in the MEPS by calculating the additive error terms in equations (2) and (4).

We impute mothers' BMI under the same conditions as regression based imputation.[8] Each mother has true BMI S and there observed BMI T_j in the principle sample $j = M$ and in the validation sample $j = N$.[9] the first condition is that for true BMI S, there exists a surrogate (typically the observed BMI) T_j^{sur} such that the distribution of the outcome Y given (S, T_j^{sur}) is the same as Y given S. Essentially the observed BMI cannot contain information about the outcome that is not already reflected in true BMI. Another interpretation is that measurement error in BMI cannot be correlated with unobserved variables that influence the outcome. The second condition is the transportability of the surrogate; that the underlying distributions of true BMI in both datasets are equal conditional on the surrogate. Transportability implies that,

$$E(S|T_M) = E(S|T_N).^{10} \tag{7}$$

Hotdeck imputation must satisfy these same conditions derived for regression based imputation. Both the MEPS and the NHANES are nationally representative datasets. After incorporating sample weights, we assume that the use of self-reported BMI in both datasets as the surrogate satisfies transportability conditional on the covariates (Z_j) shared in both datasets.

[8]These conditions are restated from Courtemanche et al. (2014) in terms of our model.

[9]In our analysis, the MEPS is the principle sample and the NHANES serves as the validation sample.

[10]This is known as weak transportability (Lee and Sepanski, 1995).

$$E(S|T_M, Z_M) = E(S|T_N, Z_N). \tag{8}$$

The shared covariates are categorical variables which are then used to determine the hotdeck imputation strata.

3 Data and Empirical Model

3.1 Data

3.1.1 Medical Expenditure Panel Survey

The Medical Expenditure Panel Survey (MEPS) is a comprehensive, nationally representative survey of the U.S. civilian non-institutionalized population.[11] In the MEPS, families are surveyed five times during a two year period about their medical care utilization and expenditures. For each family (the responding unit in the MEPS), a single individual is the primary respondent. For most families in the MEPS, the mother is the primary respondent. In two parent households, the second most common primary respondent is the father. We can identify the primary respondent in each family (usually a parent) and we use restricted-use biological linkage variables to match parents to their biological children. Heights and weights are not measured in the MEPS. The primary respondent typically reports the heights and weights of everyone in the reporting unit. This means that the primary respondent self-reports her height and weight, and heights and weights for her spouse and children are generated from proxy-reports.

We use data from the 2000-2010 household component of the MEPS and inflate all expenditures in each year to 2010 dollars. We limit the sample to two-parent households with biological children younger than 18 and older than 11, and parents between 20 and 64; both with non-missing BMI. We do not incorporate children younger than 11 due to high rates non-response. We eliminate children with BMIs in excess of 65 and below

[11] To account for the complex survey design of the MEPS, we use the method of balanced repeated replications to estimate standard errors in all models, which implements clustering at the PSU-level, stratification, and weighting.

10 (39 observations) and children whose parents had BMI in excess of 55 and below 10 (29 observations). We eliminate 543 underweight children from the sample. Our model is capable of capturing the non-linear relationship between weight and expenditures, however some underweight individuals are outliers in height and weight measures, and we are only interested in the changes in medical spending due to excess body weight.

3.1.2 National Health and Nutrition Examination Survey

We correct for reporting error in BMI by using the National Health and Nutrition Examination Survey (NHANES) as a validation dataset. The NHANES is a nationally representative survey of adults and children. In addition, all survey respondents have their heights and weights measured. Adults and children aged 16 or older self-report their weight. The NHANES does not contain medical expenditures, but does share with the MEPS rich covariates.

We use hotdeck imputation to assign every child in the MEPS a measured BMI for their self-reporting mother. Categorical variables for race, education, age, and income generate 180 exclusive strata. Within each strata mothers' self-reported BMIs are then imputed within exclusive BMI categories that are 2.5 BMI units wide. To impute child BMI, we separate both the MEPS and the NHANES into separate subsets by gender-age pair. Each subset is then stratified into half-percentile bins. Measured BMI in each gender-age subset in the NHANES is imputed onto observations in the MEPS with proxy-reported BMI that share the same half-percentile rank. The observations in the lowest and highest percentile were dropped to ensure that differences in BMI are only due to parental-misreporting behavior, and not due to measurement error from other sources such as imputation error by the survey-taker.

Imputation from the NHANES into the MEPS further reduces the sample size, as some MEPS observations do not have a donor observation in the NHANES that shares all of the same matching covariates. We drop 5,516 observations with missing imputed child BMI, and we drop 1,175 observations for which one or both parents have missing imputed BMI, generating a sample of 12,311 children. We use both self-reported BMI and imputed BMI as IVs to compare estimates in the presence of different reporting errors. We eliminate children for whom we cannot identify mothers as the primary respondent (2,470 observations). The resulting estimation dataset has 9,841 children aged 11-17 with mothers who were the primary-respondent and proxy-reported the child's BMI.

3.2 Model Specification

As with adult medical expenditures, medical spending on children is highly positively skewed with a substantial number with zero expenditures in any survey year (Monheit et al., 2009; Finkelstein and Trogden, 2008). To account for the shape of distribution of expenditures we employ a two-part model. The first part is a Logit model that estimates the probability of having positive expenditures. The second part estimates the level of medical expenditures conditional on having positive spending and is specified as a a GLM with Gamma variance structure and log link. We conduct the specification tests suggested by Manning and Mullahy (2001) to identify the proper link function and distribution for our data.[12] Both parts of the model include child characteristics, and household characteristics. We acknowledge that parents education and SES can partly determine child medical expenditures. We do not include income in the model as it is likely endogenous. We include measures of both parent's education as covariates, which serve as a proxy for parental SES. We also control for whether the child self-reported their height and weight.[13]

It is possible to estimate models using the z-score of child BMI from the appropriate CDC prior distribution as the explanatory variable. Child weight status is determined using the z-score of BMI, however it is difficult to interpret the weight change associated

[12]We conduct Park tests to confirm our choice of conditional variance, in particular that the variance is proportional to the square of the conditional mean. We find $\lambda = 1.91 - 2.13$ across our samples. We also perform a modified Hosmer-Lemeshow test by regressing prediction error from each model on deciles of the distribution of predicted expenditures. We fail to reject the null-hypothesis that the decile coefficients are jointly equal to zero, indicating the choice of distribution and link function is appropriate. Monheit et al. (2009) tested alternate specifications on the 2001-2003 MEPS and selected a two-part model with a Probit first stage and a Gamma Log-linear second stage.

[13]Fewer than one percent of children self-reported their BMI when their mother was the primary respondent.

with a unit change in the z-score. We use child BMI as the measure of youth obesity and include controls for child gender and age in months. BMI is an imperfect measure of body fat since it does not distinguish fat from fat-free mass such as muscle and bone (Burkhauser and Cawley, 2008) however, BMI is the only measure of fatness in the MEPS. We do not estimate marginal effects using binary indicators of obesity. Instrumenting for binary measures of obesity can cause biased estimates in the the first stage regression. We can only estimate bounds for the true effect when instrumenting for a binary indicator for reported child BMI is both endogenous and non-classically mismeasured (Frazis and Loewenstein, 2003).

4 Results

4.1 Descriptive Statistics

Descriptive statistics for the model covariates are presented in tables 3 and 4. Sample means in the left columns are taken from the broader sample of children aged 11-17 which both primary responding fathers and mothers. The right columns contain the sample means from the estimation sample of children whose mothers are the primary respondent. We believe that since the estimation sample does not differ on observables from the broader sample, we can generalize estimates from the estimation sample to households in which mothers were not the primary respondent.

