W. J. Usery Workplace Research Group Paper Series

Working Paper 2017-4-3
April 2017

Parental Work Hours and Childhood Obesity: Evidence Using Instrumental Variables Related to Sibling School Eligibility

Charles Courtemanche
Georgia State University, NBER, and IZA

Rusty Tchernis
Georgia State University, NBER, and IZA

Xilin Zhou
Georgia State University

Georgia State University
Andrew Young School
of Policy Studies

PARENTAL WORK HOURS AND CHILDHOOD OBESITY: EVIDENCE USING INSTRUMENTAL VARIABLES RELATED TO SIBLING SCHOOL ELIGIBILITY

Charles Courtemanche[*]
Georgia State University, National Bureau of Economic Research, and Institute for the Study of Labor (IZA)

Rusty Tchernis
Georgia State University, National Bureau of Economic Research, and Institute for the Study of Labor (IZA)

Xilin Zhou
Georgia State University

April 20, 2017

Abstract

This study exploits plausibly exogenous variation from the youngest sibling's school eligibility to estimate the effects of parental work on the weight outcomes of older children in the household. Data come from the 1979 cohort of the National Longitudinal Survey of Youth linked to the Child and Young Adult Supplement. We first show that mothers' work hours increase gradually as the age of the youngest child rises, whereas mothers' spouses' work hours exhibit a discontinuous jump at kindergarten eligibility. Leveraging these insights, we develop an instrumental variables model that shows that parents' work hours lead to larger increases in children's BMI z-scores and probabilities of being overweight and obese than those identified in previous studies. We find no evidence that the impacts of maternal and paternal work are different. Subsample analyses find that the effects are concentrated among advantaged households, as measured by an index involving education, race, and mother's marital status.

JEL classification: I12; J22
Key words: childhood obesity, maternal employment, women's labor supply

---

[*] Corresponding author. Department of Economics, Andrew Young School of Policy Studies, Georgia State University, Box 3992, Atlanta, GA 30302-3992. E-mail: ccourtemanche@gsu.edu. We thank Barry Hirsh, Rachana Bhatt, Sara Markowitz, James Marton, Kurt Schnier, Darren Lubotsky, and seminar participants at the Southern Economic Association Annual Meeting and the Western Economics Association Annual Conference. We also thank Patricia Anderson for sharing parameter estimates from Anderson et al. (2003). This research was conducted using restricted data from the Bureau of Labor Statistics. The views expressed in this paper do not reflect those of the BLS. Any errors are ours.

I. Introduction

The statistics on childhood obesity in the U.S. are alarming. From 1971 to 2014, the childhood obesity rate rose from 5 percent to 17 percent (Fryar et al., 2016). The increase is especially notable among school-aged children, as the obesity rate quadrupled for children ages 6 to 11 and tripled for those ages 12 to 19, compared to doubling for those ages 2 to 5 (Fryar et al., 2016). The prevalence of obesity among children is considered a major public health concern because of its immediate and long-term effects on health and well-being. According to the Centers for Disease Control and Prevention (CDC), obese children are at a higher risk of developing cardiovascular disease, prediabetes, bone and joint problems, sleep apnea, and psychological problems. Obese children are also likely to grow up as obese adults and therefore face the risk of adult obesity-related health problems.[1] Obesity imposes substantial costs on society. As of 2005, the annual medical cost of treating childhood obesity was $14.1 billion for prescription drugs, emergency room, and outpatient visit costs (Trasande and Chatterjee, 2009), plus $237.6 million for inpatient costs (Trasande et al., 2009). Among adults, obesity leads to an estimated $210 billion of annual medical expenses as well as indirect costs such as unfavorable labor market outcomes (Cawley and Meyerhoefer, 2012; Cawley, 2004).

Another remarkable trend in the second half of the 20th Century was increased employment among women. From 1960 to 2013, the labor force participation rate (LFPR) of women 16 years old and older increased from 38% to 57%. The male LFPR fell from 83% to 70% in response, but the overall LFPR combining both genders still rose, from 59% to 63%. Similar trends were observed for those with children under age eighteen in the household.

[1] http://www.cdc.gov/healthyyouth/obesity/facts.htm

Between 1970 and 2013, the LFPR increased from 42% to 70% among mothers and declined from 97% to 93% among fathers).[2]

The concurrent nature of these trends in LFPR and childhood obesity has led researchers to ask whether a causal connection is possible. Some important changes occur when mothers increase their labor supply that could influence children's weight. First, their children have less supervision and watch more television than the children of stay-at-home mothers (Fertig, Glomm, and Tchernis, 2009; Cawley and Liu, 2012). Second, working mothers spend less time on cooking than other mothers, and their children eat more away-from-home meals (Cawley and Liu, 2012). Next, more market work increases household income, which could affect children's weight in either direction. The loosening of the budget constraint could either mean more across-the-board food purchases or a switch away from cheap processed foods toward more expensive, healthier options. Finally, to the extent that fathers reduce work hours in response to mothers entering the labor force, this could counteract whatever effects might otherwise occur. Indeed, Cawley and Liu (2012) find some evidence of offsetting time use behaviors by fathers, but it is not nearly enough to offset the changes by mothers.

Several studies document a modest positive relationship between maternal employment and children's weight. Anderson et al. (2003) find that an extra ten hours worked per week during weeks worked by a mother are associated with around a one percentage point increase in the probability of a 3-11 year old child being obese. The impact is largest for high socioeconomic status (SES) children. Similar magnitudes are obtained by Ruhm (2008) and Courtemanche (2009). Fertig et al. (2009) estimate that a 10% increase in mothers' work hours is associated with approximately a 1.6 percentage point rise in the probability a child is obese. Liu

[2] These numbers are authors' calculations from the Current Population Surveys.

et al. (2009) find that full-time maternal employment raises a child's body mass index (BMI) by about half a unit and probability of being obese by 12%. Morrissey et al. (2011) and Morrissey (2012) estimate that every survey period in which a mother is employed increases her child's BMI Z-score by 0.02 and 0.03, respectively.

Such analyses, however, are complicated by the endogeneity of maternal employment. A mother's unobserved characteristics likely affect both her labor supply and child care decisions. For instance, greater intelligence might increase both the likelihood of a mother participating in the labor force and her ability to develop effective strategies to prevent her children from becoming obese. Similarly, highly conscientious mothers could be more likely than others to both work outside the home and also to closely monitor their children's behaviors. In either case, associational estimates may underestimate the effect of maternal employment on childhood obesity, potentially explaining the small magnitudes obtained by prior studies. On the other hand, if entering the labor market reflects an underlying preference for income versus family time, associational estimates could be overstated. Reverse causality is another possible concern. Having a child with health problems may cause a mother to either exit the labor force to care for the child or enter the labor force to obtain health insurance or extra income.[3]

To address these endogeneity concerns, this study implements an instrumental variables (IV) strategy based on the idea that the opportunity cost of working is substantially reduced

[3] Some of the papers in the literature have implemented panel data methods to control for unobserved heterogeneity (Anderson et al., 2003; Courtemanche, 2009; Miller, 2011; Morrissey et al., 2011), but these methods do not account for time-varying sources of bias or reverse causality. Anderson et al. (2003) also estimated an IV specification, using as instruments state-level variables including unemployment rate, child care regulations, wages of child care workers, welfare benefit levels, and the status of welfare reform in the state. However, these instruments were relatively weak in terms of their predictive power on maternal work. They also relied on questionable exclusion restrictions, as the instruments could influence childhood obesity through pathways besides maternal work. For instance, unemployment rate and the generosity of a state's welfare program could be associated with changes in household disposable income or wealth even if mothers' work hours do not change, and this in turn could affect children's weight.

when one's youngest child is attending school. Several studies have established that mothers increase labor supply when their youngest child becomes eligible for or enrolls in public school (Gelbach, 2002; Cascio, 2009; Fitzpatrick, 2010; Morrill, 2011; Fitzpatrick, 2012). Morrill (2011) used the youngest child's kindergarten eligibility as an instrument to show that maternal employment increases the probability of older children in the household experiencing hospitalizations, asthma episodes, and injuries/poisonings. We utilize a related strategy to examine the effects of parental work on childhood obesity.

We begin by investigating how the age of the youngest child relative to the kindergarten eligibility cutoff influences parental work. Data come from the National Longitudinal Survey of Youth 1979 Cohort (NLSY79). We find that mothers' work hours gradually increase as the age of the youngest child rises, as opposed to jumping discontinuously when the child becomes eligible for kindergarten. This is consistent with graphical evidence provided by Morrill (2011) and Lubotsky and Qureshi (2016). The effect on mothers' work occurs along both the extensive margin (probability of working) and the intensive margin (work hours conditional on working). In contrast, mothers' spouses' work hours do not exhibit a smooth trend across youngest child's age, but they jump discontinuously at kindergarten eligibility. This effect occurs completely along the intensive margin of work rather than the extensive margin.

Next, we leverage these insights to develop an instrumental variable (IV) model in which plausibly exogenous variation in the youngest child's age identifies the impact of parental employment on the weight of older children in the household. Our first instrument is youngest sibling's relative age (with respect to the kindergarten eligibility cutoff), which predicts maternal work in an approximately linear manner. Given the discontinuity observed for mothers' spouses' work hours, the second instrument is the interaction of an indicator for youngest sibling's kindergarten eligibility with mother's marital status. Using this strategy, we show that greater parental work hours lead to statistically significant increases in children's BMI Z-score and probabilities of being overweight and obese that are much larger than those observed in the associational literature. While the estimates are imprecise, we are nonetheless able to rule out the consistency of the ordinary least squares (OLS) estimator in most specifications. Also in contrast to findings from the associational literature, we find no evidence that mothers' and mothers' spouses work hours differentially affect children's weight outcomes. This result implies that the contribution of the rise in maternal employment to the childhood obesity epidemic has largely been offset by the resulting drop in paternal employment. Next, we conduct subsample analyses and show that the effect of parental work hours on children's weight is concentrated among advantaged households, as measured by an index reflecting parents' education, race, and mother's marital status. Finally, falsification tests using health behavior-related outcomes that should not be affected by parental work provide evidence to support our model's identifying assumptions.

