The Effect of Maternal Employment on Youth Overweight and Obesity[1]

James Bishop

Preliminary paper prepared for the Australian Conference of Economists, September 2010

ABSTRACT

Drawing on insights from household production theory and using data from the Household, Income and Labour Dynamics in Australia Survey, this paper seeks to provide the first estimates of the causal effect of maternal employment on the obesity status of older children in the Australian and international literatures. To achieve this aim, proxy variables, sibling-differences and instrumental variables are used to account for potential endogeneity in maternal labour supply. The results show that part-time or full-time work by the mother is associated with decreased excess body weight in youths, relative to not working at all. Further analysis reveals that this relationship does not operate through increased earned income. This suggests a potential weakness in the underlying theory, at least in terms of its predictions for weight outcomes in adolescents.

JEL classification: J22; I10

Keywords: Maternal employment; Childhood obesity; Health production; HILDA

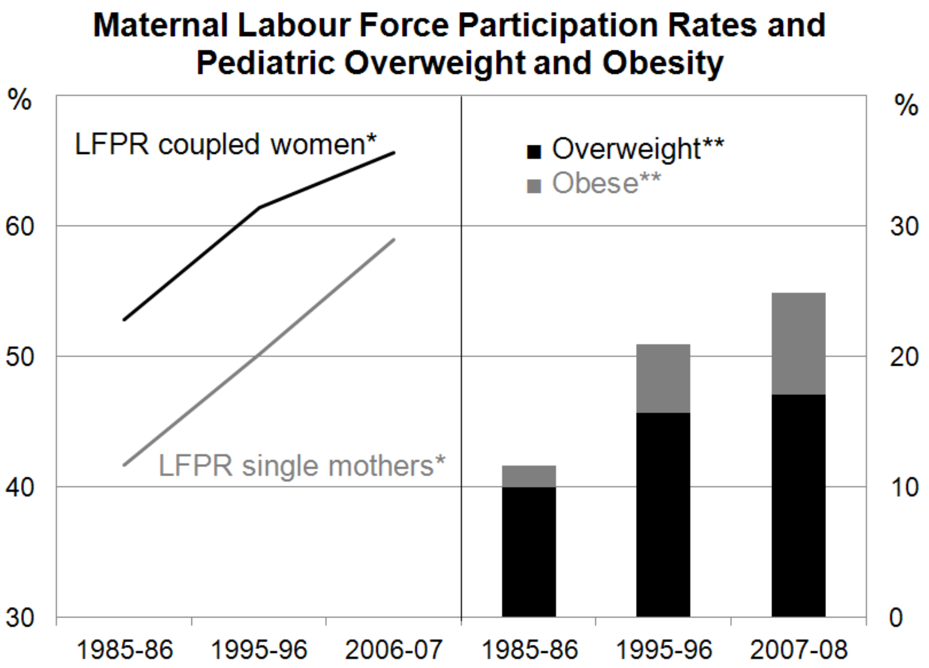
---

[1] I would like to acknowledge the excellent supervision of Joan R. Rodgers and Peter Siminski and thank two anonymous thesis examiners for their comments. I also acknowledge the financial assistance provided by the RBA Cadetship Award and a student stipend funded from an ARC Discovery Grant. This work is based on an undergraduate honours thesis, which can be accessed electronically at http://www.melbourneinstitute.com/hilda/Biblio/hbiblio-stu.html. This work was performed at the University of Wollongong. This article uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views reported in this article, however, are those of the authors and should not be attributed to either FaHCSIA or the MIAESR.
Correspondence: James Bishop, Reserve Bank of Australia, GPO Box 3947, Sydney, NSW 2001, Australia. Email: bishop@rba.gov.au

I. Introduction

In the two decades to 2007-08, the proportion of 5-17 year-olds classified as overweight or obese more than doubled (ABS 2009a; Magarey *et al.* 2001). Recent data suggest that one quarter of Australian children and adolescents are now overweight or obese and if recent trends continue almost half will be overweight by the year 2025 (ASSO 2004). As Figure 1 shows, this growing epidemic has broadly coincided with a trend toward rising labour force participation of mothers with dependent children. According to the ABS Census of Population and Housing, the labour force participation rate of coupled women with children aged 0-14 years increased by 12.8 percentage points between 1986 and 2006; and by 17.3 percentage points for single mothers. From a policy standpoint, it is of interest to determine whether these parallel trends represent a causal relationship, or simply a spurious association.

Figure 1



* Mothers with children aged 0-14 years
** Prevalence rates are for children aged 7-15 years in 1985 and 5-17 years in 1995 and 2007
Sources; ABS 1986, 1996 and 2006 Census of Population and Housing; ABS (2009a); Magarey *et al.* (2001)

To date, there has been little investigation of this relationship for Australia, with the solitary analysis concluding that increased maternal full-time employment is significantly and positively associated with the probability of obesity in young children (Zhu 2007). The current paper provides a better indication of the causal effects of labour supply on weight by analysing the robustness of the findings to a range of econometric approaches that account for endogeneity. Moreover, it fills an important gap in the literature by providing the first estimates, in Australia or elsewhere, on labour supply effects on children older than 12 years of age.[2] As this analysis shows, the effects of maternal employment on older children can differ substantially to those for younger children.

Section II of the paper describes the theory of child health production which underpins the econometric analysis. Section III discusses the issues associated with obtaining consistent estimates of the effects of maternal labour supply on youth weight outcomes. Section IV outlines the empirical findings from the existing literature. Section V details the empirical specification and methodology. Section VI presents the characteristics of the data used. The empirical results are presented in Section VII, and Section VIII offers some concluding remarks.