Table 5 contains descriptive statistics for boys and their parents' BMI and Table 6 shows the same descriptive statistics for girls. Comparing the mean reported BMI in the MEPS to the imputed measured BMI from the NHANES suggests the BMIs in the MEPS are under-reported. For example, the mean reported BMI of girls in the sample is 21.71. The mean imputed BMI from the NHANES is higher at 22.80. The same relationship exists for mothers, whose self-reports are lower, on average, than their imputed measured BMI.

4.2 Proxy-Reporting Error

Figure 1 compares the distribution of self-reported BMI in the NHANES to the measured BMI of adult females.[14] The self-reported distribution is shifted to the left of the measured BMIs, suggesting that mothers are under-reporting their own BMI. A necessary assumption to impute measured BMI from the NHANES into the MEPS is that the misreporting behavior is the same in both samples. Only primary respondents in the MEPS self-report their data, the large majority of which are women. Figure 2 shows the distribution of self-reported BMI in the MEPS and measured BMIs imputed from the NHANES. The self-reports in the MEPS are similarly distributed to those in the NHANES. When measured BMI is imputed, we observe similar reporting as in the NHANES. There is less mass in the distribution of measured BMI relative to self-reported BMI for BMI > 30. There is greater mass in the distribution of self-reports over the normal weight and overweight range of BMI.

Children rarely self-report; instead their BMI is proxy-reported by the primary respondent. Differences between error caused by proxy-reporting and self-reporting would violate transportability. Courtemanche et al. (2014) propose using percentile rank in lieu of observed BMI as the surrogate to predict true BMI.[15] They demonstrate that as long as both samples are representative of the same population, the percentile rank satisfies transportability, even if the misreporting behavior is different in both samples. Transportability is satisfied when the expected true BMI conditional on it's percentile rank is the same in both datasets.

Figure 3 shows the distribution of child BMIs proxy-reported in the MEPS and the distribution of measured child BMI in the NHANES. Mothers' misreporting of their children's height and weight results in under-reporting of BMI similar to that caused by mothers' self-reports. There is greater mass in the distribution of imputed measured BMI

[14] The distributions are generated using the NHANES directly, with BMI restricted to be under 55 to match our sample.

[15] A necessary assumption is that the expected true BMI is monotonically increasing in the reported BMI. Courtemanche et al. (2014) test this assumption in the NHANES and find no violations. Monotonicity is fundamentally untestable in the MEPS.

above BMI = 25 up to around 40 and less mass below BMI of around 23. The standard BMI cutoffs for weight status do not strictly apply for children, whose BMIs tend to be lower than adults. Thus misreporting that over-represents the number of children with BMI under 20 may be indicative of the same over-representation of normal weight individuals that we observe in mothers' self-reports.

We estimate the sample covariances between measurement error in reported BMI and imputed measured parent and child BMI by calculating the error terms in equations (2) and (4). This allows us to indirectly observe how mothers' misreporting can generate measurement error in child BMI that is correlated with both the child's and parent's BMI. Figure 4 plots the additive error in boys' proxy-reported BMI against their imputed measured BMI. There is a moderate relationship ($\rho = -0.69$) between boys' BMIs and the degree to which parents misreport their height and weight. At lower imputed BMIs the proxy reporting error is mean zero, turning negative as imputed BMI increases. There is a greater portion of boys' BMIs under-reported relative to over-reported. Figure 5 separates the plot by age. Although the 11 and 14 year old boys have positive correlation coefficients, the general trend is higher magnitudes of under-reporting among heavier boys. The gradient of under-reporting also becomes steeper as boys become older.

Figure 6 plots the additive error in girls' BMI values against their imputed measured BMIs. The negative correlation is slightly stronger ($\rho = -0.71$) than for boys, although far more observations are under-reported. Parental under-reporting of girls increases monotonically with imputed girls' BMI. When we split up observations by age in figure 7 we observe some variation in parental reporting by child age, but a consistent downward gradient due to under-reporting. Interestingly, the degree of misreporting moves towards zero at very high BMI levels for girls in some age groups.[16] One possible explanation is that parents are more acutely aware of their child's weight because it is significantly higher than average in relative terms, or because their children have weight related co-morbidities that increase their contact with the healthcare system. It may be that this

[16]This causes 11 and 14 year old girls exhibit slight positive correlation between measured BMI and the measurement error, even though the general trend is negative.

salience of higher BMI is associated with more honest reporting, either by resolving lack of information or by mitigating the effect of stigma associated with relatively high BMI.

By comparing the reported BMIs in the MEPS to those imputed from the NHANES, we indirectly observe measurement error that warrants IV estimation. Equation (6) shows that the correlation between the IV and the measurement error in child BMI can cause overestimation if this correlation is negative. In Figure 8, we plot the additive error in boys' BMIs against the imputed measured BMI of that child's mother. We observe a slight negative correlation ($\rho = -0.16$). Figure 9 plots the additive error in girls' BMIs against the imputed measured BMI of that child's mother. The negative correlation is larger than for boys ($\rho = -0.22$). Additionally, a larger share of observations are under-reported than for boys. These negative correlations imply that IV estimation using proxy-reported child BMI can cause overestimation of the true effect of obesity on child medical costs.

4.3 Impact of Youth Obesity on Medical Expenditures

We begin by estimating a non-IV two-part model with the same specification as our main model. The results are presented in the left column of Table 7. Each estimated coefficient represents the marginal effect of a one unit increase in BMI on annual medical expenditures. From our non-IV model we find that, on average, gaining an extra unit of BMI raises medical care costs by \$30.95 per year. To approximate the impact of a normal weight child becoming obese, the estimated marginal effect can be multiplied into the difference in mean BMI among obese and normal weight children. For example, the \$30.80 estimated coefficient for girls can be transformed into the average marginal effect of becoming obese by multiplying it into the difference of means found in table 6, which are calculated using proxy-reported BMI in the MEPS. The average marginal effect is calculated as $30.80\,(29.42 - 19.46) = 306.61$. Table 8 approximate impacts of moving from normal weight to overweight and moving from normal weight to obese for the estimates in columns 1 - 4 in table 7. We find that, when not instrumenting, obese children aged 11-17 incur additional costs of \$304.30, and being overweight increases expenditures by \$131.10.

Column 2 presents the coefficient estimates using the mother's self-reported BMI as the IV for the proxy-reported BMI of their child. Compared to the non-IV estimates, the effect sizes are much larger, though no longer significant for boys. These estimates are likely biased by the correlation between the mother's BMI and measurement error in child BMI as well. In column 3 we use the mother's BMI imputed from the NHANES as the IV. All estimates increase in magnitude by between \$30 and \$40.

Column 4 contains coefficient estimates from models using imputed child BMI from the NHANES and imputed mothers' BMI from the NHANES as the IV. Since the imputed data are measured, any error in child BMI is random due to imputation, and is uncorrelated with the mother's BMI. The coefficients are smaller than those in column 3, where the only source of bias is reporting error correlated with the instrument. This implies that the correlation between the IV and the additive error in child BMI is negative. This is consistent with the under-reporting indirectly observed in figures 8 and 9, where we observe negative correlation between the IV and the additive error in child BMI.