Our study makes three main contributions. First, we present, to our knowledge, the first evidence on the relationship between youngest child's age and *paternal*, rather than just maternal, employment. The investigation yields the interesting result that mother's spouse's father's) work does indeed respond to youngest child's age, but in a much different manner than mothers' work: discrete (at kindergarten eligibility) rather than continuous, and along the intensive rather than extensive margin. Second, we provide the first application of a youngest-sibling's-age-based IV strategy to study the impact of parental work on a chronic health condition (obesity), as opposed to the acute conditions studied by Morrill (2011). Since chronic conditions represent capital stocks, one might expect them to be less responsive than acute episodes to changes in inputs to the health production function. Our finding that short-run changes in parental work can still have large effects on children's weight is therefore noteworthy. Finally, our third contribution is to provide guidance for best practices when using the youngest-sibling's-age IV design. Specifically, using a kindergarten eligibility dummy variable as an instrument for maternal work while omitting paternal work is likely to lead to overstated magnitudes. A continuous age measure is a more appropriate instrument for mother's work, while a discrete measure is better suited to identify the effect of father's work.

II. Data

Data come from the restricted version of the NLSY79. The original sample of the NLSY79 contains 12,682 individuals, half male and half female, who were between the ages of 14 and 21 in 1979. These individuals were followed annually from 1979 to 1994 and then every two years thereafter. Starting in 1986, a supplemental survey, the NLSY79 Child and Young Adult (NLSY79CYA), was conducted biannually which includes assessments of all biological children of the female participants. Information was collected from either the mother or child, and it can be linked to the main NLSY79 through the mother's identifier.[4] We use the paired mother-children records from all waves in which both the NLSY79 and the NLSY79CYA were available as of the writing of this paper, i.e. biannually from 1986 to 2010.

There are three outcomes of interest, BMI z-score and indicators for overweight and obesity, all of which are constructed based on children's BMI.[5] BMI is a commonly-used proxy for body fat in adults. However, it is not a proper measure for children since their healthy weight range varies by age and sex. Therefore, for children the CDC suggests using BMI z-score: a

[4] Before 1994, a mother reported information for all her children regardless of the age of children. After 1994, children above 15 years of age answered interview questions by themselves.
[5] BMI is calculated as weight in kilograms divided by height in meters squared (kg/m^2).

standardized measure of BMI using age-and-gender specific BMI distributions from the 2000 growth chart (National Center for Health Statistics, 2002). The other two outcomes are also computed according to the 2000 growth chart. If a child's BMI is above the 85th (95th) percentile of the BMI distribution of the corresponding reference population, the child is considered overweight (obese).

Mothers' and mothers' spouse's employment variables are fraction of weeks worked in the past year, hours worked per week in weeks worked in the past year (undefined if no work weeks), and hours worked per week over all weeks in the past year (zeros assigned in weeks not worked). The first of these variables therefore reflects the extensive margin of employment, the second reflects the intensive margin, and the third reflects overall work accounting for both the extensive and intensive margins. Since the variables are one-year averages, the estimates will capture relatively short run effects compared to some papers in the literature that measure maternal work as averages over the course of the child's entire life (e.g. Anderson et al., 2003; Courtemanche, 2009; Ruhm, 2008). Our IV strategy – which relies on sharp discontinuities at a particular age – is inherently better suited for the identification of short-run rather than long-run impacts. It is therefore noteworthy that, despite this limitation, we will still obtain much larger effects than these prior studies.

A key component to this analysis is the use of instrumental variables. The restricted NLSY79 has not only the date of birth (DOB) of all children but also their states of residence. We first calculate the age in weeks for the youngest child in each household. Then the first IV, proportion of kindergarten-eligible weeks in the last year, is given by the proportion of the previous 52 weeks in which the youngest child has been over the state's cutoff date to be eligible for kindergarten. This discrete variable takes a value of zero if the child has not reached the cutoff date during the whole past year, one if the child is at least 52 weeks older than the cutoff date, and between zero and one for those less than 52 weeks older than the cutoff date. We use the 52-week proportion rather than simply a dummy variable for being over the cutoff in order to match the 52-week averages used for our employment variables. State cutoff dates come from Evans et al. (2010). In practice, cross-state policy variation contributes very little to variation in kindergarten eligibility; almost all the variation comes from youngest child's age. The second IV, relative age, is a continuous measure of youngest child's age relative to the kindergarten eligibility cutoff. This variable is equal to the difference, measured in number of weeks divided by 52, between youngest child's age and the date of the kindergarten eligibility cutoff. Functionally, then, it is the number of years away from the cutoff, with fractions allowed.

We also utilize the extensive information available in the NLSY79 and NLSY79CYA to include a detailed array of control variables. The first set of control variables is for demographic characteristics. The demographic variables taken from the NLSY79, which pertain to the mother, are race/ethnicity (Hispanic and non-Hispanic black, with other as the reference group), family size, age in years and its square, and an indicator for married and living with the spouse. Demographic variables from the NLSY79CYA, which pertain to the focal child, are an indicator for gender, age in months, and an indicator for close child-father attachment (equals one if the biological father lives in the household, biological father lives within 10 miles, or child has seen biological father at least once a week in the past year).

The second set of control variables relates to parents' human capital. These variables, which all come from the NLSY79, are mother's AFQT score as well as both mother's and mother's spouse's education (high school graduate, some college, and college degree or greater, with less than high school degree being the reference group). We do not control for household income since this is one of the pathways through which parental employment may affect children's weight. Nonetheless, results remain very similar if we include it.

The third set of control variables is named "child's health". It includes four variables from the NLSYCYA: whether the child had a high birth weight (> 8.8 pounds)[6], whether the child was breastfed, and whether height or weight are self-reported[7]. The latter two variables are included because self-reported data on height and weight usually suffer from systematic reporting error that leads to underestimation of the prevalence of obesity (Goodman et al., 2000; Kuczmarski et al., 2001; Courtemanche et al., 2015).

The regression sample is restricted to children who meet three criteria: 1) they are seven to seventeen years old, 2) they have at least one younger sibling, and 3) their youngest sibling's schooling eligibility changed during the sample period. The first restriction ensures that school eligibility does not change for the sample children. As discussed above, this eliminates the obvious concern that one's own school eligibility could affect one's own weight for reasons other than maternal employment. The second restriction is necessary for the use of IVs. The third restriction is used to eliminate those whose mothers never receive the treatment induced by the IVs.[8]

The resulting sample includes 13,332 observations for 3,438 children of 2,220 mothers. Table 1 presents descriptive statistics for this merged, child-level dataset, with all estimates

---

[6] The threshold of high birth weight can be found http://www.cdc.gov/pednss/what_is/pednss_health_indicators.htm.
[7] The interview questions concerning the measurements of height and weight change frequently during the research period. There were only two modes at the beginning: mother report and interviewer measure. The questions evolved gradually and eventually there are four options: mother report, child report, interviewer measure, and others. In addition, young adults who are above age 15 were interviewed independently since 1996. Their height and weight data are all self-reported. To simplify the classifications, I create an indicator which represents all modes except interviewer measure for height and weight data and call it self-reported mode.
[8] Other steps to improve data quality include dropping children with extreme BMIs (z-score exceeding +/-5), children who have shrinking height from the previous interview, children who do not live with their mothers, female children who are pregnant or ever have given birth, and those whose mothers do not have any valid employment data.

weighted by the children's sampling weights. The average BMI z-score is 0.27, and 26% of the children are overweight while 12% of them are obese. On average, mothers worked 66% of weeks in the past year while spouses worked 93%. In weeks worked, average work hours were 35 for mothers and 47 for spouses. Across all weeks, including zeros for weeks not worked, mothers worked an average of 24 hours compared to 43 for spouses.

III. Effect of Youngest Child's Kindergarten Eligibility on Parents' Work

Our first objective is to identify the effect of the youngest child's age relative to the kindergarten eligibility cutoff on parents' work hours. This investigation will both provide interesting information on its own and help motivate the appropriate specification for the instrumental variable analysis of the impact of parental work on childhood obesity. Since the dependent variables in this section are measured at the parent rather than child level, we use a version of the dataset that is at the mother-by-year level and includes only the control variables from the NLSY79, omitting those from the NLSY79CS. This decision is not consequential for the results, as we will see from the first stage of the IV results in the next section, which use child-level data and include the controls for the focal child and lead to the same conclusions.

Before discussing the regressions, we first present non-parametric plots of the relationships between youngest child's relative age and mothers' (Figure 1) and mothers' spouses' (Figure 2) average hours worked per week over all weeks in the past year. In both figures, the horizontal axis represents youngest child's age relative to kindergarten eligibility, with positive values indicating that a child is older than the cutoff and negative values meaning the child is younger than the cutoff. In each figure, work hours are fit separately to the left and right of a relative age of zero, allowing for a discontinuous break at the time of kindergarten eligibility. For the sake of brevity, we only present the graphs for the hours worked per week over all weeks, i.e. including zeros for weeks not worked, since these incorporate both the extensive and intensive margins of employment. Graphs for the other work variables (fraction of weeks worked, hours worked per week in weeks worked) are available upon request.

Figure 1 shows that mothers' work hours increase smoothly and gradually in youngest child's age, consistent with the observations of Morrill (2011) and Lubotsky and Qureshi (2016). The graph also shows a small, discontinuous jump in work hours at the time of kindergarten eligibility, but the magnitude of this increase is small compared to the gradual changes throughout the rest of the child's upbringing. Specifically, the discontinuous jump at the kindergarten cutoff is less than 0.25 hours per week, whereas the overall rise in mothers' weekly work hours is from around 16 when the youngest child is a baby to around 31 ten years after the child becomes eligible for kindergarten.

