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Abstract

Childhood obesity has increased dramatically in the developed world. One cause of this trend, suggested by studies in the United States, is the increase in maternal employment. This paper explores if the causal relationship exists in Australia. Using recent data from the Longitudinal Survey of Australian Children (LSAC), a 2SLS procedure and a Full Information Maximum Likelihood (FIML) model that jointly estimates a multinomial treatment and binary outcome is used to control for endogeneity and self-selection bias, respectively. The results consistently show that maternal employment does have an impact on the likelihood of a child being overweight and that this impact is positive and statistically significant.

Keywords

Child obesity (I10), Maternal employment (J22), Regression analysis (C30), Two-Stage Least Squares (2SLS) (C31), Full-Information Maximum Likelihood (FIML) (C35), Endogeneity (C30), Self-selection bias (C30).

I Introduction

Childhood obesity is a growing problem experienced in many parts of the world. In Australia, a nation already with the second highest percentage of overweight children in the world, the annual rate of increase is 1 per cent which suggests that half of all Australian children will be overweight by the year 2025 (Australasian Society for the Study of Obesity, 2004).

The implications of such a growth pattern are bleak for the health of the individual and for Australia's already-struggling public health care system. Obesity at a young age is likely to persist into adult life. An overweight 3-year-old child is nearly 8 times more likely to become an overweight young adult than a typically developing 3-year-old (Bouchard, 1997; Dietz, 1997). The health risks associated with being overweight include Type II diabetes, coronary heart disease, atherosclerosis and colorectal cancer (Power, Lake, Cole, 1997; Dietz, 1998; Strauss, 1999; Fruhbeck, 2000). These illnesses drastically reduce the quality of life for the individual and imply large increases in health expenditure by individuals, health care providers and governments. Recent figures showed the cost of obesity in Australia reached $21 billion in 2005 (Access Economics, 2006).

There are also economy-wide implications. It has been shown that being overweight or obese is negatively related to education and earnings (Averett and Korenman, 1996; Gortmaker, Must, Perrin, Sobol and Dietz, 1993), dampens productivity growth and reduces participation rates (Murphy, 2005). Obese individuals are more likely to take sick-leave and twice as likely to have high-level absenteeism (Burton et al, 1998; Tucker, 1998).

Despite the pervasive effects of childhood obesity, the underlying cause/s of the increasing trend is unclear. An econometric investigation by Anderson, Butcher and Levine (2003), links the rise in childhood obesity in the United States to the rise in maternal employment.

Maternal employment has also risen dramatically in the developed world. There are more mothers joining the labour force and increasing the number of hours worked per week, than ever before. In Australia, the rate of increase in maternal employment is highest amongst women with a youngest child aged less than five years old, rising from 36 to 43 per cent between 1986 and 2000 (ABS, 2001).

Despite experiencing upward trends in maternal employment and child obesity, mirroring those seen in the US, there is no econometric study of the attendant causal relationship in Australia. This has been due to the lack of adequate data.

Recent data, from the Longitudinal Study of Australian Children (LSAC), compiled by the Department of Family and Community Services (FaCS) in 2004, is both relevant and adequate. However, as only one wave of the survey has been released (at the current time), this study is a cross-sectional one.

The aim of this paper is to explore one feasible cause of the rise in the percentage of overweight children in Australia: the rise in maternal employment.

Studies of causality share the common problem of endogeneity in the treatment. This problem occurs when an independent variable is correlated with the unobservable factors in a model, which are relegated to the disturbance term. Consider the scenario whereby high-ability mothers work more hours per week in the labour force and have children with better outcomes than mothers who choose to work less hours per week. Failing to control for the influence of the mother's innate ability implies that employment causes better child outcomes, when in reality, it is ability that may be causing these outcomes. The main implications of ignoring endogeneity are biased and inconsistent parameter estimates.

First, a Two-Stage Least Squares (2SLS) procedure is used to address the endogeneity problem, as well as to reproduce the findings in Anderson et al. (2003). The parameters of the model are identified with two binary instruments: whether English was the first language the mother was exposed to or not, and whether the mother is a volunteer or not.

The 2SLS estimator of the maternal employment coefficient is positive and statistically significant. It suggests a 1-hour increase in maternal employment will increase the likelihood of a child being overweight by 0.6 percentage points. This result is slightly larger in magnitude but similar in sign and statistical significance to the findings in Anderson et al. (2003).