II. THE ECONOMIC THEORY OF CHILD HEALTH PRODUCTION

The theory of child health production, which has its origins in household production theory (Becker 1965) and health capital theory (Grossman 1972), considers the stock of child health to be the output of a multivariable production process in which the

[2] Classen and Hokayem (2005) examine US children aged 2-18 years and Garcia *et al.* (2006) examine 2-15 year-old Spanish children, though the effect sizes in these studies potentially correspond to an average of differential effects for younger and older children. Scholder (2008) examines obesity outcomes among 16 year-old English children, but using a 4-year-lagged measure of employment.

productive entity is an utility maximising household. In this model, the stock of child health, Q_t, is one argument of the household utility function:

$$U_t = U(Q_t, C_t, L_{Lt}; Z_{Ut}, \varepsilon_{Ut}) \qquad (1)$$

where U_t is instantaneous utility for a family, C_t is other "commodities" consumed by the household,[3] L_{Lt} is parental leisure time, and Z_{Ut} and ε_{Ut} are exogenous observable and unobservable factors influencing U_t, respectively. For this paper, 'child health' is generalised to 'child obesity', which is assumed to enter inversely in health. The household converts inputs into health according to a production function (Grossman 1972):

$$Q_t = Q(Q_{t-1}, L_{Qt}, F_t; Z_{Qt}, \varepsilon_{Qt}) \qquad (2)$$

where Q_{t-1} is the stock of child health in the previous period, L_{Qt} is the amount of parental time used in the production of child health, F_t is purchased inputs like food, medical care, sporting equipment, clothing and housing and Z_{Qt} and ε_{Qt} are the other exogenous observable and unobservable variables respectively affecting Q_t. Accordingly, parents do not purchase the commodity 'child health' from the market but produce it by spending time on health improving activities as well as by purchasing health inputs (Becker 1965; Grossman 1972; Jacobson 2000).

The household determines the optimal stock of child health by maximising the household utility function (1) with respect to two constraints: the household *budget constraint*, which limits purchases of health inputs and other market goods to the amount of earned and unearned income; and the household *time constraint*, which

[3] In Becker's (1965) household production model, "commodities" are produced by households using purchased market goods, own time inputs and various environmental inputs, such as human capital.

recognises that parents have an endowment of time which they allocate between leisure, the production of child health or market work.[4]

From this model, the clearest mechanism through which maternal employment might positively impact children is through an increase in household income, which Becker alludes to as the 'income effect'. There is a well established income-health gradient for children (Case *et al*. 2002; Currie and Stabile 2003), though the evidence is weaker for Australia (Khanam *et al.* 2009). More income allows a household to increase investments in health for their children, including better diet, better health care and safer neighbourhoods. Potentially offsetting the income effect of increased maternal labour supply is the reduction in the mother's time available to invest in children, provided the increase in time in market work is not matched by an equal reduction in maternal 'leisure' time.[5] A mother who works for an additional hour may find it optimal to allocate less time to preparing healthy meals and supervising the child's activity. The existence of competing income and substitution effects suggests a potential trade-off between the positive effects of direct parental time investments in children and the positive effects of household income. This leads to an ambiguous net effect.

III. Endogeneity Concerns

From an empirical standpoint, indentifying the effects of employment on child obesity is complicated because a mother's labour supply decision is potentially endogenous; a mother may decide her work hours at least partly based on her child's health. A mother whose obese child is chronically ill may elect to stay at home to care for her child, inducing a negative correlation between employment and obesity through a

[4] This yields a Marshallian demand function for the stock of child health (see Khanam *et al*. 2009).
[5] Leisure time is defined as time spent in any activity other than child health production or work.

reverse relationship. Conversely, the effects of employment on obesity will be biased upwards if a mother decides to work more hours in order to support an obese child with a high-cost disability.

Another reason to suspect that estimates of the basic relationship between maternal labour supply and youth obesity are not causal is that labour supply may be correlated with unobserved factors that directly affect children's weight (ε_{Qt} in Equation 2). For instance, if unobserved maternal ability is positively correlated with labour supply and negatively correlated with children's weight (via increased productivity in the home), then the beneficial effect of ability will be incorrectly attributed to maternal employment. Market ability and health production efficiency could also be negatively correlated, if for instance, women who work have less interest or skill in raising children, *ceteris paribus*. This concern has led researchers to employ a variety of fixed-effects (FE) approaches to account for time-invariant unobserved maternal (and sometimes child and household specific) characteristics (Anderson *et al.* 2003; Ruhm 2004; Scholder 2008; Chia 2008).

IV. RELATED LITERATURE

The relationship between the labour supply of mothers and the health of their children has been a subject of interest among empirical researchers for over three decades.[6] It is only recently, however, that studies have begun to examine the link between maternal labour supply and child obesity more specifically. The 'first-generation' work in this area consistently found that maternal employment increases obesity risk for children, irrespective of differences in data and methodology and the age and

[6] This literature, mostly for the US, has focused primarily on child developmental outcomes, largely due to the wider availability of objective measures of development, such as standardised test scores (see Ruhm 2004 for a review). The estimated effect of maternal labour supply in this literature is generally quite small.

nationality of children examined (Classen and Hokayem 2005; Phipps *et al.* 2006; Garcia *et al.* 2006; Takahashi *et al.* 1999). However, as these studies did not account for endogeneity, interpretation of the labour supply effects, and their policy implications, are uncertain.

The seminal study of Anderson *et al.* (2003) was the first to contend with the issue of causality. Using data on 3-11 year-old children from the US National Longitudinal Survey of Youth, Anderson *et al.* found that 10-hour-a-week increase in employment over the child's life raises the probability child overweight by 2 to 4 percentage points; a finding robust to using instrumental variables and fixed-effects. Chia (2008) also found no evidence of omitted variable bias using a sibling-difference specification and data on 0-11 year old Canadian children. Overall however, evidence for the endogeneity of mothers' employment is mixed; Ruhm (2004) finds some evidence of reverse causation and several recent studies finding that the basic OLS estimates of labour supply effects are biased downward (Liu 2006), including in recent work for Australia (Zhu 2007).

There has been only one investigation of the causal effect of maternal employment on child obesity in Australia, despite the relevance of this issue from a policy perspective (Zhu 2007). Using data on 4-5 year old children from the first wave of the Longitudinal Survey of Australian Children (LSAC), Zhu found that full-time maternal employment increases the probability of child overweight by 19 percentage points, whilst part-time employment had no significant effects (relative to not working). However, Zhu's instruments for maternal employment – whether English was the mother's first language and whether the mother participates in volunteer work

– are questionable, as they are likely to be correlated with the disturbance term in the structural equation.[7]