Figure 2 shows a less clear pattern for the relationship of youngest child's age relative to kindergarten eligibility and mothers' spouses' work hours. This may be partly attributable to the larger confidence intervals coming from the smaller sample size for spouses. We do, nonetheless, observe some evidence of a gradual upward trend in the early years of the child's life as well as a discontinuity at kindergarten eligibility.

In order to control for observable characteristics and specifically test whether changes in work hours are better characterized by gradual upward trends or discontinuous breaks, we next turn to regression analyses. The regression equations take the following form:

$$WORK_{it} = \beta_0 + \beta_1 ELIG_{it} + \beta_2 RELAGE_{it} + \boldsymbol{\beta_3 X_{it}} + \tau_t + \varepsilon_{it} \tag{1}$$

where $WORK_{it}$ is one of the work measures, i.e. fraction of weeks worked, hours worked per week in weeks worked, and hours worked per week over all weeks, for parent *i* in year t. $ELIG_{it}$ is the discrete measure of proportion of kindergarten-eligible weeks for youngest child.

$RELAGE_{it}$ is the continuous measure of youngest child's relative age to the eligibility cutoff. $\boldsymbol{X_{it}}$ contains the control variables. We use three variants of controls in separate models: (i) includes only the "demographic controls" pertaining to mothers, (ii) adds the "human capital controls", and (iii) further adds the baseline value of the outcome variable. τ_t is a year fixed effect and ε_{it} is the error term. In the regressions for spouse's work outcomes, we restrict the sample to mothers with spouses. Regressions for the intensive margin outcomes (mother's/mother's spouse's hours worked in weeks worked) drop mothers/mothers' spouses with no work weeks.

Ideally, we would also include mother fixed effects in equation (1). However, doing so would lead to extreme multicollinearity, as the relative age variable would be almost completely explained by the year and mother fixed effects. The collinearity is not perfect since there is some additional variation in youngest child's age relative to kindergarten eligibility coming from differences in state eligibility laws, new births among mothers (which reset the age of the youngest child), and the fact that relative age is measured in weeks rather than years. In practice, though, these additional sources of variation are insufficient to estimate the coefficients of interest with meaningful precision.

Because of this inability to include mother fixed effects, we take a different approach to controlling for unobserved heterogeneity, which is to include the baseline value of the work outcome. This value is measured in the period immediately preceding the mother's first entry into the sample. Recall that mothers make their first entry into the sample when one of their older children reaches 7 years old; therefore, the baseline value is usually from when this older child is 5-6 years old. If that particular value is missing, we use the preceding period (e.g. when the older child is 3-4 years old). With all this said, it is unclear that unobserved heterogeneity will be of consequence for this particular set of analyses since, conditional on having children, the age of the youngest child is plausibly exogenous. Indeed, we will see that controlling for the baseline work outcome will make almost no difference in the results.

Table 2 reports the results for the coefficients of interest. Panel A shows the results for mother's work outcomes, while Panel B does the same for the mother's spouse's work outcomes. Panel A reveals two key results. First, consistent with the graphical evidence, the impact of youngest child's relative age on mothers' work is much better characterized as smooth and gradual than as a discontinuous jump at kindergarten eligibility. In all models, coefficients on the continuous measure of relative age are highly significant, while none of the coefficients on the discrete measure of proportion of eligible weeks are significant. Second, the effect occurs along both the extensive and intensive margins of employment. The former is shown by the positive and significant effect of youngest child's relative age on the fraction of weeks worked, while the latter is illustrated by the positive and significant effect of youngest child's relative age on hours worked per week in weeks worked. Combining the extensive and intensive margins into the overall work outcome, i.e. hours worked per week over all weeks, shows that each additional year of youngest child's relative age increases the mother's weekly work hours by 0.9-1.2 hours depending on the set of controls included.[9]

Panel B shows that the results are quite different for mothers' spouses. While mothers' spouses' labor supply does appear responsive to the relative age of the youngest child, as evidenced by the existence of at least some positive and significant coefficients, the pattern of responsiveness differs from that of mothers in two key ways. First, spouses' responses appear to occur discontinuously rather than gradually. We see this from the significant effects of the discrete kindergarten eligibility variable compared to the lack of significance of the continuous

---

[9] The coefficient estimates are an order of magnitude smaller because the hours worked variable is in units of 10.

variable relative age. Specifically, the point estimates suggest that the youngest child switching from ineligible to eligible for kindergarten increases mothers' spouses' work hours per week in weeks worked by 1.9-2.2 and their work hours per week over all weeks by 2.0-2.1. A second key difference compared to mothers is that the effect on spouses occurs completely along the intensive, rather than extensive, margin. We see this from the significant effect on hours worked per week in weeks worked compared to the lack of a significant impact on the proportion of weeks worked. The absence of an effect along the extensive margin is consistent with the very high sample mean for proportion of weeks worked by spouses: 0.93 for spouses compared to 0.65 for mothers. If most spouses work continuously throughout their children's upbringing, there is little opportunity for an increase in their labor force participation rate as the children get older.

One potential concern with the above analyses is that the sample selection criteria – mothers with at least two children where the older ones are between seven and seventeen years old – raise questions about generalizability. To address this issue, we re-estimate the models using a broader sample of all mothers with any children seventeen or younger. The results for this "unrestricted sample" from regressions with the full set of demographic and human capital controls are shown in Table 3 alongside the results from the analogous specification in Table 2 ("main sample"). In spite of the fact that relaxing the selection criteria roughly doubles the sample size, the results remain very similar.

IV. Effect of Parents' Work on Childhood Obesity

Models

We next leverage the insights gained from the previous section to develop an IV strategy to estimate the causal effect of parental work on childhood obesity. Specifically, such a strategy should incorporate the following features. First, since youngest child's age influences the work hours of both mothers and their spouses, instrumenting for only mothers' work would likely lead to a violation of the exclusion restriction. Thus, spouses' work should be incorporated as well. Second, since youngest child's age influenced both mothers' and their spouses' work along the intensive margin, the endogeneous work variable needs to incorporate intensity of work; simply using a dummy for employment status would likely lead to a violation of the exclusion restriction as well. Third, the continuous measure of youngest child's relative age is a better predictor of mothers' work than the variable for proportion of eligible weeks, whereas the reverse is true for mothers' spouses' work. This points toward using the continuous measure as one instrument and the interaction of the discrete measure with mother's marital status as another. In other words, since the discrete measure has little to no predictive power over mother's work, it should only "turn on" if the mother is married. Similarly, since the continuous measure has little predictive power over spouse's work, interacting it with marital status would serve little purpose.

Given the inherent difficulties in obtaining meaningfully precise IV estimates with multiple endogenous variables in datasets with modest sample sizes such as the NLSY79, our main IV specification uses just one endogenous variable: parents' hours worked per week over all weeks in the past year. This is the sum of mothers' and spouses' weekly work hours, with zeros assigned in cases of no work or no spouse. (Recall that our set of controls includes marital status, allowing differentiation between mothers with no spouse and mothers whose spouses do not work.) Accordingly, the IV model takes the following form:

$$WORK_{it} = \alpha_0 + \alpha_1 RELAGE_{it} + \alpha_2 (ELIG_{it} * MARRIED_{it}) + \boldsymbol{\alpha_3 X_{cit}} + \tau_{2t} + \varepsilon_{2cit} \quad (2)$$

$$BMI_{cit} = \theta_0 + \theta_1 \widehat{WORK}_{it} + \boldsymbol{\theta_2 X_{cit}} + \tau_{3t} + \varepsilon_{3cit} \quad (3)$$

where (2) is the first-stage regression for parental work ($WORK_{it}$) and (3) is the second stage for children's weight status (BMI_{cit}). Since we now use the child-level dataset, there are three indices: *c* for child, *i* for mother, and *t* for year. $RELAGE_{it}$ and $ELIG_{it} * MARRIED_{it}$ are the two instruments; as discussed in the previous paragraph, the former strongly predicts the mother's hours component of $WORK_{it}$ while the latter strongly predicts the spouse's hours component. BMI_{cit} is one of the child-BMI-related outcome variables: BMI Z-score, overweight, and obese. $\boldsymbol{X_{cit}}$ is the set of mother- and child-level control variables. Again, we utilize multiple variants of controls in separate models: (i) including only the "demographic controls", (ii) adds the "human capital controls", (iii) further adds "child health controls", (iv) adds also the baseline value of the dependent variable, measured in the survey wave immediately prior to the child aging into the sample. τ_{2t} and τ_{3t} are the year fixed effects in equations (2) and (3), and ε_{2cit} and ε_{3cit} are the error terms. The coefficient of interest θ_1 provides the local average treatment effect of parents' work hours on children's weight outcomes – i.e. the effects of changes in work hours on older children's weight induced by youngest sibling's kindergarten eligibility. We also estimate a model that allows for differential effects of mothers' and spouses' work by instrumenting for them both in one model – a model that is exactly identified because we have two instruments.

<u>*Results*</u>

Table 4 reports the results from the IV models with parents' work as the lone endogenous variable. The three panels display the results for the three weight outcomes. The top row of each panel contains OLS results for the sake of comparison. The second row present the second-stage coefficient estimates of interest from the IV models. The remaining rows shows results from three standard diagnostic tests of the IV models: the F test that the instruments are jointly insignificant in the first stage, the test for endogeneity of parents' work, and the overidentification test. The columns show the sensitivity of the results to the gradual inclusion of additional control variables.

We begin by discussing the OLS results. Ten additional parental work hours per week are associated with a statistically significant but small increase in BMI z-score of 0.025-0.03. The estimates for the binary outcomes are also positive and small – 0.3-0.5 percentage points for Pr(Overweight) and 0.3 percentage points for Pr(Obese) – but are statistically insignificant.