While discussion of endogeneity in the literature is energetic, the problems associated with self-selection bias are largely ignored. These concepts entail distinct differences, requiring unique solutions. Typically, maternal employment is specified as a continuous variable, with hours of work for non-working mothers censored at zero. The associated assumption is that the unobservable factors which motivate a mother to join the labour force are equivalent to the unobservable factors that motivate her to work an extra hour, once she is already employed. This assumption is felt to be unrealistic. In fact, there is reason to believe that the unobservable factors that motivate a mother to choose part-time work are different to the unobservable factors that motivate her to choose full-time work.

Therefore, in order to distinguish between non-working, part-time and full-time employment, maternal employment is modelled as a multinomial choice. A latent factor structure is adopted to specify a joint distribution of the endogenous treatment and outcome. A major benefit of this structure is that it provides a parsimonious representation of the unobservable factors that affect maternal employment choice and also influence the likelihood of a child being overweight. This model was developed by Deb and Trivedi (2006) to investigate the impact of managed plans on health care utilisation.

The result of the joint model suggests a married mother who changes her employment status from non-working to full-time will increase the likelihood of her child being overweight by approximately 19 percentage points. This result is comparable, in terms of sign and statistical significance, with the estimates obtained in the 2SLS procedure. Yet, the main notable difference is the finding that part-time employment, unlike full-time employment, does not have an effect on the likelihood of a child being overweight and does not appear to suffer self-selection bias. Consequently, the 2SLS procedure which effectively averages the three unobservable effects, pertaining to non-working, part-time and full-time employment, together, overestimates the impact of full-time maternal employment but most dramatically mis-interprets the effect of part-time employment.

II Literature review

The dramatic increase in the percentage of women participating in the labour force over the last decade has motivated debate on the externalities of maternal employment, in particular, its impact on the child. Several econometric studies have found that an increase in the number of hours a mother works per week has a damaging effect on child outcomes, such as, cognitive, behavioural and health related development, and more recently and specifically, obesity (Blau and Grossberg, 1992; James-Burdumy, 2005; Ruhm, 2004; Gregg, Washbrook, Propper, Burgess, 2005; Waldfogel, Han and Brooks-Gunn, 2001; Anderson et al. 2003).

Nobel laureate, Gary Becker, in 'A Theory of the Allocation of Time' (1965), describes the economic motivations which dictate human behaviour in the reality of time-scarcity. In a similar light, the dual responsibilities mothers have as caretakers and economic providers for the child cause a conflict in time use. As a result, mothers substitute their time caring for the child with market-based goods, such as, childcare and foods that require less time-intensive preparation. This substitution pattern intensifies as the opportunity cost of the mother's time increases. The problem, however, is that these market goods are an inferior substitute for the mother's time and ultimately the child suffers the indirect consequences of time scarcity.

The effects of maternal employment on the child's weight are not entirely damaging. As mothers increase the number of hours worked in the labour force, higher earnings and purchasing power improves the quality of foods and services consumed by the child. Becker (1965) alludes to this economic relationship as the 'income effect'.

Then, when several econometric findings show maternal employment as having a damaging impact on child outcomes, one naturally concludes that the disadvantages associated with the substitution effect outweigh the beneficial impact of the income effect. The non-economic benefits associated with a mother devoting her time to caring for the child could be more important then any income gained from having a second earner in the family. For example, a care-taker is likely to provide inferior supervision relative to the child's mother (Anderson et al, 2003): a child may snack more (on less healthful foods) and watch more television rather than exercise outdoors (Fertig, Glomm and Tchernis, 2005). Also, the increased reliance on convenient and pre-prepared foods which contain higher levels of saturated fats, sodium, sugars and lower fibre can contribute to a higher Body Mass Index (BMI) level (Cutler, Glaeser and Shapiro, 2003).

Anderson et al. (2003), using the National Longitudinal Survey of Youth (NLSY), strongly support this view. A simple probit, fixed effects (individual long-differences as well as sibling-differences at the same time and at the same age) and an instrumental variables model are estimated. The results are comparable in terms of sign and magnitude, and with the exception of the latter, are also statistically significant. Anderson et al. (2003) report that a 10-hour increase in the average number of hours a mother works per week, increases the likelihood of a child being overweight by 2-4 percentage points; the effects were stronger for white, highly educated mothers and more affluent households. Ruhm (2004), using a proxy variable technique, derives similar results to Anderson et al. (2003). This consistency across different models and studies bestow an apparent credibility to the results.