V. EMPIRICAL SPECIFICATION AND METHODOLOGY

Baseline OLS and Probit

In this paper, the simplest approach to measuring the association between maternal employment and child weight outcomes is an OLS regression of the form:

$$y_i = \alpha + \mathbf{E}_i \boldsymbol{\gamma} + \mathbf{x}_i \boldsymbol{\beta} + u_i \qquad i = 1, ..., n \qquad (1)$$

where y_i is a continuous dependent variable measuring the body mass index (BMI) of the i^{th} youth,[8] $\mathbf{E}_i$ is a vector of maternal employment variables (part-time, full-time; see Section VI for details), $\mathbf{x}_i$ is a vector of exogenous child and household characteristics and u_i is a disturbance. There are two main issues in estimating Equation (1). First, for the reasons discussed in Section III, $\mathbf{E}_i$ may be correlated with u_i, leading to inconsistent estimates of the maternal employment parameters, $\boldsymbol{\gamma}$. Second, because children and adolescents experience changes in body composition which depend on their age and gender, BMI is less suitable as a measure of excess weight than in adults (WHO 2000, p.9). To address the second concern, this paper also specifies a binary dependent variable equalling one if the i^{th} child is overweight (or obese), and zero otherwise. The advantage of the binary specification is that the BMI cut-offs points for overweight and obesity can be adapted to account for age and gender-specific sensitivities in body composition. Following previous Australian research, this paper uses the thresholds developed by Cole *et al.* (2000) which are

---

[7] Volunteer work is potentially jointly chosen with employment (each entering the mother's time constraint). English as a first language conceivably influences the mother's information on the benefits and costs of exercise and nutrition (and is arguably correlated with other unobserved factors).
[8] BMI is defined as weight in kilograms divided by height in metres, squared (WHO 2000, p.8)

reproduced in Table 1 for adolescents aged 15-18 years.[9] Due to the limitations of the linear probability model (see, e.g., Wooldridge 2002), this paper uses a probit model for regression analysis of binary overweight and obesity.

Table 1. Australian Reference Standard BMI Thresholds for Overweight and Obesity: Males and Females, 15 to 18 years

	BMI Equivalent to 25 in Adults		BMI Equivalent to 30 in Adults	
Age (years)	*Males*	*Females*	*Males*	*Females*
15.0	23.29	23.94	28.30	29.11
15.5	23.60	24.17	28.60	29.29
16.0	23.90	24.37	28.88	29.43
16.5	24.19	24.54	29.14	29.56
17.0	24.46	24.70	29.41	29.69
17.5	24.73	24.85	29.70	29.84
18.0+	25.00	25.00	30.00	30.00

Source: Cole *et al.* (2000)

A related concern is that BMI (and classifications based on BMI) is a less than optimal measure of ideal body weight. BMI cannot distinguish muscle-mass and fat-mass and can be affected by health conditions such as osteoporosis or pregnancy (WHO 2000, p.8). Self-reported BMI data, as is used in this study, can also be measured with error. In particular, there is a well-documented tendency for respondents to overstate their height and understate their weight in surveys (Wang *et al*. 2002).[10] Whilst this results in larger standard errors than in the case where BMI is not reported with error, estimates of the labour supply effect will remain unbiased provided the errors of measurement in BMI are uncorrelated with $\mathbf{E}_i$ and the error term.

[9] These definitions have been adopted by the International Obesity Task Force (IOTF), the Australian Department of Health and Ageing and the Longitudinal Survey of Australian Children (LSAC). These definitions have not been adopted in the HILDA survey, which categorises overweight and obesity in respondents 15-18 years according to the adult cut-offs of 25kg/m^2 and 30kg/m^2, respectively.

[10] This reporting bias is not immaterial; Wang *et al*. (2002) demonstrates that it resulted in an incorrect classification of overweight and obesity in 30 per cent of Australian 15-19 year-olds in the 1995 National Health Survey. The magnitude of the bias was also larger for overweight and obese adolescents than normal and underweight adolescents.

Specifications Accounting for Endogeneity

This paper uses three main strategies to account for the potential endogeneity of maternal employment. First, an extensive set of proxy variables are used to "soak up" as much heterogeneity as possible. These variables, which are listed in Table A2 in Appendix A, are assumed to have no direct effect on y_i but are assumed to be correlated with unobserved characteristics of the mother, youth and household that do directly affect y_i. Second, a sibling-difference approach is used to account for family specific unobserved heterogeneity, α_f:

$$y_i = \alpha_f + \mathbf{E}_i \boldsymbol{\gamma} + \mathbf{x}_i \boldsymbol{\beta} + u_i \qquad i = 1, \ldots, n \qquad (2)$$

As long as the fixed unobserved genetic and environmental influences are constant within sibling pairs, $\alpha_{if} = \alpha_{jf}$, taking the difference between the BMI/overweight/obese outcomes of siblings in the sample will difference out the family fixed effect:

$$y_i - y_j = (\mathbf{E}_i - \mathbf{E}_j)\boldsymbol{\gamma} + (\mathbf{x}_i - \mathbf{x}_j)\boldsymbol{\beta} + (\alpha_{if} - \alpha_{jf}) + (u_i - u_j) \qquad (3)$$

for siblings i and j at the same point in time. Identification of $\boldsymbol{\gamma}$ requires the siblings be of different ages at the time weight is observed, since identification is achieved through variation within sibling pairs.

Lastly, to address the possibility of simultaneous determination of youth weight and maternal employment, this paper also uses instrumental variables for maternal employment. Following Anderson *et al.* (2003), the instruments relate to economic conditions in the mother's area, such as the unemployment rate and the hours worked by other employed females, which conceivably influence labour supply decisions (see Section VI for details). The interpretation of the IV estimate $\boldsymbol{\gamma}_{\mathrm{IV}}$ as the causal effect is reliant on the assumption that the effect of these instruments on the outcome operates solely through maternal employment. In this paper, the IV estimator for continuous BMI and binary overweight/obese is two-stage least squares (2SLS).[11] For the binary outcome specifications, this corresponds to a 2SLS linear probability model.

VI. DATA

To conduct this analysis, information on a child's weight and height and the mother's labour supply are needed. A sample is selected from the HILDA survey, Waves 1-7, which collected information on height and weight in Wave 6 and 7, along extensive information on maternal employment and other characteristics of the household.

Selecting the Sample

The estimation sample consists of a balanced panel of children between the ages of 15 and 19 years in Wave 7.[12] The sample is not extended to younger children due to the focus on older children, and since height and weight data are only available for persons 15 years and older in HILDA. Maternal employment and other key variables are measured during the years in which the child is an 'adolescent', defined here as the four year period spanning the ages of 12 to 15 years. The exception is 19 year-olds, for whom adolescence is the three year period between the ages of 13 and 15, as necessitated by the 7-year panel.[13]

[11] Whilst the 2SLS estimator is well-suited for continuous BMI, it ignores the binary nature of overweight and obesity. Another option would be to specify a bivariate probit model by invoking some strong assumptions about the distribution of the error terms in the structural equation and reduced form equation (i.e., that both have a bivariate normal distribution). However, because maternal employment is specified as two discrete variables rather than a normal random variable (see Section VI), the violation of multivariate normality could lead to bias in the estimates (Wooldridge 2002).