The IV estimates are, in all cases, positive and substantially larger than the corresponding OLS estimates. Ten additional parental work hours per week are predicted to increase BMI z-score by 0.15-0.19 units, Pr(Overweight) by 6.6-8.1 percentage points, and Pr(Obese) by 4.9-6 percentage points. The impacts on overweight and obesity are statistically significant at the 5% level in all specifications, while the effect on BMI z-score is only significant in the regression with all controls. The first-stage F statistics are all around 11-12, slightly above the conventional rule of thumb of 10. The endogeneity test rejects the null hypothesis that the OLS estimator is consistent in all overweight and obesity regressions as well as in the BMI z-score regression with all controls. The overidentification test never rejects the null hypothesis that our set of instruments is valid.

Further discussion is warranted regarding magnitudes. The IV point estimates are quite large, as they represent 13%-22%, 15%-18%, and 15%-18.7% of the sample standard deviations for BMI z-score, overweight, and obesity, respectively.[10] However, we caution against a literal interpretation of these point estimates since they are accompanied by fairly wide confidence intervals – as evidenced by the fact that the estimates never reach the 1% level of statistical

[10] These calculations are based on dividing the coefficient estimates by the standard deviations reported in Table 1 and then multiplying by 100%. Note that the coefficient estimate for BMI z-score is not exactly interpretable as the effect in standard deviations because z-score is based on the historical CDC growth charts rather than an in-sample calculation.

significance despite their size. This is likely due to the relatively modest sample size of the NLSY79 combined with the fact that the instruments, though technically strong enough to rule out substantial weak instrument bias, are not overwhelmingly strong. Nonetheless, it is noteworthy that, in spite of the relative imprecision of the IV estimates, we are still able to reject the consistency of the OLS estimator in most cases. All things considered, our preferred interpretation of the results is simply that they provide evidence that parental work increases child weight and that the magnitude of the effect is understated if the endogeneity of weight is ignored.

Table 5 displays the results for the models that instrument for two endogenous variables at the same time – mothers' and their spouses' work hours – and thus differentiate between the effects of maternal and paternal work. The OLS estimates show that higher mothers', but not mothers' spouses', work hours are associated with small increases in child weight that are significant at the 10% level or better in most cases. The magnitudes for the effects of ten additional mothers' work hours per week range from 0.03-0.04 units for BMI z-score, 0.7-0.8 percentage points for overweight, and 0.4-0.5 percentage points for obesity, while the magnitudes for the effects of spouses' work hours are all close to zero. These results are consistent with those from the prior associational literature discussed in Section I. The IV results, however, are quite different. The magnitudes of the effects increase considerably for both mothers and spouses, as ten additional mothers' work hours per week increase BMI z-score by 0.12-0.16 units, Pr(Overweight) by 6.1-7.3 percentage points, and Pr(Obese) by 4.7-5.7 percentage points, while ten additional spouses' work hours per week increase BMI z-score by 0.3-0.35 units, Pr(Overweight) by 9.3-12.9 percentage points, and Pr(Obese) by 5.7-8.0 percentage points. Instrumenting for multiple endogenous variables puts considerable demands on the data, so the estimates are only precise enough to reach statistical significance for 7 of the 24 IV coefficients. Nonetheless, the results provide reasonably convincing evidence that the conclusion from prior literature that only mothers' work hours matter for children's weight no longer holds after accounting for endogeneity. The estimated effects of mothers' and spouses' work hours are never statistically different in any of the IV specifications (see the equality test p-values in the table), and the magnitudes are actually larger for spouses in all cases. This is an important result, as it suggests that the decline in male labor force participation may have partially offset the increase in childhood obesity from the rise in female labor force participation.

Specification Checks

In this section, we discuss issues related to internal and external validity and provide checks of the extent to which they are problematic. With regard to internal validity, the key assumption in the IV model is that the instruments $RELAGE_{it}$ and $ELIG_{it} * MARRIED_{it}$ can be excluded from the second-stage regression. In other words, conditional on the controls, youngest sibling's age is only related to older sibling's BMI via parental work hours. One potential concern is that the youngest child becoming eligible for kindergarten might relax parents' time constraints more generally, freeing up time not only for market work but also activities such as exercise and food preparation that could conceivably affect the weight of their children. For instance, if a mother begins an exercise program and develops enthusiasm for it, she may seek to also increase the physical activity of her children. If she has more time to prepare home-cooked meals, this would presumably decrease reliance on restaurant food and lead to healthier eating habits for the entire family. While we cannot rule out such scenarios, it is important to note that they both point in the direction of youngest child's relative age reducing, rather than increasing, children's BMI. They would therefore cause us to underestimate the impact of parental work on children's BMI, meaning that the large effects documented in the preceding section would actually be conservative.

Another potential concern is that the youngest child aging into kindergarten likely increases disposable income for at least some parents by reducing the need for paid child care. This additional income could conceivably be spent on either health-promoting (e.g. fresh produce) or health-detracting (e.g. junk food) items. However, we do not feel that this income effect is likely to be consequential for our results. Household income is well known to be negatively associated with childhood obesity (e.g. Singh et al., 2008), implying that the income effect would work in the direction of making our IV estimates more conservative. That said, whether this relationship is causal remains an open question, and it is also possible that earned income might affect health differently than a reduction in expenditures, which is essentially unearned income. To address both of these issues, we use our data to conduct an investigation of the effect of income on child weight. We (at least partially) address the concern of causality by including child fixed effects, and we address the issue of earned versus unearned income by including not only household income but also benefits received from welfare/Temporary Assistance for Needy Families (TANF). Results from regressions with the full set of controls for each of the three outcomes are shown in Table 6. In OLS regressions that do not include child fixed effects, we observe the expected negative relationship between household income and the child weight outcomes, but no significant effects of welfare/TANF benefits. In the fixed effects regressions, we observe no significant effects of either household income or welfare/TANF on any of the child weight outcomes, and the magnitudes of the coefficient estimates are small (e.g. an additional $1,000 of income reduces the probability of being obese by less than one one-hundredth of a percentage point). In sum, the available evidence suggests that it is unlikely that the income effect is sufficiently large for the potential decline in child care expenses after the youngest child becomes eligible for kindergarten to meaningfully influence child weight.

An additional possible concern is that parental attitudes toward health may change systematically with the youngest child's age. For instance, if parents relax their emphasis on healthy behaviors as their children age start to require less direct supervision, we might observe an increase in child BMI even if the parents' work schedules do not change. This would lead to upward bias in the IV estimator. In Table 7, we present results from falsification tests designed to rule out the possibility of confounding from such changes in attitudes toward health. Specifically, we re-estimate our IV model using each one of four different outcomes that reflect health attitudes but should not be causally affected by parental work: whether the mother is currently trying to lose weight, the mother always or often reads nutritional information (as opposed to sometimes, rarely, or never), the child had a well-patient doctor checkup in the past year, and the child had a dental checkup in the past six months.[11] The first two regressions involve mother's outcomes, so we utilize the mother-level dataset used in Tables 2 and 3. We use the child-level dataset for the last two regressions as those feature children's outcomes. If the IV models reveal "effects" on these outcomes, this would suggest a violation of the exclusion restriction that the youngest child's age instruments only affect health-related outcomes via parental work. Reassuringly, we find no evidence of any such effects, as the coefficient of interest is insignificant in all cases.

[11] One might worry that these outcomes do not provide "pure" falsification tests since stories could be devised in which they could plausibly be affected by parental work. We conducted additional analyses (results available upon request) to rule out at least the most obvious of these stories. Specifically, a mother might gain weight herself after returning to work, which could potentially increase her likelihood of making weight loss attempts or showing an interest in nutritional information. We therefore verified that our results for these outcomes are robust to the inclusion of mother's BMI (or overweight or obesity status) as a control. For the child health care outcomes, perhaps additional parental work could influence these by increasing income. We therefore verified that the results are robust to the inclusion of income and/or health insurance status (which likely affects the income elasticity of health care).

Regarding external validity, potential concerns mirror those from Section II, as results from a sample of 7-17 year old children with at least one younger sibling might not generalize to other children. To at least partially address this issue, we re-estimate the OLS models with a broader sample of all children between the ages of 3 and 17 (the same age cutoffs used by Courtemanche, 2009). The results, shown in Table 8, are virtually identical to those from the main analysis sample. Since OLS estimates are not sensitive to restrictions based on age and siblings, it seems reasonable to infer that IV estimates would also not be meaningfully sensitive if it were possible to conduct the IV estimation with the unrestricted sample. Nonetheless, our results are still susceptible to the usual critiques of LATEs in IV models, namely that effects of increases in work hours induced by youngest child's age may not be reflective of the effects of work more generally. Further research using different identification strategies is necessary to fully investigate this possibility.

Subsample Analyses

We next conduct subsample analyses by parental education, race/ethnicity, and mother's marital status. The objective is to examine whether the effect of parental work on child weight varies by a household's relative level of disadvantage. Anderson et al. (2003) find that the association between mothers' work and childhood obesity is strongest for children in households with a high income, with a highly educated mother, and with non-Hispanic white race/ethnicity. Similarly, Ruhm (2008) finds that this relationship is strongest for white children, those with a highly educated mother, and those where a spouse/partner is present. He also stratifies by an overall "disadvantage index" that is based on the predicted value of a regression of household income on mother's age, score on the Armed Forces Qualifying Test (AFQT), mother's education, and presence of a spouse/partner. The advantage of stratifying by predicted rather than actual income is that it circumvents the endogenous sample selection problem caused by income being a function of work hours. Ruhm (2008) finds that the association between maternal employment and childhood obesity is stronger for those below the median (less disadvantaged) of this index. Our objective is to test whether this finding that the association between work hours and child weight is concentrated among advantaged households persists in IV analyses that account for endogeneity.