But these models share a fundamental flaw- the problem of self-selection bias has not been addressed; they are only concerned with endogeneity. Consequently, the parameter estimates in all of these models may be biased and inconsistent. The familiar implications of ‘sample’ selection bias, as described by Heckman (1974), also apply to ‘self’ selection bias.

Deb and Trivedi (2006), in measuring the causal effect of health care insurance plan enrolment on health services utilisation in the US, address the self-selection bias problem in an efficient and effective way. A joint model between a binary outcome (measuring health services utilisation) and a polychotomous choice model (for health care insurance plans) is estimated. Self-selection bias is subsequently accounted for and the parameter estimates represent causal effects.

This model has the potential to achieve the aims of this paper. First, the unobservable factors that motivate a mother’s decision to join the labour force are allowed to differ from the unobservable factors that influence her decision to work part-time, and again for full-time. As distinct disturbance terms are assigned to each employment choice, the estimated error correlation parameters between the outcome and treatment equations control for self-selection bias. Second, we are able to test for the statistical significance of each selection bias term. Third, the general specification of the joint-model allows for a more flexible and realistic interpretation of the behaviours and the environments relevant to the people studied in the sample.

III Data and Descriptive Statistics

Overweight status

Body Mass Index (BMI), which is defined as the weight (in kilograms) divided by the height (in meters) squared, is widely accepted as an indicator of being overweight or obese for adults, however, its use on children has been criticised (Dietz and Bellizzi, 1999). In particular, the sample of 4-5-year-old children used in my analysis have not experienced puberty, with its associated body changes, which may make BMI a less accurate approximation to measures of adiposity.

Cole, Bellizzi, Flegal and Dietz (2000) have addressed this concern by adapting the definition of child obesity to incorporate age, gender and ethnicity specific sensitivities. They conducted an international survey of six large nationally representative cross-sectional growth studies from Brazil, Great Britain, Hong Kong, the Netherlands, Singapore, and the United States to produce a specification for the measurement, the reference population, and the age and sex-specific cut-off points. 97,876 males and 94,851 females from birth to 25 years of age were surveyed. The proposed cut-off points which are less arbitrary and more internationally based than current alternatives provide internationally comparable prevalence rates of overweight and obese children.

The Australian Government Department of Health and Welfare has endorsed the usage of the Cole et al. (2000) definition and LSAC has adopted it to provide a measure that categorises the sample of children into normal weight, overweight or obese weight range. Conveniently using the LSAC construction, the overweight and obese children are merged into the one category of overweight. There are several reasons for this. First, there are only 207 observations in the sub-sample of obese children which represent approximately 4% of the entire sample. Second, the binary specification makes feasible the analysis this paper wishes to conduct concerning endogeneity and selectivity over adopting an ordered alternative. Last, the binary specification is adopted in Anderson et al. (2003) and therefore, will assist with the purpose of a reproduction exercise. Further, the binary specification is preferred to the continuous specification as the latter solely relies on the BMI measure which can be subject to volatility.

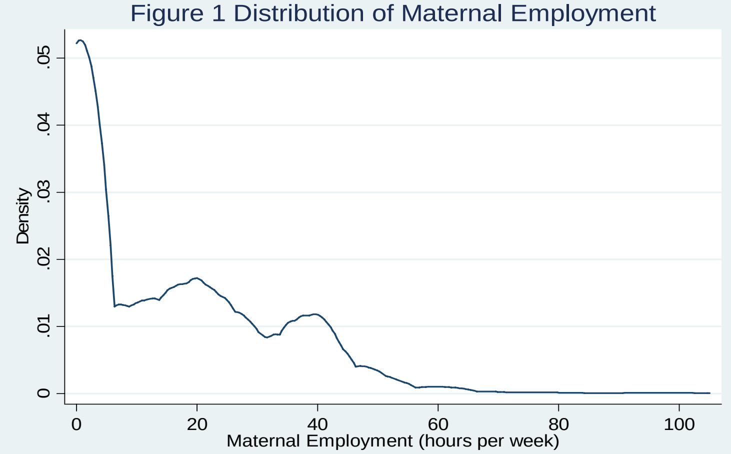
Maternal employment

Two definitions, or more precisely, specifications of maternal employment are adopted in this paper. The first is simply a continuous variable that measures the average number of hours a mother worked, per week, over the previous month. Non-working mothers are assigned a value of 0. The second specification divides maternal employment into three categories; non-working, part-time and full-time. Part-time employment is defined as working greater than 0-hours but less than 30 hours per week and full-time employment is defined as working 30-hours or more per week.