[12] The sample is drawn from a balanced panel, rather than an unbalanced panel, since 'longitudinal weights' can be validly applied to account for non-response and attrition between Wave 1 and Wave 7 (and for unequal probabilities of selection into the HILDA survey sample). The main results are not sensitive to taking the sample from an unbalanced panel, rather than a balanced panel, and using unweighted estimates (available on request).

[13] 19 year-olds are included for sample size considerations, though excluding 19 year-olds from the estimation sample does not qualitatively alter the results.

Of the 1,078 children between the ages of 15 and 19 years in Wave 7, 18 were excluded from the estimation sample because their mother was not present at any time over adolescence. A further 7 children had to be excluded from the estimation sample due to missing employment data on the mother in every year during adolescence. Six female children who reported to have become pregnant in the 12 months prior to the Wave 7 interview were also excluded from the estimation sample given BMI is not a valid measure of excess body weight for pregnant women (WHO 2000, p.8). The estimation sample was further reduced due to missing data on height and/or weight for 130 youths.[14] After exclusions, the estimation sample numbered 917 children.

Maternal Employment

Maternal employment is measured by the number of years in which the mother is observed to be working full-time, part-time, or not working at all, during adolescence. This is represented by two separate count variables with the number of years the mother was not working as the omitted category. Hence, the effects on BMI/obesity of working full-time and part-time are estimated relative to the effect of not working (in a given year).[15] Two separate variables are also used to indicate the number of years the mother is non-responding (i.e. no person questionnaire) or living in a different household, respectively.[16]

Household Income

Household income is potentially related to both youth obesity and maternal work. As discussed in Section II, income is also one mechanism through which maternal

---

[14] 258 youths had incomplete BMI data in Wave 7. However, of those 258 youths, 128 had complete height and weight data in Wave 6, which was used in place of the Wave 7 missing BMI observation.

[15] In each year during adolescence, the mother's level of employment (part-time, full-time or otherwise) is observed only once (i.e. at the interview date). Hence, these variables are a noisy measure of employment over the full adolescent period.

[16] A dummy equalling one if the youth was observed in only three waves was also used to ensure that the sum of these (five) variables was equal to four for all sample members.

employment plausibly impacts youth obesity. As such, controlling for total household income may not allow the "full" effect of maternal employment to be measured. The approach taken in this paper is to control for household income, but to exclude from the income variable any wage and salary income earned by the mother. [17] In doing so, the coefficient on maternal employment should measure the sum of the direct effect of employment controlling for any increment in income (i.e. the substitution effect) and the indirect effect due to increased earned income (i.e. the income effect).

Other Explanatory Variables

The analysis exploits the extensive child, maternal, household and geographic information in HILDA.[18] A vector of "basic" youth, parental and household characteristics, frequently used in prior research, contains the youth's age, gender, indigenous status and ethnicity (measured by the mother's country of birth). Most models also control for mothers' and fathers' level of education (6 variables), given that education is a correlate of employment and a productivity shifter in the child health production model (an element of Z_{Qt} in Equation 2). In addition, a vector of "supplemental variables" frequently used in prior research contains mother's age (and its square) and marital status, household income, paternal employment (2 variables) and the socioeconomic status of the youth's neighbourhood. The fourth and final set of regressors comprises the full set of proxy variables detailed in Appendix Table A2.

[17] Household income is the log of average of annual data on the youth's real, household, equivalised, disposable income (excluding the mother's earned income) during adolescence. Disposable income is adjusted to take account of differences in household size and composition using the 'modified OECD' equivalence scale, and is converted into real terms using the Consumer Price Index, so that income in all Waves is expressed in 2006-07 dollars. To impute after-tax income accruing from the mother's employment, the tax model described in Wilkins (2009) is used to estimate taxes payable on the mother's wage and salary income, which is then subtracted from gross income from the mother's wages and salary. Income is averaged over the 3-4 years of adolescence to provide a less noisy measure of income and a better approximation of the 'permanent' component of household income.

[18] Table A1 in the Appendix A details the full set of variables used in this analysis.

Instrumental Variables

This paper uses local economic conditions and variables external to the mother and family as instruments for part-time and full-time maternal employment. First, following several studies (Anderson *et al.* 2003; James-Bardumy 2005) the local unemployment rate is used, given that higher unemployment rates make it harder for women to find employment and that the unemployment rate should be uncorrelated with the unobserved determinants of youth obesity. The unemployment rate is measured at the level of the mother's industry division (current or previous) and Australian State/Territory. The benefit of such disaggregation is that the instrument exhibits more variation, and hence, is more likely to produce efficient results.[19] The downside is that mothers may exhibit a high degree of mobility between industries, and hence the unemployment rate in a given industry may not adequately reflect the labour market conditions they actually face. This variable is constructed by matching external data from the ABS (2009b) to the mother's information.[20]

The second instrument for mothers' employment is the average number of hours worked by employed females in the same industry, occupation and State/Territory as the mother (or previous industry-occupation if not employed).[21] For example, it may

---

[19] The most disaggregated geographic-region identifier in the general release HILDA files is the 'major statistical region' (i.e. Sydney, Melbourne, Brisbane, Adelaide and Perth statistical divisions and the balance of each state, in addition to Tasmania, the Northern Territory and the ACT). Using only variation in the unemployment rate by 'major statistical region' will produce inefficient results.

[20] Data on the number of unemployed persons by industry division of last job (1 digit ANZSIC 2006) and by Australian State from the ABS (2009b, Data Cube UQ2) is combined with information on the number of employed persons by industry division (1 digit ANZSIC 2006) and State from the ABS (2009b, Data Cube E09) to a produce a disaggregated measure of the unemployment rate. In cases where the mother is not in paid work, the ANZSIC 2006 division of her last job is used, and in cases where information on the current main job or last job is unavailable, the overall unemployment rate of the state is used. The relevant industry-State unemployment rate is averaged over the child's adolescent years (ages 12-15 inclusive) for those years in which the mother was present in the household.