We find that on average an increase of one BMI unit is associated with a \$97.49 increase in medical expenditures. For girls, this effect is \$126.09 for each BMI unit. The overall effect is significant at the 90% level and the effect for girls is significant at the 95% level. We do not identify a precisely estimated effect for boys. We multiply these average marginal effects into the difference between average BMI in weight categories to get the average effect of moving form normal weight into overweight and obese on medical expenditures. We find that, on average, overweight children incur \$478.21 in additional expenditures relative to normal weight children, and obese children cost \$1098.23 more relative to normal weight children. Girls who are overweight incur \$628.39 in additional expenditures relative to normal weight girls and girls who are obese incur \$1448.94 in additional expenditures relative to normal weight girls.

4.4 Bias Due to Measurement Error

The use of measured BMI imputed from the NHANES in our IV-GLM model is an *ex ante* correction for measurement error. It is the same as recovering the true BMI in equations (2) and (4). We can alternatively correct for the bias in the coefficients *ex post* by estimating the sample covariances in equation (6) and recovering the true β coefficient.

We implement the adjustment by rearranging equation (6) to isolate the true β,

$$\beta = \delta \beta_{IV}, \quad \text{where } \delta = \frac{\sigma_{SX} + \sigma_{Xv} + \sigma_{Su} + \sigma_{uv}}{\sigma_{SX} + \sigma_{Xv}}. \tag{9}$$

We estimate δ using sample covariances where S is the mother's imputed BMI and X is the child's imputed BMI and the error terms u and v are predicted using the self- and proxy-reported BMIs in the MEPS and equations (2) and (4).

Column 5 in table 7 contains the coefficients from column 3 adjusted using $\hat{\delta}$ where the IV is measured from the NHANES. In this case, $\sigma_{Xv} = \sigma_{uv} = 0$ since the IV is not mismeasured. The associated $\hat{\delta}$ for each coefficient is displayed in brackets. Each $\hat{\delta}$ is less than one, suggesting that $\sigma_{Su} < 0$ as indicated in figures 8 and 9. The coefficients on column 5 correspond closely to those when both parent and child BMI are imputed in the model. This suggests that virtually all of the difference between estimates in columns 3 and 4 is due to the correlation between the true IV and the measurement error in child BMI.

We use the sample covariances to investigate the difference in effect sizes between columns 2 and 3. When we replace mothers' self-reported BMI as the instrument with imputed measured BMI from the NHANES, the effect sizes increase further. The estimated $\hat{\delta}$ are very similar to those in column 5 when incorporating measurement error in the IV. The similarity is due to very small magnitudes of $Cov(X, v)$ and $Cov(u, v)$. This implies that the measurement error in the instrument is not strongly correlated with the child's BMI or the measurement error in child BMI.

Additive error in mothers' BMI may cause omitted variables bias in the first stage. We rule out this possibility because the sample covariance between v and X is nearly zero. Measurement error in the IV may be correlated with unobserved factors that affect spending ($Cov(v, \epsilon) \neq 0$). We cannot directly test this in our data, yet it does not pose a threat to the validity of our instrument after we impute measured child and their mother's BMI. The results in column 5 suggest that after stripping the instrument of measurement error, correlation between the measured IV and child BMI is the only significant source of bias. This implies that the imputed measured BMI is not correlated with any unobserved factors.

5 Discussion

We estimate the effect of youth obesity on medical expenditures using data from the 2000-2010 Medical Expenditures Panel Survey (MEPS). These are the first estimates of this effect using instrumental variables. IV estimation will generate biased estimates of the true marginal effect of BMI on expenditures if the instrument is mismeasured, or if there is correlation between the instrument and measurement error in the endogenous variable. We use a novel approach to correct for this bias due to measurement error by imputing measured BMI values into the MEPS from the National Health and Nutrition Examination Survey. We hotdeck impute measured BMI for mothers from the NHANES by matching on self-reported BMI in both datasets and impute children's measured BMIs from the NHANES into the MEPS within finely defined strata across the BMI distribution.

Imputation allows us to indirectly identify the proxy-reporting behavior of parents with regard to their children's BMI without imposing a functional form on the imputation through correction equations. We find evidence of systematic under-reporting by mothers when reporting their children's weight, which is more pronounced for daughters. We also find under-reporting in maternal self-reports that are consistent with findings in previous research as well as in the NHANES where each adult both self-reports and has their weight measured. The observed pattern of proxy-reporting error confirms the need for our empirical strategy by demonstrating correlation between the IV and additive error in child BMI that would otherwise result in biased estimates of the impact of BMI on medical care costs in conventional IV estimation.

We find, among children aged 11-17, obesity is associated with \$304.30 in higher medical care costs per year relative to healthy weight children, and being overweight increases expenditures by $131.10 relative to healthy weight children in our non-IV model. Finkelstein and Trogden (2008) estimated a two-part GLM model on 2001-03 MEPS with binary indicators for obesity and found that obese children and adolescents incur $220 more medical expenditures than those of normal weight, and overweight incur $180 more in medical expenditures. Monheit et al. (2009) estimated separate models by gender and found that adolescent girls who become obese cost $790 more per year than normal weight girls. We find similar results to Finkelstein and Trogden (2008), considering their estimates in 2010 dollars are $260.72 and $213.32 respectively. Our estimate of the impact of obesity on girls medical costs is significantly lower than found by Monheit et al. (2009). Unlike these studies, we cannot use the full sample of children in the MEPS, and subset to children in two-parent households due to availability of instruments. Children in single parent households may have different underlying health or access to care that will cause our estimates to differ from prior studies. In all non-IV studies of the impact of obesity, we cannot interpret estimated coefficients as causal effects, and expect that these effects the result of attenuating bias due to the endogeneity of weight, and the measurement error.

Instrumenting using self-reported mothers' BMI in the MEPS dramatically increases the effect sizes. Although IV estimation mitigates bias due to endogeneity and proxy-reporting error in child BMI it can introduce upward bias if the instrument is negatively correlated with the proxy-reporting error in child BMI. We compute sample covariances to demonstrate that the instrument is correlated with the proxy-reporting error in child BMI, and even calculate the degree to which this error is upwardly biasing estimates. We find that this upward bias only depends on the correlation between the true instrument and the proxy-reporting error in child BMI, and that the self-reporting error in the IV is not correlated with child BMI or its error component. We do however observe bias due to measurement error in the IV as when we correct for measurement error in the IV, but not child BMI, the coefficient estimates further increase in magnitude. This difference suggests that measurement error in the instrument is introducing a distinct downward bias from the upward bias we hypothesized. We rule out omitted variables bias in the first stage as the mechanism of this bias due to negligible correlation between the measurement error in the IV and proxy-reported child BMI in the first stage regressions. It is possible that measurement error in the IV is correlated with unobserved factors, even though the true component of the IV is exogenous. There is little discussion in previous IV studies on the impact of obesity regarding mismeasured instruments. Although many studies utilize instruments measured without error, some data only contain instruments measured with error. Our findings suggest that researchers using instrumental variables that are possibly measured with error must consider that error component may be correlated with unobserved factors in the model error term. By imputing measured BMI we strip the instrument of self-reporting error and remove this bias.

We then impute measured child BMI in place of proxy-reported child BMI, correcting for bias due to correlation between the instrument and the error component of child BMI. After adjusting for proxy-reporting error in child BMI and self-reporting error in mothers' BMI, we find that, on average, an increase of one BMI unit is associated with a \$97.49 increase in medical expenditures. For girls, this effect is \$126.09 for each BMI unit. When we compare medical costs of overweight or obese children to those who are healthy weight, we find that the medical expenditures on overweight children are \$478.21 more than expenditures on normal weight children and that medical expenditures on obese children are \$1098.23 more than normal weight children. Girls who are overweight cost \$628.39 more per year than normal weight girls and and girls who are obese cost \$1448.94 more annually than normal weight girls on average. These effect sizes are significantly larger than those found in the non-IV model, both overall, and for just girls. However, these effect sizes are still smaller than those found by Cawley and Meyerhoefer (2012) for adults, which is reasonable given that adolescents have lower incidence of more serious co-morbidities associated with higher body weight.