This demarcation has been decided upon after careful inspection of the relevant data; it does not follow the usual juridical definition of part-time employment as 35 hours per week.

The Kernel Density plot[1] (Figure 1), clearly illustrates that employment hours worked by mothers follow a distinct trimodal pattern. This suggests two things. First, a trinomial specification for maternal employment may be more appropriate than a continuous specification. Second, defining part-time employment as working more than 0 hours and less than 30 hours per week is a better reflection of the employment behaviour of mothers in the sample, than the 35 hours per week threshold.

Figure 1 Distribution of Maternal Employment



Data and Descriptive Statistics

[1] The Kernel function chosen is the Epanechnikov kernel and the window width is just the default chosen by the Stata 9.2 'kdensity' command, which is a function of the sample size as well as of the spread and variability of the data.

The analysis in this paper is based on data from the 1st wave of the Longitudinal Survey of Australian Children (LSAC) conducted in 2004 and released near the end of 2005. LSAC is a 10-year study funded by the Australian Government Department of Family and Community Services and only one wave has been released thus far. A sample of 10,000 children and their families were selected from the Health Insurance Commission's Medicare database and only one child per family was interviewed. Clustered sampling, based on postcodes, was chosen for its cost-effectiveness and ability to analyse community level effects (LSAC, 2005).

The sample comprises two age groups: infants aged 0-12 months and children aged 4-5 years. The former group is discarded in this analysis as the measure used to determine whether a child is overweight or not, BMI, is inappropriate to apply to infants. Thus, the analysis will only study children aged 4-5 years-old, reflected as a reduction in the sample size to 4989 observations.

The data were collected from face-to-face interviews with the 'parent who knew the child best'. In 97% of cases, this parent was the biological mother. The interviewer was responsible for taking direct physical measurements of the child, such as, the weight and height. Questionnaires to be self-completed were also given to the other resident parent/ guardian of the study child and returned at a later date.

The LSAC data offers several advantages. It is the most comprehensive and recent dataset in Australia to contain matched information on children, below the age of 15 years old, to detailed background information on their mothers and fathers[2]. The LSAC dataset includes a detailed set of demographic, health and behavioural-related information on the child as well as extensive information on the labour market characteristics and behaviours of the mother and father.

A number of observations were excluded from analysis. 702 observations pertaining to single mothers were deleted as single-mothered households may exhibit unobservable characteristics that simultaneously influence the likelihood of a child being overweight and the mother's labour market behaviour. For example, a dummy for whether the mother is single or not is likely to be endogenous, yield biased coefficient estimates

[2] Health, Income, Labour Dynamics Australia (HILDA) and National Health Survey (NHS) (2001, 2004-05) only contain matched information on children aged more than 14 and 15 years old, respectively.

and bias the coefficient estimates of the other variables if included into the regression model. 55 observations pertaining to the overweight indicator for the child[3], 28 observations pertaining to maternal employment and 104 observations pertaining to the instrument ‘volunt’ were excluded due to non-response in these survey items.

A number of other variables in the regression model contained missing observations due to non-response in the relevant survey questions. These include: whether the mother receives a government pension or not (0.8 percent missing), income of the partner (15 percent missing), paternal employment (0.8 percent missing), highest education degree obtained by the mother (0.2 percent missing), the child’s country of birth (2 percent missing), and the mother’s country of birth (3 percent missing). These missing observations were not deleted. Instead, dummy variables named: ‘pensnmiss’, ‘incpartnermiss’, ‘dadempmiss’, ‘mumeducmiss’, ‘cofbirthmiss’, and ‘cofbirthmummiss’ respectively, were created for use in the analyses.

Table 1 presents the variables included in the regression equations, their definitions and the sub-sample averages corresponding to the three employment categories: non-working, part-time and full-time employed mothers. There are a significant proportion of overweight children in all three categories, however, the highest percentage is seen in the full-time category. Surprisingly, the proportion of overweight children in the non-working mothers’ category and the part-time mothers’ category are nearly the same, suggesting there may be a non-linear relationship between maternal employment and the likelihood of a child being overweight.

The comparison of the means of the three employment categories can provide a glimpse of the observable differences between non-working, part-time and full-time employed mothers. These factors, that may influence employment decisions, may also affect the likelihood of a child being overweight. For example, the level of education attained differs dramatically. While 18.3 percent of full-time employed mothers in the sample have completed a degree above the tertiary level, only 8.5 percent of non-working and 15.2 percent of part-time employed mothers have done the same. If the selection on

[3] As this only represents approximately 1% of the sample, and analysis of the descriptive statistics does suggest these data are missing at random, sample selection bias is not expected to arise from their deletion.

education is ignored in estimation then the coefficients on maternal employment may unduly capture part of the education effect on the likelihood of a child being overweight.