[21] Data on the average hours worked is the average hours worked per week by employed females by industry division (1 digit ANZSIC 2006), major occupation (1 digit ANZSCO 2006) and Australian State/Territory. This data is sourced from the ABS (2009b, Data Cube E09), and is matched to the mother's industry and occupation codes and state identifier in HILDA. If the mother is employed, the industry division and major occupation of the mother's current main job is used; otherwise the industry and occupation of her last job are used. If information is unavailable on the last job of the mother, or if

be the norm for a woman employed as a manager in the Victorian finance industry to work more hours per week than a woman working in sales in the retail industry in South Australia. However, it could be argued that mothers self-select into industries and occupations based on unobserved factors also correlated with youth obesity. In this case, this instrument would not be suitably independent of the error process (the same could be argued of the first instrument). This cannot be resolved *a priori*.

VII. EMPIRICAL RESULTS

Baseline Model Estimates

This section discusses the baseline OLS and probit results. The results are presented in Table 2 for BMI and Tables 3 and 4 for overweight and obesity, respectively. The estimates accounting for endogeneity are discussed in the next section.

With controls only for basic youth, parental and household characteristics (Specification 1), a youth whose mother worked part-time for one additional year is around 0.305kg/m^2 lighter and 1.4 percentage points less likely to be obese relative to a youth whose mother had not worked in that year. The coefficient on full-time employment is statistically insignificant, as is the coefficient on part-time employment with a combined overweight/obese outcome. This suggests that there may be beneficial effects of maternal part-time employment for older children, at least at the upper end of the BMI distribution.

---

the mother has never engaged in paid employment, the average hours worked by females in the relevant State/Territory is applied.

Table 2. OLS, 2SLS and Sibling-Difference Estimates of Maternal Employment
DV = BMI

	(1)		(2)		(3)		(4)		
	OLS	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*	*Sibling-Difference*
years PT	-0.305**	-0.240	-0.279**	-0.211	-0.301**	-0.441	-0.287*	-0.484	-0.355
std. error	*(0.131)*	*(0.315)*	*(0.134)*	*(0.319)*	*(0.151)*	*(0.394)*	*(0.152)*	*(0.378)*	*(0.615)*
years FT	-0.088	-0.500*	-0.082	-0.498*	-0.134	-0.826*	-0.178	-0.718	-0.827
std. error	*(0.137)*	*(0.256)*	*(0.143)*	*(0.279)*	*(0.164)*	*(0.493)*	*(0.164)*	*(0.480)*	*(0.844)*
age	0.441***	0.441***	0.482***	0.486***	0.468***	0.466***	0.357**	0.351**	0.496**
med_Yr 12			-0.347	-0.266	-0.170	-0.007	-0.274	-0.142	—
med_Cert			0.305	0.502	0.451	0.706	0.438	0.61	—
med_Uni			0.106	0.492	0.418	0.322	0.091	0.401	—
fed_Yr 12			-0.987	-0.973	-0.769	-1.031	-0.631	-0.815	—
fed_Cert			-0.450	-0.531	-0.377	-0.631	-0.287	-0.46	—
fed_Uni			-1.089**	-1.246**	-0.863	-1.360**	-0.651	-0.997*	—
log(income)					-0.124	-0.375	-0.049	-0.217	-0.060
SEIFA					-0.157**	-0.474**	-0.119*	-0.395*	—
BMI mum							0.125***	0.126***	—
BMI dad							0.167***	0.173***	—
Proxy Variables							X	X	—
First-stage F: PT	—	41.565	—	43.714	—	43.517	—	47.568	—
First-stage F: FT	—	88.739	—	64.730	—	32.698	—	31.545	—
F test of exogeneity	—	2.037	—	1.797	—	1.367	—	0.710	—
Prob > F	—	0.131	—	0.167	—	0.256	—	0.492	—
χ^2 test of exogeneity: PT	—	0.828	—	0.883	—	0.708	—	0.164	—
Prob > χ^2	—	0.363	—	0.374	—	0.400	—	0.685	—
χ^2 test of exogeneity: FT	—	2.838*	—	2.719*	—	2.308	—	1.033	—
Prob > χ^2	—	0.092	—	0.099	—	0.129	—	0.309	—
Adjusted R^2	0.023	0.014	0.025	0.024	0.024	0.023	0.085	0.117	0.018
F	2.231***	1.830**	2.039***	1.850**	1.756***	1.770***	2.778***	2.850***	1.200
Prob > F	0.005	0.028	0.004	0.011	0.007	0.008	0.000	0.000	0.284
N	912	912	912	912	912	912	912	912	252

Notes: *, ** and *** means estimates are statistically significant at 10% and 5% and 1% levels, respectively. Standard errors are robust and clustered on the mother's identification code (in parentheses for maternal employment). Estimates are weighted. Specifications (1)-(4) include dummies for indigenous status, mothers' country of birth and for 19-year olds. Specifications (1)-(4) also include controls for number of years the mother is non-responding or living in a different household; Specifications (3)-(4) include controls for fathers' employment, mothers' marital status and a quadratic in mothers' age. Household income excludes mothers' wage and salary income. Instruments include the average unemployment rate by mothers' industry division and state and the average hours worked by females in the mother's occupation, industry and state. Sibling-difference specification also includes controls for age, gender, household income and fathers' employment. Five observations have a zero population weight.