There are some limitations to our modeling approach. Like previous research using instrumental variables, the validity of the IV depends on an untestable exclusion restriction. There is a large behavioral genetics literature that supports the genetic linkage between the weight of biological relatives, and little support for shared environmental effects that are correlated with weight. But genes which influence weight may be inherited alongside genes that also affect demand for medical care. We cannot observe genetic information in the MEPS and acknowledge this possible limitation.

We use only a single round of imputation to generate measured BMI in the MEPS. We performed multiple imputations to confirm that the sample estimates of the covariance between the measurement error in child BMI and the IV are stable across imputations. However, we do not account for the extra variation due to imputation. In future work we plan to bootstrap over multiple imputations, instead of using a single round of imputations.

Despite these limitations, we make an important contribution by providing the first estimates of the causal impact of youth obesity on medical expenditures. The discrepancy between our IV estimates and the non-IV estimates from previous studies suggest the costs of youth obesity are larger than previously believed. This has important implications for the cost effectiveness of weight-management interventions targeted at children. Previous estimates of the cost of childhood obesity have been used to motivate local and national level childhood obesity interventions (Trasande, 2010; Brown et al., 2007; Wang et al., 2003) For example, Trasande (2010) estimated the cost-effectiveness of government spending to reduce childhood obesity using estimates from Finkelstein et al. (2009). Our IV estimates suggest that Trasande (2010) significantly underestimated the economic impact of these interventions. Whitlock et al. (2010) examined the effectiveness of both behavioral and pharmacologic weight-management interventions, and found that comprehensive behavioral interventions of medium-to-high intensity resulted in 1.9 to 3.3 BMI unit reduction. Using our estimates, a 1.9 BMI unit reduction would translate into a $185.23 cost savings, as much as $239.57 for girls. They also found that behavioral interventions combined with prescription medicine can cause small to moderate reductions in BMI. Our estimates suggest that these and other treatments may be cost-effective, or even lead to cost savings, where using previous estimates may under-estimate the benefits relative to the costs of these interventions.

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Table 1: Clinical Weight Classifications for Youth

Clinical Weight Classification	BMI Percentile Range for Youth
Underweight	BMI $\leq 5^{\text{th}}$
Healthy Weight	$5^{th} \leq$ BMI $< 85^{th}$
Overweight	$85^{th} \leq$ BMI$< 95^{th}$
Obesity	BMI $\leq 95^{th}$
Severe Obesity	BMI $\geq 99^{th}$

Source: CDC (2014); Skelton et al. (2009)
Notes: The percentiles correspond to a reference (historic), not the current, distribution of weight-for-height that is specific to gender and age. Youths defined as aged 2 to 19 years.

Table 2: Prevalence of Youth Obesity in the United States Defined Using BMI

Study	Years	Ages 2-5	Ages 6-11	Ages 12-19
NHES II	1963-1965		4.2	
NHES III	1966-1970			4.6*
NHANES I	1971-1974	4.0	6.1	
NHANES II	1976-1980		6.5	5.0
NHANES III	1988-1994	7.2	11.3	10.5
NHANES Continuous	1999-2002	10.3	15.9	16.0
	2003-2006	12.5	17.0	17.6
	2007-2010	11.2	18.8	18.2

Source: NCHS (2014)
Notes: Based on measured weight and height from the nationally representative samples in the National Health and Nutrition Examination Surveys. Obesity defined as a weight-for-height exceeding the 95th percentile in a historic reference population; see Table 1. Youth defined as individuals aged 2 to 19 years. NHANES stands for National Health and Nutrition Examination Survey. NHES stands for National Health Examination Survey. NHES I sampled adults aged 18-79, NHES II included children aged 6-11, NHES III included youths aged 12-17 years. *NHES III included youths aged 12-17, not 12-19.

Table 3: Descriptive Statistics

Variables	**Boys**		**Girls**	
	Full Sample	**Self-reporting mothers**	**Full Sample**	**Self-reporting mothers**
Child Characteristics				
Annual medical expenditures > 0	0.86	0.88	0.88	0.90
	(.34)	(.33)	(.32)	(.30)
Annual medical expenditures*	$2,144.39	$2,164.40	$2,150.65	$2,189.68
	(6,171.63)	(6,171.82)	(4,841.47)	(5,633.4)
BMI (MEPS)	22.25	22.14	21.71	21.77
	(4.4)	(4.37)	(4.43)	(4.47)
Hispanic	0.14	0.13	0.14	0.14
	(.35)	(.34)	(.35)	(.34)
Black	0.07	0.06	0.07	0.07
	(.25)	(.24)	(.26)	(.25)
Other race	0.06	0.04	0.06	0.04
	(.23)	(.20	(.23)	(.20)
Age in months	173.89	173.39	173.52	173.36
	(24.28)	(24.25)	(24.9)	(24.98)
Self-reported	0.13	0.01	0.14	0.01
	(.34)	(.43)	(.34)	(.09)
Mother Characteristics				
HS diploma	0.31	0.31	0.31	0.31
	(.46)	(.46)	(.46)	(.46)
Some college	0.24	0.26	0.27	0.28
	(.43)	(.44)	(.44)	(.45)
Bachelor's degree	0.20	0.20	0.19	0.18
	(.4)	(.4)	(.39)	(.39)
BA plus	0.12	0.11	0.11	0.11
	(.32)	(.32)	(.31)	(.31)
Father Characteristics				
HS diploma	0.32	0.32	0.32	0.32
	(.47)	(.47)	(.47)	(.47)
Some college	0.22	0.22	0.22	0.22
	(.42)	(.42)	(.41)	(.42)
Bachelor's degree	0.18	0.18	0.18	0.17
	(.39)	(.38)	(.38)	(.38)
BA plus	0.13	0.13	0.14	0.13
	(.34)	(.34)	(.35)	(.34)

Table 4: Descriptive Statistics Continued

Variables	**Boys**		**Girls**	
	Full Sample	**Self-reporting Mothers**	**Full Sample**	**Self-reporting Mothers**
Household Characteristics				
People in the household aged 0 - 5	0.18	0.18	0.17	0.17
	(.48)	(.48)	(.46)	(.46)
People in the household aged 6 - 17	2.16	2.19	2.14	2.17
	(1.05)	(1.04)	(1.02)	(1.03)
Midwest	0.24	0.24	0.23	0.24
	(.43)	(.43)	(.42)	(.43)
South	0.33	0.33	0.33	0.32
	(.47)	(.47)	(.47)	(.47)
West	0.24	0.23	0.25	0.24
	(.42)	(.42)	(.43)	(.43)
Urban	0.82	0.81	0.82	0.81
	(.39)	(.39)	(.39)	(.39)
Year 2000	0.09	0.08	0.08	0.08
	(.28)	(.28)	(.27)	(.27)
Year 2001	0.10	0.10	0.09	0.09
	(.3)	(.3)	(.29)	(.29)
Year 2002	0.09	0.09	0.09	0.09
	(.29)	(.29)	(.28)	(.29)
Year 2003	0.09	0.09	0.09	0.09
	(.29)	(.29)	(.29)	(.29)
Year 2004	0.10	0.10	0.09	0.09
	(.3)	(.29)	(.28)	(.29)
Year 2005	0.10	0.10	0.09	0.09
	(.3)	(.29)	(.29)	(.29)
Year 2006	0.10	0.10	0.10	0.10
	(.29)	(.29)	(.3)	(.3)
Year 2007	0.09	0.09	0.10	0.10
	(.28)	(.29)	(.3)	(.3)
Year 2008	0.08	0.08	0.09	0.09
	(.27)	(.28)	(.29)	(.28)
Year 2009	0.09	0.09	0.09	0.09
	(.28)	(.29)	(.29)	(.29)
Year 2010	0.08	0.08	0.09	0.09
	(.27)	(.27)	(.29)	(.28)
Observations	6,486	5,159	5,825	4,682
*Observations with positive medical expenditure	5,292	4,296	4,848	3,969

All entries are in 2010 dollars.