Variable	Definition	Non-working (40%)	Part-time (39%)	Full-time (21%)
childoverw	1 if child is overweight or obese	0.20	0.20	0.22
pensionmum	1 if the mother receives a pension from the government	0.80	0.65	0.52
pensnmiss	1 if pensionmum is missing	0.01	0.01	0.01
percpc1000	Percentage of households in the current postcode that earn an income below $1000 per week	52.77	51.68	50.54
percpcengl	Percentage of households in the current postcode that only speak English at home	83.50	87.23	84.80
incpartner	Amount of income earned or received per week by the father/ partner from all sources	1074.36	1129.62	981.89
dademp	Average number of hours worked per week by the father/ partner; non-working observations = 0	42.31	47.03	43.38
dadempmiss	1 if dademp is missing	0.01	0.01	0.01
beyondhs	1 if the mother has completed a degree higher than the high-school certificate such as a TAFE certificate or Bachelor (including honours) degree	0.48	0.57	0.57
beyondtert	1 if the mother has completed a degree higher than a tertiary qualification such as a graduate or postgraduate degree	0.08	0.15	0.18
mumeducmiss	1 if beyondhs and/or beyondtert is missing	0.00	0.00	0.00
bweightz	Birth weight Z-score	-0.07	0.01	-0.04
bstfed	1 if child was ever breast fed	0.90	0.94	0.91
ausborn	1 if child is born in Australia	0.93	0.98	0.95
cofbirthmiss	1 if ausborn is missing	0.03	0.01	0.02
nzukbornmum	1 if mum is born in New Zealand or the United Kingdom	0.06	0.05	0.07
oceabornmum	1 if mum is born in an Oceanic country excluding Australia and New Zealand	0.02	0.00	0.01
eurbornmum	1 if mum is born in either Western or Eastern Europe	0.03	0.02	0.02
asiabornmum	1 if mum is born in Asia (including South Asia and Central Asia)	0.10	0.04	0.11
otherbornmum	1 if mum is born in the Middle-East, Africa, Americas or the Carribean	0.02	0.02	0.02
cofbirthmumiss	1 if information on the mum's country of birth is missing	0.04	0.02	0.03
anyngsib	Number of younger siblings in the household	0.71	0.56	0.39
anoldsib	Number of older siblings in the household	1.02	0.84	0.80
agemum	Age of the mother	34.55	35.28	35.58
agedad	Age of the father	37.15	37.38	37.91
fstengl	1 if English is the first language the mother was exposed to	0.76	0.89	0.78
volunt	1 if the mother participates in volunteering work	0.62	0.69	0.52

IV Regression modelling

2SLS

The aim of this sub-section is to reproduce the findings in Anderson et al. (2003). A 2SLS procedure is applied to the regression model in order to explore the effect of maternal employment on the likelihood of a child being overweight in Australia. Instrumental variable techniques, such as 2SLS, have the potential to control for endogeneity of a fixed or variable form. As the maternal employment variable is suspected to be correlated with the disturbances in the outcome equation, a 2SLS procedure can provide a more accurate reflection of the relationship than methodologies that assume exogeneity.

Consider the regression model:

$$y_{i1} = \mathbf{x}_i^{'}\beta + y_{i2}\gamma + \varepsilon_i \qquad (1)$$

$$y_{i2} = \mathbf{x}_i^{'}\alpha + \mathbf{z}_i^{'}\delta + u_i \qquad (2)$$

where i = 1, 2, …N and y_{i1} is the dependant binary variable that denotes whether the ith child is overweight or not. **x** is a vector of observable characteristics associated with the ith child and ε_i is a random i.i.d. term. y_{i2} is a continuous variable denoting maternal employment and measures the number of hours a mother works per week where non-working mothers are censored at 0. γ is the parameter of interest, measuring the effect of a 1-hour increase in the number of hours worked per week by the mother on the likelihood of a child being overweight. $\mathbf{z}_i$ represents a vector of instruments and u_i is a random i.i.d. term. Equation (1) can be referred to as the structural model. Equation (2) is a reduced form model. OLS regression can be used to characterise the factors that determine the probability that a child is overweight in Equation (1) and maternal employment hours in Equation (2). The same vector of exogenous covariates, **x**, that feature in the structural model is also included in the reduced-form equation to control for observable heterogeneity.