Table 3. Marginal Effects of Maternal Employment
DV = Overweight

	(1)		(2)		(3)		(4)		
	probit	*IV-LPM*	*Probit*	*IV-LPM*	*probit*	*IV-LPM*	*probit*	*IV-LPM*	*Sibling-Difference*
years PT	-0.015	-0.013	-0.013	-0.004	-0.014	-0.016	-0.017	-0.021	-0.002
std. error	*(0.012)*	*(0.031)*	*(0.012)*	*(0.030)*	*(0.015)*	*(0.038)*	*(0.015)*	*(0.038)*	*(0.060)*
years FT	-0.006	-0.043*	-0.005	-0.038	-0.007	-0.058	-0.015	-0.051	-0.106
std. error	*(0.012)*	*(0.024)*	*(0.013)*	*(0.026)*	*(0.016)*	*(0.047)*	*(0.016)*	*(0.049)*	*(0.079)*
age	0.016	0.018	0.020	0.025	0.017	0.024	0.009	0.014	-0.041
med_Yr 12			-0.048	-0.043	-0.045	-0.029	-0.050	-0.031	—
med_Cert			-0.020	-0.009	-0.017	-0.001	-0.013	-0.005	—
med_Uni			0.003	0.028	0.009	0.04	-0.014	0.008	—
fed_Yr 12			-0.067	-0.076	-0.057	-0.081	-0.063	-0.077	—
fed_Cert			-0.048	-0.06	-0.048	-0.069	-0.044	-0.057	—
fed_Uni			-0.112**	-0.133**	-0.105**	-0.141**	-0.098*	-0.114*	—
log(income)					-0.006	-0.027	-0.001	-0.014	-0.002
SEIFA					-0.010*	-0.011	-0.010	-0.008	—
BMI mum							0.008***	0.008**	—
BMI dad							0.015***	0.015***	—
Proxy Variables							X	X	—
First-stage F: PT	—	41.565	—	43.714	—	43.747	—	47.734	—
First-stage F: FT	—	88.739	—	64.730	—	32.588	—	31.410	—
F (test of exogeneity)	—	1.800	—	1.269	—	1.070	—	0.433	—
Prob > F	—	0.167	—	0.282	—	0.344	—	0.649	—
χ^2 (test of exogeneity: PT)	—	0.669	—	0.962	—	1.147	—	0.531	—
Prob > χ^2	—	0.413	—	0.323	—	0.284	—	0.466	—
χ^2 (test of exogeneity: FT)	—	2.613	—	2.339	—	2.197	—	1.118	—
Prob > χ^2	—	0.106	—	0.126	—	0.138	—	0.290	—
Pseudo R^2	0.014	—	0.023	—	0.028	—	0.080	—	0.054
Adjusted R^2	—	0.000	—	0.010	—	0.010	—	0.074	—
Wald χ^2	13.120	—	24.500	—	30.610**	—	82.280***	—	13.231
Prob > χ^2	0.360	—	0.178	—	0.023	—	0.000	—	0.270
F	—	1.180	—	1.320	—	1.090	—	2.070***	—
Prob > F	—	0.290	—	0.162	—	0.340	—	0.000	—
Log likelihood	-518.817	—	-513.835	—	-511.098	—	-484.520	—	-144.400
N	912	912	912	912	912	912	912	912	252

Notes: see note on Table 2. Marginal effects (at the mean) are calculated at the mean values of the continuous variables; for dummy variables the marginal effect of a change from 0 to 1 is calculated. The dependent variable equals one if the youth is obese; and zero otherwise.

Table 4. Marginal Effects of Maternal Employment
DV = Obese

	(1)		(2)		(3)		(4)		
	probit	*IV-LPM*	*Probit*	*IV-LPM*	*probit*	*IV-LPM*	*probit*	*IV-LPM*	*Sibling-Difference*
years PT	-0.014**	-0.009	-0.014*	-0.012	-0.015**	-0.021	-0.011*	-0.026	-0.038
std. error	*(0.007)*	*(0.021)*	*(0.007)*	*(0.022)*	*(0.007)*	*(0.026)*	*(0.006)*	*(0.026)*	*(0.025)*
years FT	-0.007	-0.023	-0.007	-0.025	-0.011	-0.036	-0.009	-0.028	-0.084**
std. error	*(0.007)*	*(0.016)*	*(0.007)*	*(0.018)*	*(0.008)*	*(0.031)*	*(0.006)*	*(0.029)*	*(0.035)*
age	0.009	0.009	0.010	0.008	0.007	0.006	0.002	0.003	-0.005
med_Yr 12			0.017	0.018	0.027	0.030	0.017	0.026	—
med_Cert			0.037	0.040	0.043	0.049	0.038	0.048	—
med_Uni			0.017	0.029	0.032	0.048	0.018	0.030	—
fed_Yr 12			-0.017	-0.015	-0.008	-0.006	-0.002	0.006	—
fed_Cert			-0.013	-0.017	-0.011	-0.020	0.002	-0.004	—
fed_Uni			-0.032	-0.038	-0.022	-0.037	-0.001	-0.018	—
log(income)					-0.001	-0.008	-0.000	0.001	-0.000
SEIFA					-0.009***	-0.010***	-0.007***	-0.008**	—
BMI mum							0.005***	0.008***	—
BMI dad							0.006***	0.007**	—
Proxy Variables							X	X	—
First-stage F: PT	—	41.565	—	43.714	—	43.747	—	47.734	—
First-stage F: FT	—	88.739	—	64.730	—	32.588	—	31.410	—
F (test of exogeneity)	—	0.835	—	0.827	—	0.483	—	0.219	—
Prob > F	—	0.434	—	0.438	—	0.617	—	0.803	—
χ^2 (test of exogeneity: PT)	—	0.476	—	0.285	—	0.224	—	0.040	—
Prob > χ^2	—	0.490	—	0.593	—	0.636	—	0.841	—
χ^2 (test of exogeneity: FT)	—	1.397	—	1.262	—	0.841	—	0.111	—
Prob > χ^2	—	0.236	—	0.261	—	0.359	—	0.739	—
Pseudo R^2	0.039	—	0.050	—	0.076	—	0.171	—	0.143
Adjusted R^2	—	0.008	—	0.014	—	0.026	—	0.079	—
Wald χ^2	17.603	—	27.771	—	55.418***	—	106.369***	—	22.125**
Prob > χ^2	0.226	—	0.147	—	0.005	—	0.000	—	0.023
F	—	1.100*	—	0.910	—	0.930	—	1.160	—
Prob > F	—	0.080	—	0.573	—	0.566	—	0.221	—
Log likelihood	-228.846	—	-226.221	—	-219.857	—	-197.401	—	-69.121
N	912	912	912	912	912	912	912	912	252

Notes: see note on Table 2. Marginal effects (at the mean) are calculated at the mean values of the continuous variables; for dummy variables the marginal effect of a change from 0 to 1 is calculated. The dependent variable equals one if the youth is obese; and zero otherwise.

It is possible, however, that the coefficient on part-time employment is picking-up some of the beneficial effect of household income and other dimensions of socioeconomic status on weight. However, introducing controls for parents' education (Specification 2), household income (excluding mothers' earned income), neighbourhood socioeconomic advantage/disadvantage, fathers' employment and mothers' marital status (Specification 3) does not attenuate the part-time employment parameter. The next section explores whether this result is driven by remaining heterogeneity or reverse causality bias.

Proxy Variable, IV and Sibling-Difference Estimates

The first strategy to account for unobserved heterogeneity is to introduce the full set of proxy variables into the model (Specification 4). Here, the point estimates for mothers' part-time employment are largely unchanged and remain significant at the 10 per cent level, suggesting little evidence of omitted variable bias.