Table 9 presents the results for several subsamples. Columns (1) and (2) stratify by education, with the sample divided into children in households where no parent has any college education and those in households where at least one parent does. This division splits the sample as evenly as possible. The IV estimates are positive in all cases for both subsamples, but the effects on parental work on all three weight outcomes are larger for the higher education group – by a factor of around three times for BMI z-score and overweight. Columns (3) and (4) divide the sample by whether the mother is Hispanic or black.[12] The effects are almost completely concentrated among the non-Hispanic, non-black subsample, as the magnitudes are large and statistically significant for all three weight outcomes for that group as opposed to small and insignificant for the Hispanic/black group. Stratifying by mother's marital status in columns (5) and (6), we see that the impacts are large and significant for children whose mothers are married and small and insignificant for those whose mothers are single. In columns (7) and (8), we replicate the "disadvantage index" stratification of Ruhm (2008). The effects on all three outcomes are again clearly concentrated among the more advantaged group.

[12] It may appear surprising that the sample size is slightly larger for the Hispanic/black group, but remember that the NLSY79 intentionally oversampled minorities. Sampling weights are used in all regression estimates, but the sample sizes reflect the unadjusted number of children in each group.

Implications for Future Research

We close our empirical analyses by investigating the implications of our work for future researchers who wish to implement youngest sibling's age-based IV strategies to estimate other effects of maternal employment. As discussed previously, two primary ways in which our IV method differs from that of Morrill (2011) are that our method incorporates spouse's work and utilizes continuous variation in youngest sibling's age in addition to discrete variation at the age of kindergarten eligibility. Intuitively, using the discrete kindergarten eligibility as the only instrument and maternal work as the only endogenous variable may lead to overstated results. Such a specification would attribute the entire reduced-form effect of youngest sibling's kindergarten eligibility on childhood obesity to the change in maternal work. Given the evidence presented in Section III that discrete kindergarten eligibility influences paternal work and earlier in this section that paternal work influences childhood obesity, it seems likely that at least part of the reduced-form effect actually operates through paternal work, in which case the estimated impact of maternal work will be biased upward. Put differently, omitting spouse's work would lead to a violation of the exclusion restriction. However, recall from Section III that only discrete kindergarten eligibility predicts spouse's work; the continuous relative age variable does not. This suggests that omitting paternal work might *not* lead to a violation of the exclusion restriction if a continuous rather than discrete instrument if used for maternal work.

In Table 10, we present results from IV models that test these predictions. For the sake of comparison, the first column restates the estimated effects of parents' work from the IV specification with all controls from Table 4, while the second column does the same for the maternal work results from Table 5. The results from the two models were very similar in magnitude, with ten additional parents'/mothers' work hours increasing BMI z-score by 0.16-0.19 units, Pr(Overweight) by 6.1-6.6 percentage points, and Pr(Obese) by 4.7-4.9 percentage points. In the third column we display results from a "naïve" specification in which discrete kindergarten eligibility is the only instrument and mothers' work is the only endogenous variable. The sizes of the estimates increase substantially: ten additional hours of maternal work is now predicted to increase BMI z-score by 0.31 units, Pr(Overweight) by 8.6 percentage points, and Pr(Obese) by 7.6 percentage points. As predicted, relegating paternal work to the error term appears to exaggerate the effects of maternal work. In the fourth column, we continue to exclude spouse's hours but use continuous youngest sibling's relative age as the instrument rather than discrete eligibility. Again as predicted, the estimated effects of mothers' work shrink back down closer to those from the models that include spouses' work. These results could be of value to future researchers who wish to leverage exogenous variation from youngest child's age to investigate the effects of maternal employment using datasets in which spouse's work information is not available. In such cases, our estimates suggest that *continuous* age relative to kindergarten may be a valid instrument for maternal work even is discrete eligibility is not.

A comparison of these magnitudes to those of Morrill (2011) is instructive. As discussed in Section I, Morrill (2011) leverages youngest child's kindergarten eligibility to investigate the effect of maternal employment on children's acute health episodes. Similarly to our "naïve" specification, she uses discrete eligibility as the only instrument and maternal employment as the only endogenous variable. She finds that maternal employment increases the probability of hospitalization, injury, and asthma episodes by around 200% relative to the sample incidence rates. Recall that our "naïve" IV regressions estimate that ten additional mother's work hours increase Pr(Overweight) by 8.6 percentage points and Pr(Obese) by 7.6 (third column of Table

10). Since the average working mother in our sample works 35 hours per week, we need to multiply the coefficient estimates by 3.5 to facilitate a comparison with Morrill (2011). Doing so means that maternal employment on average increases Pr(Overweight) and Pr(Obese) by 30.1 and 26.6 percentage points, or 114% and 227% of the respective sample means. These magnitudes are broadly similar to those of Morrill (2011). In contrast, when we instrument for both mothers' and spouses' work, the effects of ten additional maternal work hours on Pr(Overweight) and Pr(Obese) fall to 6.1 and 4.7 percentage points, respectively. These imply average effects of maternal employment of 21.4 and 16.5 percentage points, or 81% and 141% of the respective sample rates. In short, allowing part of the effects of youngest child's age on children's weight outcomes to occur via spouse's work helps alleviate potential concerns about plausibility to at least some extent. (That said, as discussed previously, even our preferred point estimates are quite large, and their imprecision should be kept in mind when interpreting the results.)

V. Conclusion and discussion

This paper explores the causal effect of maternal employment on child weight. The identification strategy exploits plausibly exogenous variation in parental labor supply coming from the youngest sibling's age. Using panel data from the NLSY79, we first show that both mothers' and mothers' spouses' work hours are responsive to the age of the youngest child. Mothers' work hours gradually increase as the age of the youngest child rises, with the effect occurring along both the extensive and intensive margins of work. In contrast, spouses' work hours jump discontinuously when the child becomes eligible for kindergarten, with the effect occurring only along the intensive margin. We leverage these insights in the design of our IV model, which shows that the impacts of parental work on children's weight outcomes are positive and large – in most cases, significantly larger than the estimates obtained using OLS. We find no evidence that the effects of maternal and paternal work are significantly different. Together, these results suggest that the contribution of increased maternal employment to the rise in childhood obesity is larger than the relatively modest estimates from the prior associational literature would suggest, and also that the concurrent decline in paternal labor supply offsets this contribution to some extent. Given the relative imprecision of our IV estimates and the dangers of out-of-sample extrapolation, we are reluctant to estimate exactly how much of the trend in childhood obesity can be attributed changing labor supply patterns. Nonetheless, our results indicate that Courtemanche's (2009) estimate that 10% of the rise in childhood obesity is due to the rise in maternal employment may be conservative.

The results should not be interpreted as discouraging parental labor supply, or as claiming that the rise in female labor force participation has had a negative net impact on society. The results instead highlight the importance of further investigation into the mechanisms through which parental employment might affect children's health. Possible mechanisms include the changes in family routine, diet, and time allocation induced by mothers' labor supply. Parental employment is likely to reduce beneficial routines, such as regular family meals and physical activities with children. At the same time, parental employment might lead to unhealthy routines, such as television watching and restaurant meals. Prior research has found associations between maternal employment and time use (Cawley and Liu, 2012; Fertig et al, 2009), but little causal evidence on mechanisms exists. One exception is a new working paper by Coyer (2016), who uses a similar identification strategy to us and finds that maternal employment increases purchases of pre-prepared meals while decreasing fruit, vegetable, and milk purchases.

Another possible mechanism is the child care setting. For example, if child care subsidies, such as the child care and development fund (CCDF), encourage working mothers to rely on center-based child care service, the use of non-parental child care may influence children's diet and activity to some extent (Blau and Tekin, 2007; Herbst and Tekin, 2010). In addition, the availability of relative care, especially from grandparents, has substantial positive effect on mothers' labor supply (Compton and Pollak, 2014). Grandparents may put fewer restrictions on their grandchildren's diet and activities (Maher et al., 2008), thus increasing the risk of children being obese.

Understanding the mechanisms of the effects of parental employment on childhood obesity is not only of academic interest, but it would also shed light on policies to help reverse the obesity epidemic. For example, if supervision is an important mechanism, promoting after-school programs could be a beneficial policy. Such programs not only increase children's physical activity level directly, they also help children to form healthy habits and promote health education among parents (Annesi et al., 2007; Annesi, Moore, & Dixon, 2008). Alternatively, if nutrition is the main mechanism, policies related to food labeling (Bollinger, Leslie, and Sorensen, 2010; Tandon et al., 2010) and quality of school meals (Foster et al., 2007; Story, Nanney, and Schwartz, 2009) could potentially have an effect. Understanding the relative impact of each of the mechanisms would be the first step toward informing appropriate policy.

References

Anderson, P.M., Butcher, K. F., Cascio, E. U., & Schanzenbach, D. W. (2011) Is being school better? The impact of school on children's BMI when starting age is endogenous. Journal of Health Economics, 30, 977-986.

Anderson, P.M., Butcher, K. F., & Levine, P. B. (2003) Maternal employment and overweight children. Journal of Health Economics, 22, 477-504.

Annesi, J. J., Faigenbaum, A. D., Westcott, W. L., Smith, A. E., & Dixon, G. M. (2007) Effects of the youth fit for life protocol on physiological factors, mood, self-appraisal, voluntary physical activity, and fruit and vegetable consumption in children enrolled in YMCA after-school care. Journal of Social, Behavioral, and Health Sciences, 1, 164-197.

Annesi, J. J., Moore, J. C., & Dixon, G. M. (2008) Correlates of changes in voluntary physical activity associated with the Youth Fit For Life intervention during after-school care. Psychological Reports, 102, 911-919.

Bishop, J. (2011) The effect of maternal employment on youth overweight in Australia. Economic Record, 87, 92-104.

Blau, D. & Tekin, E. (2007) The determinants and consequences of child care subsidies for single mothers in the USA. Journal of Population Economics, 20, 719-741.