Table 5: BMI of Boys and Their Mothers

	Observations	Mean	SD	Min	Max
Child BMI (MEPS)	5,159	22.14	4.37	14.80	42.20
Normal Weight	3,141	19.60	1.94	14.80	24.40
Overweight	942	23.96	1.48	20.40	27.20
Obese	1,076	29.32	3.46	22.90	42.20
Child BMI (NHANES)	5,159	22.53	5.01	15.14	45.18
Normal Weight	3,141	19.64	2.08	15.14	25.56
Overweight	942	24.50	1.86	20.47	28.54
Obese	1,076	30.76	4.22	23.19	45.18
Mothers					
Self-reported BMI (MEPS)	5,159	26.72	5.51	14.70	54.90
True BMI (NHANES)	5,159	27.43	5.94	15.69	55.64

Overweight and obese labels are determined using imputed BMI from the NHANES. Mothers' BMI data are imputed from the NHANES by matching BMI calculated from self-reported height and weight in the NHANES to the reported BMI in the MEPS. Children's BMI data are imputed within strata unique by BMI distribution half-percentile, age, and gender.

Table 6: BMI of Girls and Their Mothers

	Observations	Mean	SD	Min	Max
Child BMI (MEPS)	4,682	21.77	4.47	14.40	44.30
Normal Weight	2,916	19.46	1.97	14.40	24.20
Overweight	861	23.55	1.88	19.70	28.10
Obese	905	29.42	4.35	22.80	44.30
Child BMI (NHANES)	4,682	22.88	4.98	14.78	45.27
Normal Weight	2,916	20.17	2.08	14.78	25.23
Overweight	861	25.15	1.93	20.73	29.95
Obese	905	31.66	4.17	24.58	45.27
Mothers					
Self-reported BMI (MEPS)	4,682	27.19	5.64	14.70	54.90
True BMI (NHANES)	4,682	27.90	6.03	15.95	55.64

Overweight and obese labels are determined using imputed BMI from the NHANES. Mothers' BMI data are imputed from the NHANES by matching BMI calculated from self-reported height and weight in the NHANES to the reported BMI in the MEPS. Children's BMI data are imputed within strata unique by BMI distribution half-percentile, age, and gender.