Similarly, accounting for endogeneity using IV has no material effect on the coefficient estimates of part-time employment. Nevertheless, the 2SLS estimates for mothers' full-time employment are around 4-8 times larger (i.e. more negative) relative to specifications assuming exogeneity. Though, in most cases, the null hypothesis of exogeneity of part-time and full-time employment cannot be rejected at conventional levels of significance.[22] The instruments themselves are highly correlated with mothers' part-time and full-time employment, evidenced by high F-statistics for joint significance of the instruments in the first-stage regressions, which are well in excess of the critical values proposed by Stock and Yogo (2005).

[22] The Durbin-Watson-Hu (DWH) test of exogeneity involves augmenting the structural equation with a vector of the fitted residuals from the first-stage regressions and testing the null hypothesis that the coefficient on the fitted residuals is zero (i.e. the maternal employment variable is exogenous). For independent, homoskedastic errors, this test is equivalent to a Hausman test comparing the OLS and IV estimates of the potentially endogenous regressors (Wooldridge 2002, p.118).

Nevertheless, due to concerns about the validity of these instruments, it is possible that the 2SLS estimator is inconsistent (see Bound *et al.* 1993). In particular, the persistence of the negative coefficient on maternal employment could reflect the possibility that potentially endogenous instruments do fully account for biases stemming from reverse causality (i.e. mothers with children with obese children with special needs may find it difficult to work outside the home). Whilst it is difficult to rule out this bias completely, the main results are robust to excluding from the estimation sample the 44 youths whose mother reports to actively care for a resident child due to a long-term health condition or disability.[23] This provides some reassurance that any reverse causality bias is minimal.

The estimates of mothers' part-time and full-time employment using sibling-differences are similar to those using IV; part-time employment has similar effects to those estimated using OLS/probit and the effects of full-time employment are substantially larger when accounting for endogeneity. This finding suggests that mothers select into full-time employment based on unobserved factors which are positively correlated with youth weight. Notwithstanding, both the IV and sibling fixed-effects estimates are imprecise, and hence, a caveat is placed on these results.

Income and Substitution Effects

This analysis highlights that the effects of mothers' employment on weight are either negative or statistically insignificant, after accounting for endogeneity. From the standpoint of child health production theory, this would suggest that the "income effect" of employment dominates, or at least offsets, the "substitution effect" of maternal employment. This explanation, however, is not supported by the data. Re-estimating the models with the mother's wages and salary income included in household permanent income does not cause

[23] This test is based on the assumption that parental labour supply will be largely unaffected by a child who has a non-limiting health condition in comparison with a child with no chronic health condition. The results are available from the author on request.

the coefficients on part-time and full-time employment to become non-negative.[24] Moreover, part-time employment continues to have a negative and significant effect on BMI and obesity at the 5 per cent level. This implies that employment lead to decreases in weight through channels other than household income.

The economic theory of health production does allow for employment to have no direct effect on health, holding income constant. That is, mothers may reduce time in leisure as hours of employment rise to "protect" the time spent producing children's health. Recent studies using time-use data provide some support for this hypothesis; increases in employment are associated with much smaller reductions in time spent with children (Craig 2005; Bianchi 2000). However, the theoretical explanation for a negative relationship between employment and weight is less clear.

One possibility is that there are weaknesses in the underlying theory, at least in terms of its predictions for weight outcomes in adolescents. The theory predicts that increased employment will lead to decreased health (holding income fixed), but does not imply that all dimensions of health will decrease. Time spent producing health may also keeping children 'safe' by driving them to and from school or supervising sedentary study routines to improve their 'cognition'. This time may increase the child's overall stock of health, but may have adverse effects on BMI. Further research is required to explore these mechanisms more clearly.

VIII. SUMMARY AND CONCLUSION

This paper sought to determine whether maternal employment has an effect on obesity in Australian youths. The results show that youths have lower BMI and are less likely to be obese if their mother worked part-time or full-time during adolescence (relative to not

[24] These results are available from the author on request.

working). This negative effect remains after accounting for the potential endogeneity of mothers' employment. This finding contrasts starkly with the evidence for younger children, which points to the opposite effect. However, the labour supply effects were also imprecise in some models, particularly the IV and sibling-difference specifications, and estimates based on larger sample sizes are required to provide confidence in these estimates.

The analysis also reveals that the beneficial effects of maternal job holding on the weight of older children do not operate through household income. A tentative conclusion is that time allocation decisions within the household are in some way influenced by the mother's decision to work. For older youths, these decisions inadvertently promote increased caloric expenditure and/or reduced caloric intake. Clarifying the precise mechanisms is an interesting avenue for future research, although high quality parental time use data matched with youth BMI does not currently exist for Australia. More fundamentally, there may be scope for further development of economic theory relating household production to youth obesity, given that the predictions of child health production models have not been substantiated here

References

Anderson, P. M., Butcher, K. F., & Levine, P. B. (2003). Maternal Employment and Overweight Children. *Journal of Health Economics.* 22(3), 477-504.

Australasian Society for the Study of Obesity (ASSO) (2004). Available: www.asso.org.au.

Australian Bureau of Statistics (2009a). *National Health Survey, Summary of Results, 2007-08*. Canberra, ABS. Cat. No. 4364.0.

Australian Bureau of Statistics (2009b). *Labour Force, Australia, Detailed, Quarterly, May 2009*. Canberra, ABS. Cat. No. 6291.0.55.003.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal.* 75(299), 493-517.

Bianchi, S. M. (2000). Maternal Employment and Time with Children: Dramatic Change or Surprising Continuity? *Demography*, 37(4), 401-414.

Bound, J., Jaeger, D. A., & Raker, R. (1993). The Cure Can Be Worse than the Disease: A Cautionary Tale Regarding Instrumental Variables. Technical Paper No. 137, National Bureau of Economic Research.

Case, A., Lubotsky, D., & Paxson, C. (2002). Economic Status and Health in Childhood: The Origins of the Gradient. *American Economic Review.* 92(5), 1308-1334.

Chia, Y. F. (2008). Maternal Labour Supply and Childhood Obesity in Canada: Evidence from the NlSCY. *Canadian Journal of Economics.* 41(1), 217-242.

Classen, T., & Hokayem, C. (2005). Childhood Influences on Youth Obesity. *Economics & Human Biology.* 3(2), 165-187.