Bollinger, B., Leslie, P., & Sorensen, A. (2010) Calorie posting in chain restaurants. NBER working paper 15648, http://www.nber.org/papers/w15648.

Brown, J. E., Broom, D, H., Nicholson, J. M., & Bittman, M. (2010) Do working mothers raise couch potato kids? Maternal employment and children's lifestyle behaviors and weight in early childhood. Social Science & Medicine, 70, 1816-1824.

Bureau of Labor Statistics (2014) Women in the labor force: A databook. Retrieved from http://www.bls.gov/opub/reports/cps/women-in-the-labor-force-a-databook-2014.pdf

Cascio, E. U. (2009) Maternal labor supply and the introduction of kindergartens into American public schools. The Journal of Human Resources, 44, 140-170.

Cawley, J., & Liu, F. (2012) Maternal employment and childhood obesity: A search for mechanisms. Economics and Human Biology, 10, 352-364.

Cawley, J. (2004) The impact of obesity on wages. Journal of Human Resources, 39, 451-474.

Cawley, J. & Meyerhoefer, C. (2012) The medical care costs of obesity: An instrumental variables approach. Journal of Health Economics, 31, 219-230.

Compton, J & Pollak, R. (2014) Family proximity, childcare, and women's labor force attachment. Journal of Urban Economics, 79, 72-90.

Courtemanche, C. (2009) Longer hours and larger waistlines: The relationship between work hours and obesity. Forum for Health Economics and Policy, 12 (2), Article 5.

Courtemanche, C., Pinkston, J., & Stewart, J. (2015) Adjusting Body Mass for Measurement Error with Invalid Validation Data. Economics and Human Biology, 19, 275-293.

Coyer, C. (2016) Into the Workforce and Out of the Home? Working paper, available http://www.christinecoyer.com/.

Duncan, G. J., Ziol-Guest, K. M., & Kalil, A. (2010) Early-childhood poverty and adult attainment, behavior, and health. Child Development, 81, 306-325.

Evans, W. N., Morrill, M. S., & Parente, S. T. (2010) Measuring inappropriate medical diagnosis and treatment in survey data: The case of ADHD among school-age children. Journal of Health Economics, 29, 657-673.

Fertig, A., Glomm, G., & Tchernis, R. (2009) The connection between maternal employment and childhood obesity: Inspecting the mechanism. Review of Economics of the Household, 7, 227-255.

Foster, G. D., Sherman, S., Borradaile, K. E., Grundy, K. M., Vander Veur, S., Nachmani, J., ... , Shults, J. (2008) A policy-based school intervention to prevent overweight and obesity. Pediatrics, 121, e794-e802.

Fryar, C. D., Carroll, M. D., & Ogden, C. L. (2016) Prevalence of obesity among children and adolescents aged 2-19 years: United States, 1963-1965 through 2013-2014. Available at https://www.cdc.gov/nchs/data/hestat/obesity_child_13_14/obesity_child_13_14.pdf

Gelbach, J. B. (2002) Public schooling for young children and maternal labor supply. The American Economic Review, 92, 307-322.

Goodman, E., Hinden, B. R., & Khandelwal, S. (2000) Accuracy of teens and parental reports of obesity and body mass index. Pediatrics, 106, 52-58.

Greve, J. (2011) New results on the effect of mothers' working hours on children's overweight status: Does quality of childcare matter? Labour Economics, 18, 579-590.

Gwozdz, W., Sousa-Poza, A., Reisch, L. A., Ahrens, W., Eiben, G., Fernandez-Alvira, J. M., ... , Bammann, K. (2013) Maternal employment and childhood obesity - A European perspective. Journal of Health Economics, 32, 728-742.

Herbst, C. & Tekin, E. (2010) Chid care subsidies and child development. Economics of Education Review, 29, 618-638.

Kuczmarski, M. F., Kuczmarski, R. J., & Najjar, M. (2001) Effects of age on validity of self-reported height, weight, and body mass index: Findings from the third national health and nutrition examination survey, 1988-1994. Journal of the American Dietetic Association, 101, 28-34.

Liu, E., Hsiao, C., Matsumoto, T., & Chou, S. (2009) Maternal full-time employment and overweight children: Parametric, semi-parametric, and non-parametric assessment. Journal of Econometrics, 152, 61-69.

Lubotsky, D. and Qureshi, J. (2016) The (Surprisingly) Smooth Rise in Mothers' Employment as Children Age. Unpublished manuscript, University of Illinois at Chicago.

Maher, E., Li, G., Carter, L., Johnson, D. (2008) Preschool child care participation and obesity at the start of kindergarten. Pediatrics, 122, 322-330.

Morrill, M. S. (2011) The effects of maternal employment on the health of school-age children. Journal of Health Economics, 30, 240-257.

Morrissey, T. W. (2012) Trajectories of growth in body mass index across childhood: Associations with maternal and paternal employment. Social Science & Medicine, 95, 60-68.

Morrissey, T. W., Dunifon, R. E., & Kalil, A. (2011) Maternal employment, work schedules, and children's body mass index. Child Development, 82, 66-81.

National Center for health Statistics (2002) Vital and Health Statistics Series 11, number 246. Retrieved from http://www.cdc.gov/growthcharts/2000growthchart-us.pdf

Neumark-Sztainer, D., Hannan, P. J., Story, M., Croll, J., & Perry, C. (2003) Family meal patterns: Association with sociodemographic characteristics and improved dietary intake among adolescents. Journal of the American Dietetic Association, 103, 317-322.

Ruhm, C. (2008) Maternal employment and adolescent development. Labour Economics, 15, 958-983.

Singh, G., Kogan, M., Van Dyck, P., and Siahpush, M. (2008) Racial/ethnic, socioeconomic, and behavioral determinants of childhood and adolescent obesity in the United States: Analyzing independent and joint associations. Annals of Epidemiology, 18, 682-695.

Story, M., Nanney, M. S., Schwartz, M. B. (2009) Schools and obesity prevention: Creating school environments and policies to promote healthy eating and physical activity. Milbank Quarterly, 87, 71-100.

Tandon, P. S., Wright, J., Zhou, C., Rogers, C. B., & Christakis, D. A. (2010) Nutrition menu labeling may lead to lower-calorie restaurant meal choices for children. Pediatrics, 125, 244-248.

Trasande, L. and Chattejee, S. (2009) The impact of obesity on health service utilization and costs in childhood. Obesity, 17, 1749-54.

Trasande, L., Liu, Y., Fryer, G., and Weitzman, M. (2009) Effects of childhood obesity on hospital care and costs, 1999-2005. Health Affair, 28, w751-60.

Yeung, W. J., Linver, M. R., Brooks-Gunn, J. (2002) How money matters for young children's development: Parental investment and family progresses. Child Development, 73, 1861-1879.

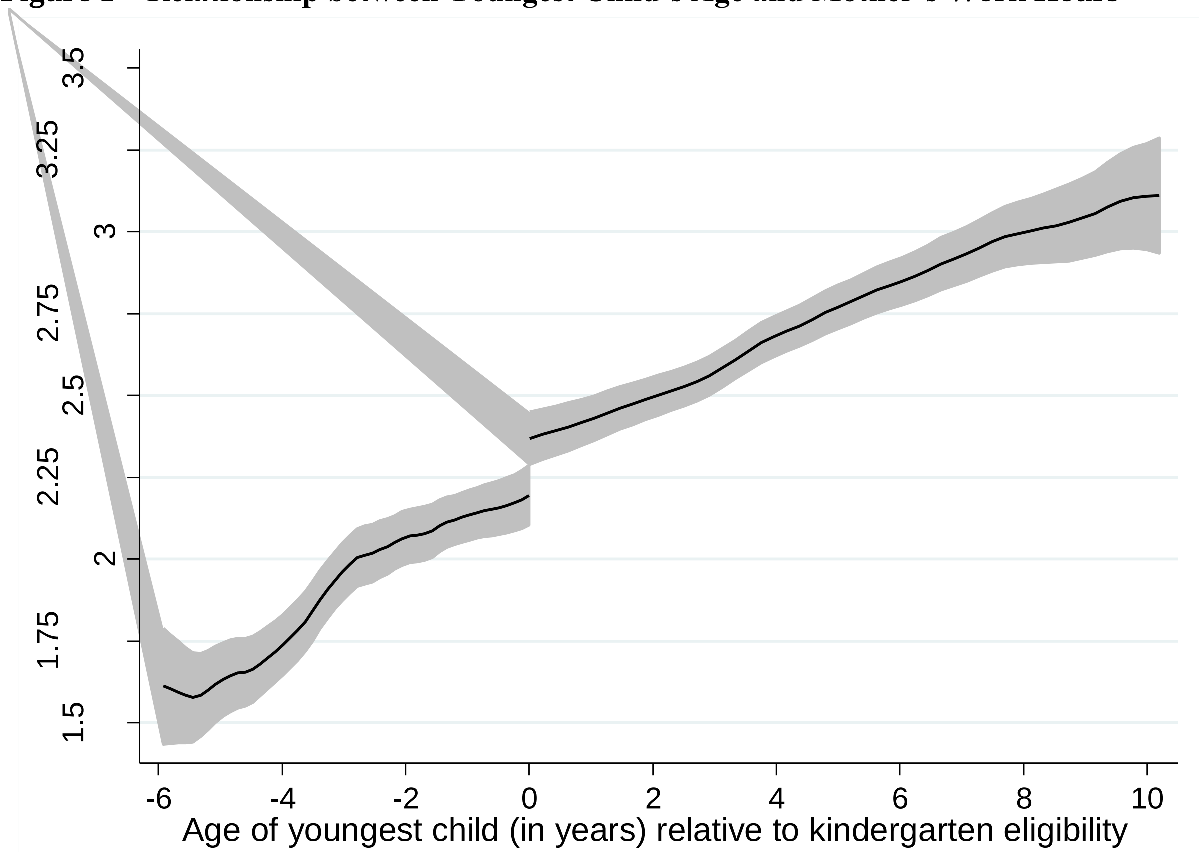
Zhang, N., & Zhang, Q. (2011) Does early school entry prevent obesity among adolescent girls? Journal of Adolescent Health, 48, 644-646.