Figure 1: Distribution of Female BMI in the NHANES

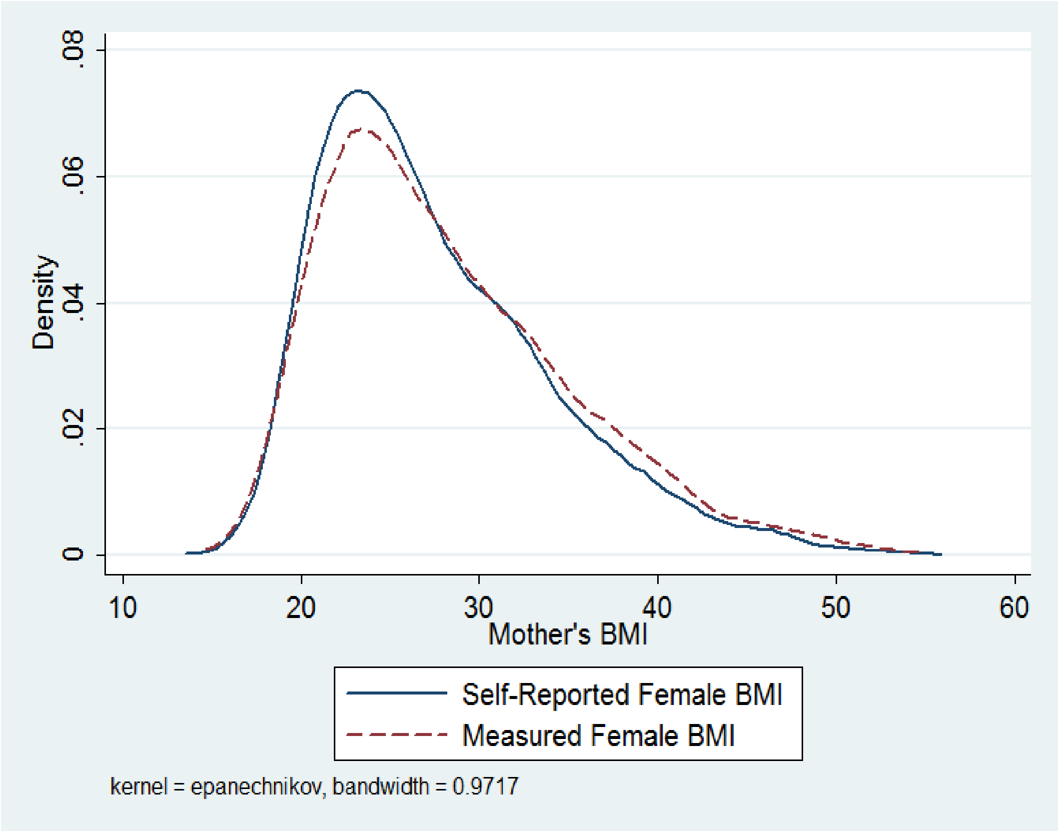

Figure 2: Distribution of Mothers' BMI in the MEPS

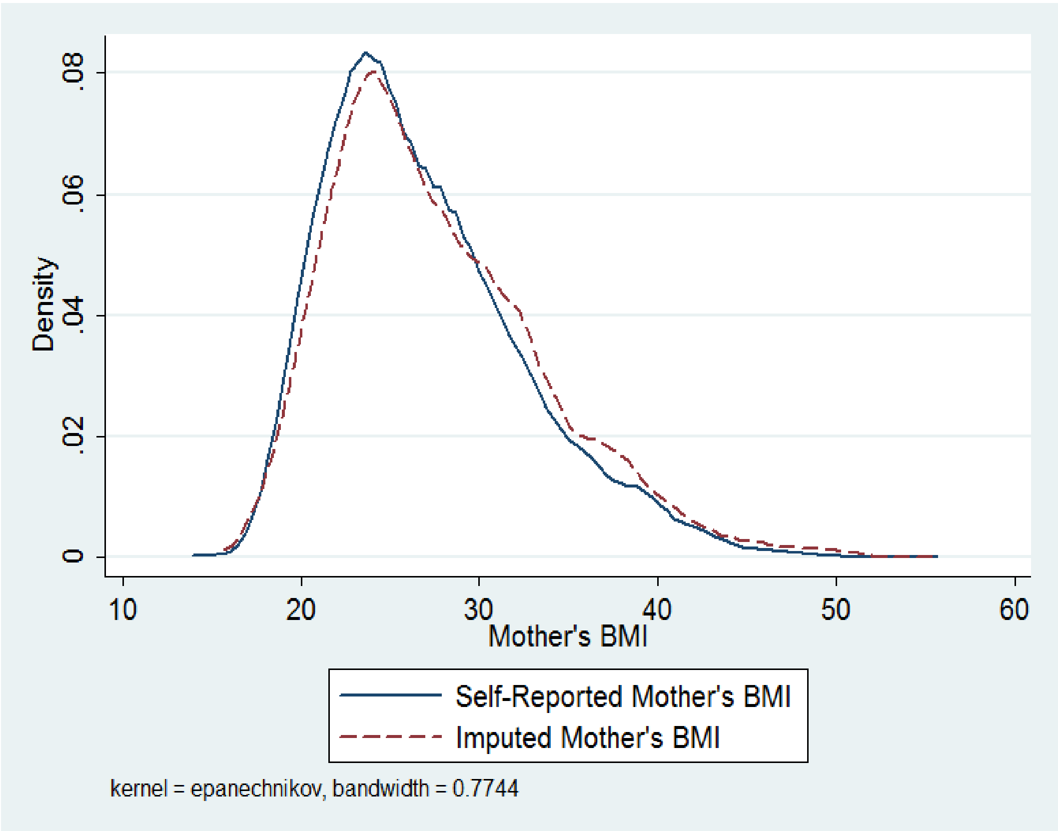

Figure 3: Distribution of Child BMI in MEPS and NHANES

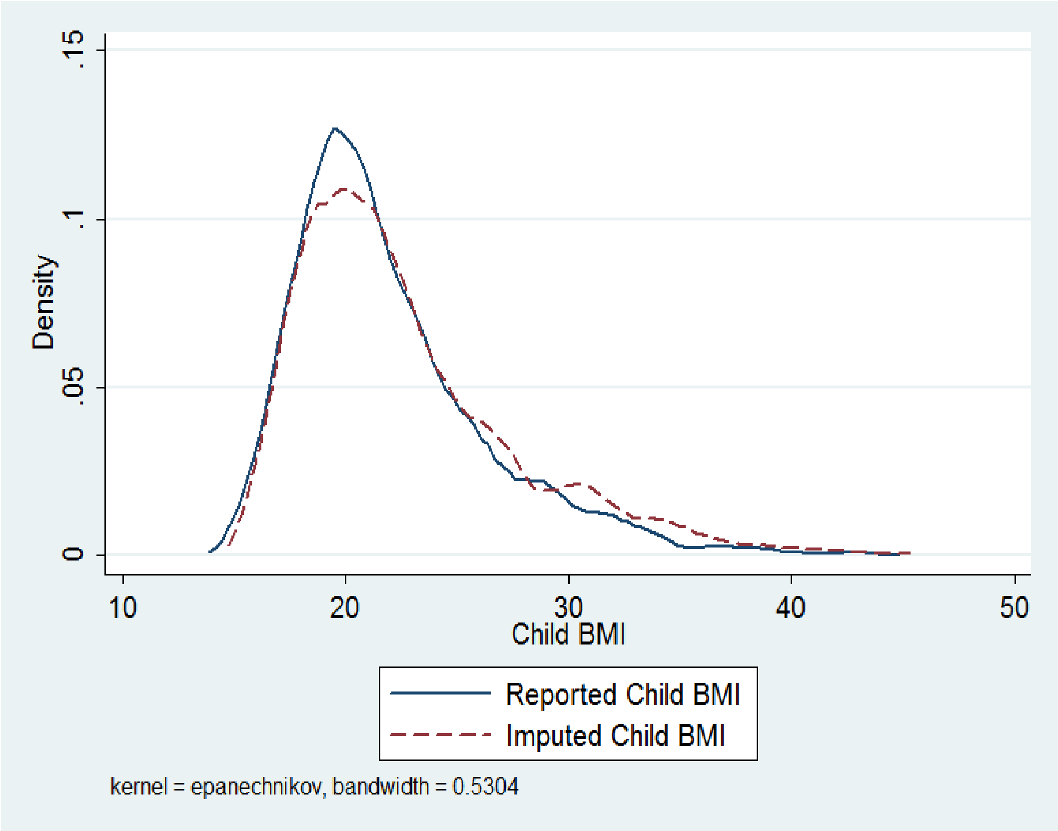

Figure 4: Proxy-Reporting Error in Boys' BMI

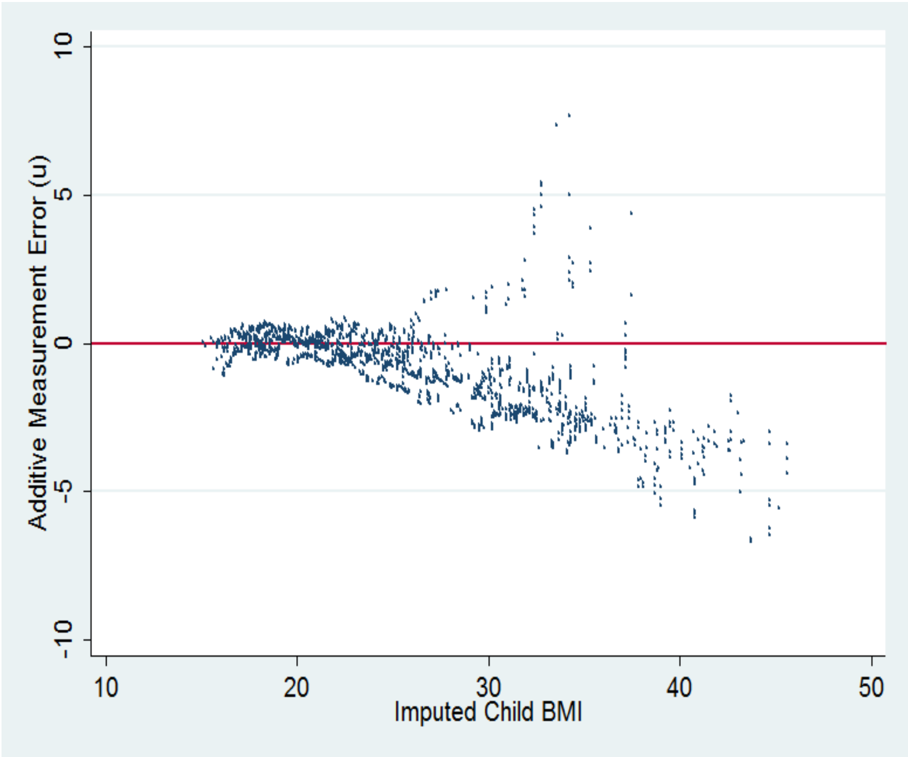

Figure 5: Proxy-Reporting Error in Boys' BMI by Age

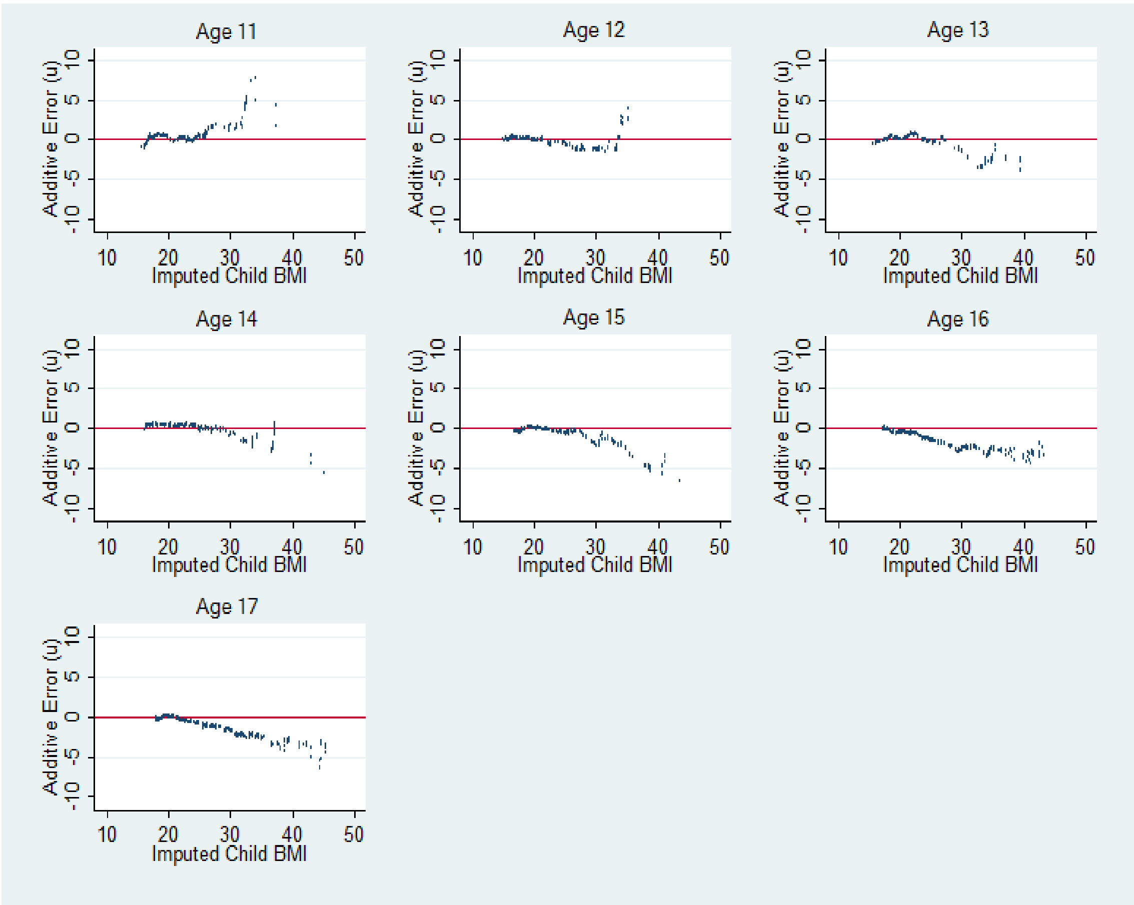

Figure 6: Proxy-Reporting Error in Girls' BMI

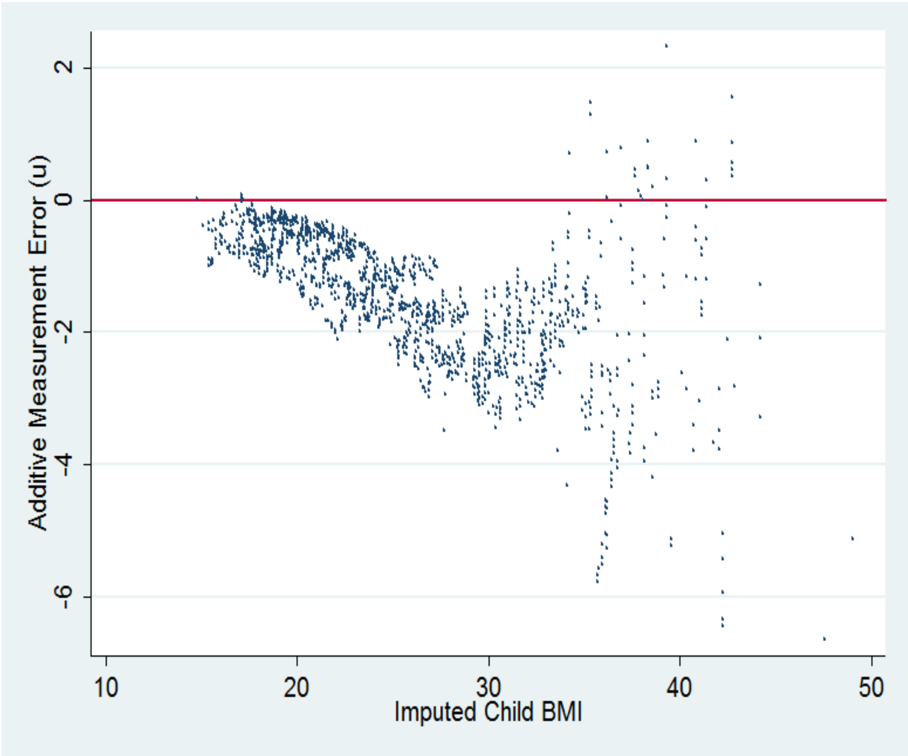

Figure 7: Proxy-Reporting Error in Girls' BMI by Age

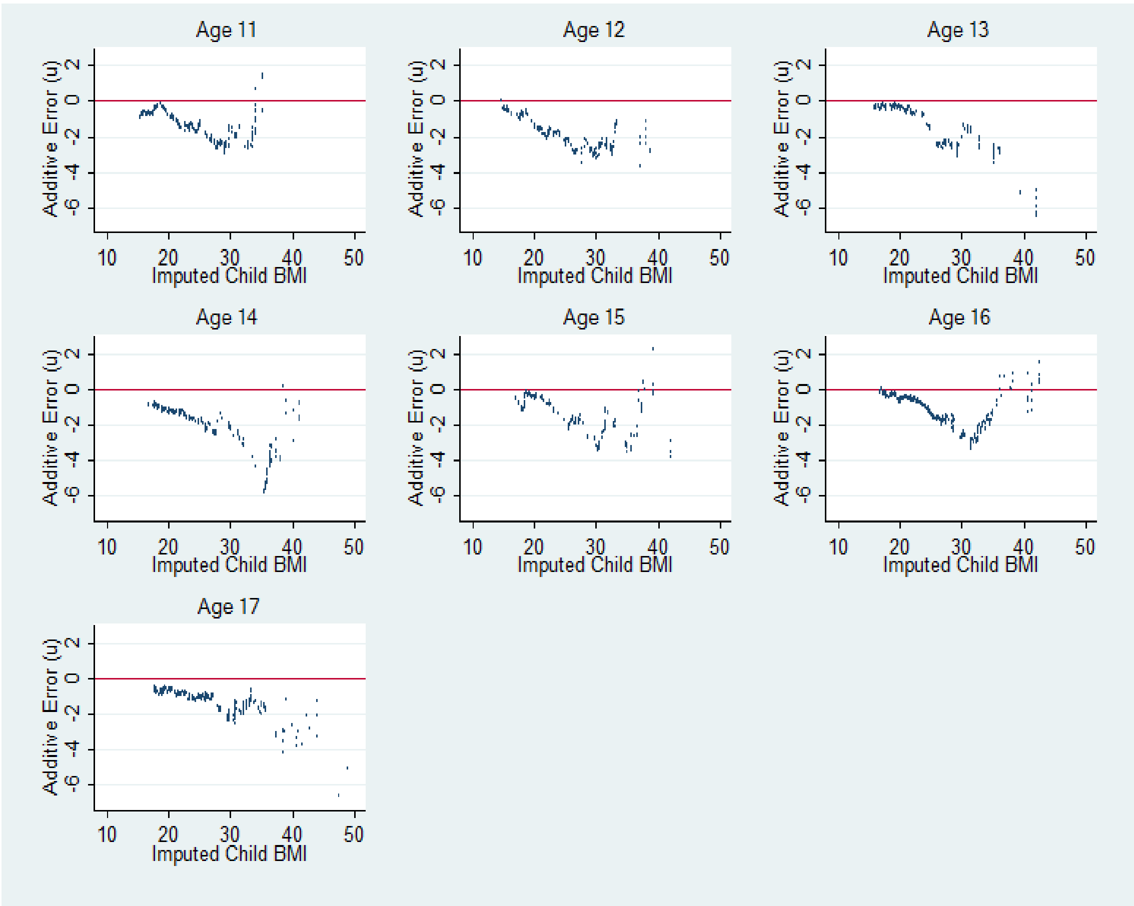

Figure 8: Proxy-Reporting Error in Boys' BMI by Mothers' Imputed BMI

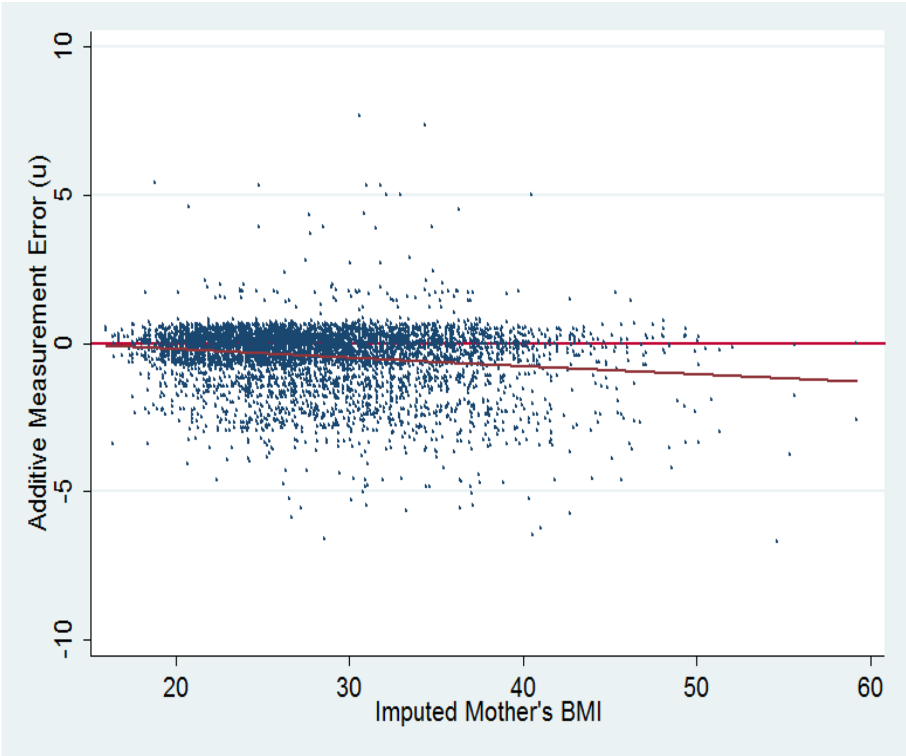

Figure 9: Proxy-Reporting Error in Girls' BMI by Mothers' Imputed BMI

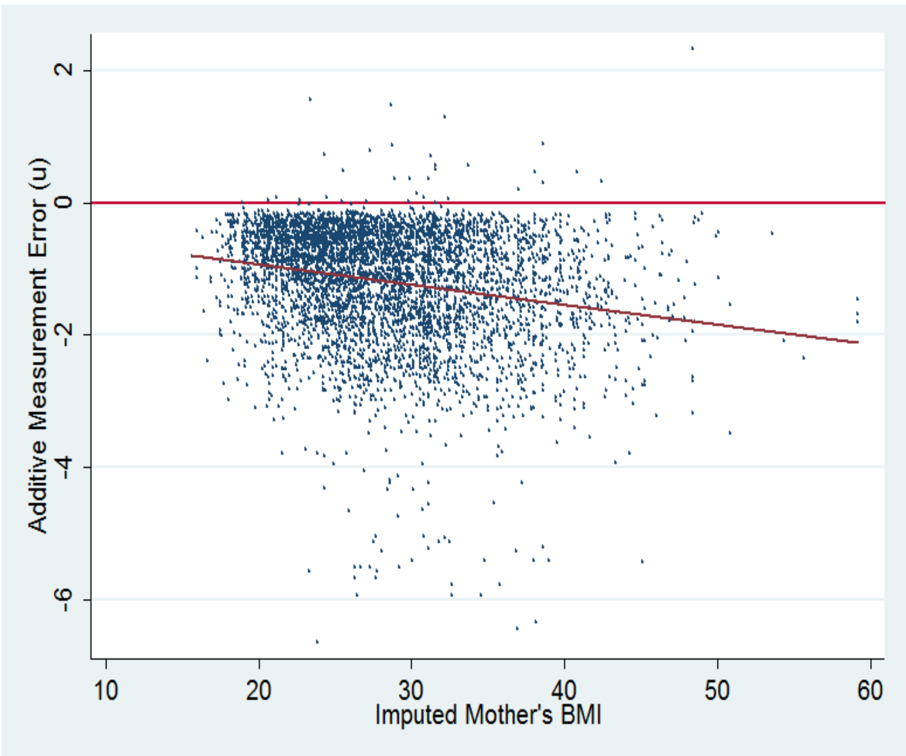