Cole, T. J., Bellizzi, M. C., Flegal, K. M., & Dietz, W. H. (2000). Establishing a Standard Definition for Child Overweight and Obesity Worldwide: International Survey. *British Medical Journal.* 320, 1240-1243.

Craig, L. (2005). How do they Find the Time? A Time-Diary Analysis of how Working Parents Preserve their Time with Children. Discussion Paper No. 136, Social Policy Research Centre, University of New South Wales.

Currie, J., & Stabile, M. (2003). Socioeconomic Status and Child Health: Why Is the Relationship Stronger for Older Children? *The American Economic Review*, 93(5), 1813-1823.

García, E., Labeaga, J. M., & Masagué Ana, C. O. (2006). Maternal Employment and Childhood Obesity in Spain. Working Paper No. 2006-17, Fundación de Estudios de Economía Aplicada.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *The Journal of Political Economy.* 80(2), 223-255.

Jacobson, L. (2000). The Family as Producer of Health - an Extended Grossman Model. *Journal of Health Economics.* 19(5), 611-637.

James-Burdumy, S. (2005). The Effect of Maternal Labor Force Participation on Child Development. *Journal of Labor Economics.* 23(1), 177-211.

Khanam, R., Nghiem, H. S., & Connelly, L. B. (2009). Child Health and the Income Gradient: Evidence from Australia. *Journal of Health Economics.* 28(4), 805-817

Liu, E. (2006). Maternal Full-Time Employment and Childhood Obesity. PhD Dissertation, University of Southern California.

Magarey, A., Daniels, L., & Boulton, T. (2001). Prevalence of overweight and obesity in Australian children and adolescents: reassessment of 1985 and 1995 data against new standard international definitions. *The Medical Journal of Australia.* 174:561-564.

Phipps, S. A., Lethbridge, L., & Burton, P. (2006). Long-Run Consequences of Parental Paid Work Hours for Child Overweight Status in Canada. *Social Science & Medicine.* 62(4), 977-986.

Ruhm, C. J. (2004). Maternal Employment and Adolescent Development. Working Paper No. 10691, National Bureau of Economic Research.

Scholder, S.V.H.K (2008). Maternal Employment and Overweight Children: Does Timing Matter? *Health Economics.* 17(8), 889-906.

Stock, J. H., & Yogo, M. (2005). Testing for Weak Instruments in Linear IV Regression. In: D. W. K. Andrews & J. H. Stock (Eds.), *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (pp. 80-108). Cambridge University Press, Cambridge.

Takahashi, E., Yoshida, K., Sugimori, H., Miyakawa, M., Izuno, T., Yamagami, T., Kagamimori, S. (1999). Influence Factors on the Development of Obesity in 3-Year-Old Children Based on the Toyama Study. *Preventive Medicine.* 28(3), 293-296.

Wang, Z., Patterson, C. M., & Hills, A. P. (2002). A Comparison of Self-Reported and Measured Height, Weight and BMI in Australian Adolescents. *Australian and New Zealand Journal of Public Health.* 26(5), 473-478.

Wilkins, R. (2009). Updates and Revisions to Estimates of Income Tax and Government Benefits. HILDA Project Discussion Paper Series No. 1/09. Institute of Applied Economic and Social Research, University of Melbourne.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press, Cambridge.

World Health Organisation (WHO) (2000). *Obesity: Preventing and Managing the Global Epidemic: Report of a WHO Consultation.* Geneva.

Zhu, A. (2007). The Effect of Maternal Employment on the Likelihood of a Child Being Overweight. Discussion Paper No. 2007/17, School of Economics, University of New South Wales.

APPENDIX A: VARIABLE DEFINITIONS

Table A1. Variables Used in Analysis

Variable	Definition
Maternal Employment	
years PT	No. years mother employed part-time during adolescence
years FT	No. years mother employed full-time during adolescence
Basic Child, Parental and Household Characteristics	
Female	=1 if female
Age	Age (in years)
Indigenous	=1 if Aboriginal or Torres Straight Islander
mcob_Oceanic	=1 if mother is other Oceanic born
mcob_NW Euro	=1 if mother is North or West Europe born
mcob_SE Euro	=1 if mother is South or East Europe born
mcob_Asia	=1 if mother is Asia born
mcob_Other	=1 if mother is 'other' born
Parental Education[1]	
med_Yr 12	=1 if Yr 12 is mother's highest education completed
med_Cert	=1 if a trade certificate is mother's highest education completed
med_Uni	=1 if University is mother's highest education completed
fed_Yr 12	=1 if Yr 12 is father's highest education completed
fed_Cert	=1 if a trade certificate is father's highest education completed
fed_Uni	=1 if University is father's highest education completed
Supplemental Variables	
log(income)	Log of real, household, equivalised, disposable income less mother's wage and salary income (averaged over adolescence).
SEIFA	The ABS's Socio-Economic Index for Areas (SEIFA), Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD) deciles.
age mother	Age of mother (in years)
age mother ^ 2	Age of mother (in years) squared
years married	Number of years mother legally married during adolescence
years PT (dad)	No. years father employed part-time during adolescence
years FT (dad)	No. years father employed full-time during adolescence

Note 1: The omitted category is highest level of education is Year 11 or less. These variables are constructed using the most recent data available during adolescence, or using the child's own reports of their parent's highest education level in cases where either parent had not reported his or her education.

Table A2. Proxy Variables Used in Analysis

Variable	Definition	Proxy for
Parental BMI	Mother's and father's BMI (2 continuous variables)	Genetics and the common home environment that parents and children share
Parental smoking	Mother and father smoke cigarettes (2 dummy variables)	Parent's rate of time preference and attitudes and behaviours towards health.
Mother's self-reported ability	Mother's self-reported ability in reading and mathematics (relative to an average adult) and the extent that the mother agrees/disagrees with the statements "I do not feel comfortable when working out amounts like discounts, the GST or percentages" and "I am good with numbers and calculations".	Mother's intelligence
Transfers ratio	Ratio of household income from Australian public transfers and foreign pensions to gross household income (1 continuous variable)	Parent's diligence, motivation and ability.
Mother's mental health	Mother's score on the mental health sub-scale of the SF-36 Health Survey (0-100 scale)	Quality of home investments
Mother's history	Mother's own mother was in paid employment when the mother was aged 14 years; mother's own mother and father were present in her household when she was aged 14; mother worked at any time in the 12 months prior to the birth of the child (3 dummy variables).	Quality of home investments and the mother's tastes for employment