Table 1 – Summary Statistics for Parents and their Children Aged 7-17 Years Old

	Source	Mean (Std. Dev.)
<u>Dependent Variables</u>		
BMI z-score	NLSY79CYA	0.274 (1.152)
Overweight	NLSY79CYA	0.264 (0.441)
Obesity	NLSY79CYA	0.117 (0.321)
<u>Work Variables</u>		
Mother's fraction of weeks worked in past year	NLSY79	0.655 (0.431)
Mother's hours worked/week (in 10s) in weeks worked in past year (undefined if no work weeks)	NLSY79	3.540 (1.401)
Mother's hours worked/week (in 10s) over all weeks in past year (0 if no work weeks)	NLSY79	2.352 (1.906)
Spouse's fraction of weeks worked in past year (undefined if no spouse)	NLSY79	0.926 (0.212)
Spouse's hours worked/week (in 10s) in weeks worked in past year (undefined if no spouse or no work weeks)	NLSY79	4.657 (1.117)
Spouse's hours worked/week (in 10s) over all weeks in past year (undefined if no spouse, 0 if no work weeks)	NLSY79	4.315 (1.487)
<u>Youngest Sibling Age Variables</u>		
Proportion of kindergarten eligible weeks in past year	NLSY79	0.519 (0.489)
Relative age (in years) to kindergarten eligibility cutoff	NLSY79	1.035 (3.638)
<u>Demographic Control Variables</u>		
Mother is Hispanic	NLSY79	0.076 (0.266)
Mother is non-Hispanic black	NLSY79	0.153 (0.360)
Family size	NLSY79	4.854 (1.240)
Mother's age in years	NLSY79	36.470 (5.211)
Spouse's age in years (0 if no spouse)	NLSY79	28.289 (18.186)
Mother is married and lives with spouse	NLSY79	0.724 (0.447)
Child is female	NLSY79CYA	0.487 (0.500)
Child's age in months	NLSY79CYA	149.400 (37.134)
Attachment to biological father	NLSY79CYA	0.775 (0.418)
<u>Human Capital Control Variables</u>		
Mother's AFQT score (2006 standardization)	NLSY79	48.353 (28.423)
Mother's education: high school graduate	NLSY79	0.445 (0.497)
Mother's education: some college	NLSY79	0.237 (0.425)
Mother's education: college degree or higher	NLSY79	0.211 (0.408)
Spouse's education: high school graduate (0 if no spouse)	NLSY79	0.287 (0.453)
Spouse's education: some college (0 if no spouse)	NLSY79	0.143 (0.350)
Spouse's education: college degree (0 if no spouse)	NLSY79	0.089 (0.285)
<u>Child's Health Control Variables</u>		
High birth weight	NLSY79CYA	0.107 (0.309)
Breastfed	NLSY79CYA	0.575 (0.494)
Height is self-reported	NLSY79CYA	0.507 (0.500)
Weight is self-reported	NLSY79CYA	0.519 (0.500)

Note: Estimates are weighted by children's sampling weights.

Figure 1 – Relationship between Youngest Child's Age and Mother's Work Hours



Notes: Local polynomial smoother is used. Gray regions represent 95% confidence intervals. Observations are weighted by mother's sampling weights. Youngest child's age is the relative age (in years) to kindergarten eligibility. Mothers' work hours are measured as the hours worked per week over all weeks in the past year.

Figure 2 – Relationship between Youngest Child's Age and Mother's Spouse's Work Hours

Notes: Local polynomial smoother is used. Gray regions represent 95% confidence intervals. Observations are weighted by mother's sampling weights. Youngest child's age is the relative age (in years) to kindergarten eligibility. Mothers' spouses' work hours are measured as the hours worked per week over all weeks in the past year.

Table 2 – Effects of Youngest Child's Kindergarten Eligibility on Mother's and Mother's Spouse's Work

Outcome variable	Youngest sibling age variable	(1) Demographic controls	(2) Add human capital controls	(3) Add baseline work
Panel A: Mother's Work				
Proportion of weeks worked	Proportion of eligible weeks	0.018	0.022	0.020
		(0.016)	(0.016)	(0.016)
(N=10,243)	Relative age to kindergarten	0.019***	0.020***	0.024***
		(0.003)	(0.003)	(0.003)
Hours worked per week (in (10s) in weeks worked	Proportion of eligible weeks	-0.090	-0.085	-0.086
		(0.065)	(0.065)	(0.063)
(N=7,747)	Relative age to kindergarten	0.040***	0.035***	0.057***
		(0.012)	(0.012)	(0.011)
Hours worked per week (in 10s) over all weeks	Proportion of eligible weeks	0.003	0.021	-0.010
		(0.069)	(0.069)	(0.066)
(N=10,243)	Relative age to kindergarten	0.093***	0.092***	0.116***
		(0.014)	(0.014)	(0.012)
Panel B: Mother's Spouse's Work				
Proportion of weeks worked	Proportion of eligible weeks	0.007	0.009	0.009
		(0.009)	(0.009)	(0.009)
(N=6,477)	Relative age to kindergarten	-0.001	0.001	0.00002
		(0.002)	(0.002)	(0.002)
Hours worked per week (in (10s) in weeks worked	Proportion of eligible weeks	0.212***	0.216***	0.194***
		(0.061)	(0.061)	(0.058)
(N=6,196) (Mean=4.657, SD=1.117)	Relative age to kindergarten	-0.018*	-0.015	-0.015
		(0.010)	(0.010)	(0.009)
Hours worked per week (in 10s) over all weeks	Proportion of eligible weeks	0.204***	0.214***	0.204***
		(0.074)	(0.074)	(0.074)
(N=6,477)	Relative age to kindergarten	-0.016	-0.008	-0.016
		(0.013)	(0.013)	(0.013)

Notes: Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. The spouse's work regressions exclude children in households where no spouse is present. Year fixed effects are included. Child sampling weights are used.

Table 3 – Effects of Youngest Child's Kindergarten Eligibility on Mother's and Mother's Spouse's Work; Comparison of Results from Main (Mothers of 7-17 Year Old Children with Younger Siblings) and Unrestricted (Mothers with any Children 17 Years or Younger) Samples

Outcome variable	Youngest sibling age variable	(1) Main sample	(2) Unrestricted sample
	Panel A: Mother's Work		
Proportion of weeks worked (N=10,243 in main sample)	Proportion of eligible weeks	0.022 (0.016)	0.030** (0.012)
(N=20,508 in unrestricted sample)	Relative age to kindergarten	0.020*** (0.003)	0.019*** (0.002)
Hours worked per week (in 10s) in weeks worked	Proportion of eligible weeks	-0.085 (0.065)	-0.004 (0.044)
(N=7,747 in main sample) (N=15,770 in unrestricted sample)	Relative age to kindergarten	0.035*** (0.012)	0.026*** (0.007)
Hours worked per week (in 10s) over all weeks	Proportion of eligible weeks	0.021 (0.069)	0.068 (0.054)
(N=10,243 in main sample) (N=20,508 in unrestricted sample)	Relative age to kindergarten	0.092*** (0.014)	0.090*** (0.010)
	Panel B: Mother's Spouse's Work		
Proportion of weeks worked (N=6,447 in main sample)	Proportion of eligible weeks	0.009 (0.009)	0.001 (0.008)
(N=13,175 in unrestricted sample)	Relative age to kindergarten	0.001 (0.002)	0.001 (0.001)
Hours worked per week (in 10s) in weeks worked	Proportion of eligible weeks	0.216*** (0.061)	0.124*** (0.047)
(N=6,196 in main sample) (N=12,659 in unrestricted sample)	Relative age to kindergarten	-0.015 (0.010)	-0.008 (0.007)
Hours worked per week (in 10s) over all weeks	Proportion of eligible weeks	0.214*** (0.074)	0.121** (0.057)
(N=6,447 in main sample) (N=13,175 in unrestricted sample)	Relative age to kindergarten	-0.008 (0.013)	-0.001 (0.009)

Notes: Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. The spouse's work regressions exclude children in households where no spouse is present. Year fixed effects and the demographic and human capital controls are included. Sampling weights are used.

Table 4 – Effects of Parents' Work Hours on Children's Weight

		(1) Demo-graphic controls	(2) Add human capital controls	(3) Add child health controls	(4) Add baseline weight
	Panel A: BMI z-score				
OLS	Parents' work hours per week (in 10s)	0.027***	0.030***	0.030***	0.025***
		(0.009)	(0.009)	(0.009)	(0.008)
IV	Parents' work hours per week (in 10s)	0.164	0.154	0.152	0.189**
		(0.100)	(0.099)	(0.098)	(0.087)
	First stage F statistic	11.856	11.767	11.775	12.076
	Endogeneity test p-value	0.131	0.156	0.158	0.029
	Overidentification test p-value	0.276	0.344	0.360	0.318
	Panel B: Overweight				
OLS	Parents' work hours per week (in 10s)	0.005	0.005	0.005	0.003
		(0.003)	(0.003)	(0.003)	(0.003)
IV	Parents' work hours per week (in 10s)	0.081**	0.071**	0.071**	0.066**
		(0.038)	(0.036)	(0.036)	(0.033)
	First stage F statistic	11.856	11.767	11.775	11.876
	Endogeneity test p-value	0.019	0.041	0.041	0.035
	Overidentification test p-value	0.499	0.634	0.666	0.660
	Panel C: Obese				
OLS	Parents' work hours per week (in 10s)	0.003	0.003	0.003	0.003
		(0.003)	(0.002)	(0.003)	(0.002)
IV	Parents' work hours per week (in 10s)	0.060**	0.053**	0.053**	0.049**
		(0.027)	(0.027)	(0.026)	(0.023)
	First stage F statistic	11.856	11.767	11.775	11.190
	Endogeneity test p-value	0.011	0.030	0.030	0.023
	Overidentification test p-value	0.688	0.867	0.935	0.856

Notes: Sample size is 13,332 in all regressions. Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects are included. Child sampling weights are used. Parents' work hours per week is the summation of mothers' and mothers' spouses' hours worked per week over all weeks in the past year.