Table 7: Marginal Effects of Child BMI on Annual Medical Expenditures

	Non-IV	Mother's BMI as IV			
Column	(1)	(2)	(3)	(4)	(5)
Boys & Girls	30.95***	79.12*	110.21*	97.49*	94.79
N = 9,841	(13.73)	(54.25)	(71.05)	(63.01)	
		[325.40]	[318.10]	[328.30]	{0.860}
Boys	31.19**	62.09	100.99	88.65	87.66
N = 5,159	(18.4)	(78.89)	(116.51)	(102.55)	
		[166.83]	[144.25]	[147.01]	{0.868}
Girls	30.80**	111.32**	141.95**	126.09**	123.91
N = 4,682	(18.58)	(62.46)	(66.15)	(58.23)	
		[164.66]	[180.08]	[192.43]	{0.873}
Source of:					
Child BMI	MEPS	MEPS	MEPS	NHANES	MEPS
Parent BMI	—	MEPS	NHANES	NHANES	NHANES

*,**,*** indicate significance at 10%, 5%, 1% level respectively for BRR standard errors in parenthesis. First-stage F-statistics in brackets. All entries are in 2010 dollars. For columns 5 and 6, $\hat{\delta}$ displayed in curly brackets.

Table 8: Approximate Average Marginal Effect of Overweight and Obese

	Non-IV	Mother's BMI as IV		
Column:	(1)	(2)	(3)	(4)
	Marginal Effect of Overweight Relative to Normal Weight			
Boys & Girls	131.10***	335.15*	466.84*	478.21*
Boys	135.99**	270.72	440.33	430.78
Girls	125.81**	454.71**	579.82**	628.39**
	Marginal Effect of Obese Relative to Normal Weight			
Boys & Girls	304.30***	777.92*	1083.60*	1098.23*
Boys	303.29**	603.76	982.01	985.77
Girls	306.61**	1108.19**	1413.11**	1448.94**
Source of:				
Child BMI	MEPS	MEPS	MEPS	NHANES
Parent BMI	—	MEPS	NHANES	NHANES

*,**,*** indicate significance at 10%, 5%, 1% level respectively. Approximate marginal effects are calculated my multiplying coefficient estimates from table 7 into the differences in mean BMI across weight status in tables 5 and 6. Columns 1 - 3 use differences in mean proxy-reported BMI. Column 4 uses differences in mean imputed BMI.