Table 5 – Effects of Mothers' and Mothers' Spouses' Work Hours on Children's Weight

		(1) Demo-graphic controls	(2) Add human capital controls	(3) Add child health controls	(4) Add baseline weight
		Panel A: BMI z-score			
OLS	Mother's hours worked per week (in 10s)	0.038***	0.041***	0.040***	0.029***
		(0.011)	(0.011)	(0.011)	(0.010)
	Mother's spouse's hours worked per week (in 10s)	0.002	0.007	0.007	0.015
		(0.015)	(0.015)	(0.015)	(0.013)
	Equality test p-value	0.044	0.061	0.059	0.352
IV	Mother's hours worked per week (in 10s)	0.134	0.121	0.121	0.157
		(0.111)	(0.112)	(0.110)	(0.100)
	Mother's spouse's hours worked per week (in 10s)	0.352*	0.309	0.297	0.347*
		(0.208)	(0.190)	(0.184)	(0.181)
	Equality test p-value	0.307	0.366	0.381	0.344
		Panel B: Overweight			
OLS	Mother's hours worked per week (in 10s)	0.007*	0.008**	0.008**	0.007**
		(0.004)	(0.004)	(0.004)	(0.004)
	Mother's spouse's hours worked per week (in 10s)	-0.004	-0.002	-0.002	-0.001
		(0.006)	(0.006)	(0.005)	(0.005)
	Equality test p-value	0.067	0.107	0.107	0.156
IV	Mother's hours worked per week (in 10s)	0.073*	0.065	0.065	0.061
		(0.042)	(0.041)	(0.041)	(0.037)
	Mother's spouse's hours worked per week (in 10s)	0.129	0.103	0.099	0.093
		(0.080)	(0.072)	(0.070)	(0.067)
	Equality test p-value	0.513	0.639	0.670	0.664
		Panel C: Obese			
OLS	Mother's hours worked per week (in 10s)	0.004	0.005*	0.005*	0.004
		(0.003)	(0.003)	(0.003)	(0.003)
	Mother's spouse's hours worked per week (in 10s)	-0.002	-0.0002	-0.0002	0.001
		(0.004)	(0.004)	(0.004)	(0.004)
	Equality test p-value	0.124	0.187	0.192	0.410
IV	Mother's hours worked per week (in 10s)	0.057*	0.052*	0.052*	0.047*
		(0.030)	(0.030)	(0.030)	(0.026)
	Mother's spouse's hours worked per week (in 10s)	0.080	0.061	0.057	0.057
		(0.055)	(0.050)	(0.049)	(0.046)
	Equality test p-value	0.693	0.877	0.935	0.857

Notes: Sample size is 13,332 in all regressions. Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects are included. Child sampling weights are used. Mothers' and mothers' spouses' work hours are measured as hours worked per week over all weeks in the past year. Equality test p-value is from t-test of equality of coefficients on mothers' and spouses' work.

Table 6 – Effect of Different Income Sources on Children's Weight

	(1) OLS	(2) Child fixed effects
Panel A: BMI z-score		
Household income (in $1,000s)	-0.0004*	-0.0002
	(0.0002)	(0.0002)
Welfare/TANF benefits (in $1,000)	-0.004	-0.0006
	(0.003)	(0.002)
Panel B: Overweight		
Household income (in $1,000s)	-0.0001*	-0.0001
	(0.0001)	(0.0001)
Welfare/TANF benefits (in $1,000)	-0.0008	-0.0006
	(0.001)	(0.001)
Panel C: Obese		
Household income (in $1,000s)	-0.0001***	-0.00003
	(0.00004)	(0.00004)
Welfare/TANF benefits (in $1,000)	-0.0003	0.0005
	(0.0007)	(0.0007)

Notes: Sample size is 13,175 in all regressions. Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects and the demographic, human capital, and child health controls are included. Child sampling weights are used.

Table 7 – Falsification Tests of Parents' Hours Worked per Week over All Weeks on Various Health Attitudes Outcomes

		(1) Mother trying to lose weight (n=2292)	(2) Mother always or often reads nutritional information (n=2287)	(3) Child had doctor checkup in past year (n=9493)	(4) Child had dental checkup in past six months (n=9492)
IV	Parents' work hours per week (in 10s)	0.033	-0.011	-0.007	0.062
		(0.050)	(0.045)	(0.037)	(0.040)
	First stage F statistic	9.892	10.694	11.805	11.712
	Overidentification test p-value	0.869	0.820	0.968	0.088

Notes: Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects and the demographic and human capital controls are included. Child health controls are also included in the child-level regressions in columns (3) and (4). Child sampling weights are used. Parents' work hours per week is the summation of mothers' and mothers' spouses' hours worked per week over all weeks in the past year.

Table 8 – Effects of Mothers' and Mothers' Spouses' Work Hours on Children's Weight: OLS Estimates from Main (7-17 Year Old Children with Younger Siblings) and Unrestricted (All Children Age 3-17 Years) Samples

	(1) Main sample (N=13,332)	(2) Unrestricted sample (N=33,217)
Panel A: BMI z-score		
Mother's hours worked per week (in 10s)	0.040***	0.040***
	(0.011)	(0.008)
Mother's spouse's hours worked per week (in 10s)	0.007	-0.0005
	(0.015)	(0.001)
Equality test p-value	0.059	0.000
Panel A: Overweight		
Mother's hours worked per week (in 10s)	0.008**	0.008***
	(0.004)	(0.002)
Mother's spouse's hours worked per week (in 10s)	-0.002	-0.0002
	(0.005)	(0.0003)
Equality test p-value	0.107	0.001
Panel A: Obese		
Mother's hours worked per week (in 10s)	0.005*	0.006***
	(0.003)	(0.002)
Mother's spouse's hours worked per week (in 10s)	-0.0002	-0.00005
	(0.004)	(0.0002)
Equality test p-value	0.192	0.000

Notes: Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects and the demographic, human capital, and child health controls are included. Child sampling weights are used. Mothers' and mothers' spouses' work hours are measured as hours worked per week over all weeks in the past year. Equality test p-value is from t-test of equality of coefficients on mothers' and spouses' work.

Table 9 – Effects of Parents' Work Hours on Children's Weight for Subsamples

	(1) Parents No College (n=7321)	(2) Parents At Least Some College (n=6011)	(3) Mother Hispanic or Black (n=7023)	(4) Mother Not Hispanic or Black (n=6309)	(5) Mother Unmarried (n=4932)	(6) Mother Married (n=8400)	(7) Above Median Disadvan-tage Index (n=6666)	(8) Below Median Disadvan-tage Index (n=6666)
Parents' work hours	0.126	0.365*	0.012	0.288**	0.047	0.281**	-0.016	0.366***
per week (in 10s)	(0.087)	(0.213)	(0.101)	(0.131)	(0.123)	(0.126)	(0.096)	(0.142)
First stage F statistic	11.225	3.0035	12.524	6.315	21.401	6.954	16.32	7.413
Overidentification test p-value	0.562	0.696	0.819	0.510	--	0.688	0.129	0.927
Parents' work hours	0.037	0.126	0.021	0.082*	0.008	0.092**	-0.004	0.113**
per week (in 10s)	(0.032)	(0.079)	(0.040)	(0.046)	(0.046)	(0.046)	(0.034)	(0.049)
First stage F statistic	11.068	2.933	12.460	6.185	21.337	6.823	16.19	7.344
Overidentification test p-value	0.273	0.393	0.801	0.978	--	0.297	0.547	0.277
Parents' work hours	0.049**	0.058	0.013	0.065*	0.008	0.074**	0.007	0.079**
per week (in 10s)	(0.024)	(0.052)	(0.031)	(0.034)	(0.034)	(0.035)	(0.026)	(0.036)
First stage F statistic	11.060	2.936	12.399	6.202	21.275	6.841	16.22	7.350
Overidentification test p-value	0.859	0.813	0.945	0.786	--	0.553	0.494	0.332

Notes: Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects are included and the full set of controls, including the baseline dependent variable, are included. Child sampling weights are used. Parents' hours worked per week is the summation of mothers' and mothers' spouses' hours worked per week over all weeks in the past year.

Table 10 – Impact of Omitting Spouse's Work Hours on Estimated Effects of Mother's Work Hours from IV Regressions

Outcome variable	Estimated effect of parents' work hours from Table 4 (IV, all controls)	Estimated effect of mother's work hours from Table 5 (IV, all controls)	Effect of mothers' work hours using proportion of eligible weeks as IV and omitting spouse's hours	Effect of mothers' work hours using relative age as IV and omitting spouse's hours
BMI z-score	0.189**	0.157	0.310***	0.191**
	(0.087)	(0.100)	(0.120)	(0.097)
Overweight	0.066**	0.061	0.086**	0.071*
	(0.033)	(0.037)	(0.044)	(0.037)
Obese	0.049**	0.047*	0.076**	0.052**
	(0.023)	(0.026)	(0.034)	(0.026)

Notes: Sample size is 13,332 in all regressions. Standard errors, which are heteroscedasticity-robust and clustered by mother, are in parentheses. *** indicates statistically significant at 1% level; ** 5% level; * 10% level. Year fixed effects and the demographic, human capital, child health, and baseline weight controls are included. Sampling weights are used. Mothers' work hours are hours worked per week over all weeks in the past year. Parents' hours worked per week is the summation of mothers' and mothers' spouses' hours worked per week over all weeks in the past year.