The problem, of course, is there are factors common to the structural and reduced form equations which are unobservable and/or unavailable in the data, such as, mother's ability; $E(\varepsilon_i, u_i) \neq 0$. If so, then maternal employment, y_{i2}, is endogenous and estimating Equation (1) by simple OLS regression will cause the estimate of the coefficient, γ, to be biased. Bias may also be present in the other coefficients of the model if their corresponding covariates are correlated with maternal employment.

Instead, a 2SLS procedure can be applied to the model. 2SLS relies on the power of instruments to purge the correlation between the maternal employment variable and disturbance term, u_i, and thus controls for endogeneity. However, in order for this to occur the instruments must satisfy two conditions. First, the instruments must be exogenous; $Cov(z_i, u_i) = 0$. Second, for identification purposes, the coefficients of the instruments must be non-zero; $\delta \neq 0$. Once these conditions are satisfied, the fitted values of y_{i2}, which is denoted as $\hat{y}_{i2}$, can be predicted by applying OLS to the reduced form equation. As $\hat{y}_{i2}$ is exogenous, it can be used as the instrument or substituted into the structural form model in place of y_{i2}. These two procedures will produce the same consistent estimate of the coefficient of interest, which reflects the impact of changes in maternal employment on the likelihood of a child being overweight, after controlling for endogeneity. Estimation is actually performed via the STATA command 'ivreg'.

Clearly, there are problems with using a Linear Probability Model (LPM) to model a binary dependant variable. These include the assumption of linearity, the predicted probabilities can nonsensically lie out of [0,1] interval and there is inefficiency due to the heteroskedastic error term. Anderson et al. (2003) acknowledge these shortfalls, however, persist with the linear model as the corresponding probit model produce nearly the same estimates.

Analogous to the problems with using the LPM for binary outcomes, estimating the reduced-form model with LPM can also produce misleading interpretations. There is a non-trivial number of non-working mothers in the sample, in fact, 40% are not employed.

These observations have been censored at 0 as we do not observe the latent values for maternal employment. Using a LPM to estimate the reduced-form equation with the limit observations included in the sample ignores the structure of the population regression function and yields biased estimates. Essentially, we are faced with an omitted variable bias problem and a typical solution involves adopting a Tobit model specification to account for the bias term. However, the Tobit model's main inadequacy is the way it treats the selection and regression equations as the same. The unobservable factors that affect the mother's decision to 'join' the labour force are assumed to be the same as the unobservable factors that determine the number of hours worked by the mother once she is already employed. A-priori, this assumption appears unrealistic. In fact, this paper believes that a distinction should be made for the mother's decision to not work, work part-time and work full-time. This will be explored in the next section. However, as the main aim here is to simulate the findings in Anderson et al. (2003) these flaws will be ignored, as they are in Anderson et al. (2003).

It is the nature of the 2SLS procedure for the estimates of the parameters to be sensitive to the instruments chosen. Therefore, it is vital that instruments used in analysis satisfy the required conditions of relevance, exogeneity, redundancy (Wooldridge, 2002) and common sense. Unfortunately, even instruments that appear to satisfy this set of formal and informal tests often manifest unintended influences in estimation and cause inconsistencies that force us to question the reliability of 2SLS in providing accurate analysis.

In linear models, the use of instruments is indispensable to the purpose of identification of the parameter estimates. Two binary instruments: whether English was the first language the mother was exposed to (fstengl) and whether the mother participates in volunteering work of any nature (volunt) are used in this analysis. The linear combination of fstengl and volunt yield the highest correlation with the maternal employment variable and is therefore, the best instrument available.

To my knowledge, these instruments have not been adopted in the literature. This presents the drawback that they have not been subjected to scrutiny. Their validity is questionable along several dimensions. First, volunteering work and employment may be jointly determined as a product of time-surplus or time-constraint. Second, mothers who choose to volunteer may affect the likelihood of a child being overweight through mechanisms other than employment, such as, knowledge acquired from fellow volunteers. However, volunteering is defined in a very flexible fashion, where participation in any non-market-related work (apart from sleep, leisure and home production) for any amount of time qualifies as ‘volunteering’. This eliminates the issue of judging whether a mother is a volunteer or not by her formal enrolment into a volunteer organisation, which can be time-consuming and a barrier to participation for working mothers. Further, as confounding covariates, such as, education and age are included in the model, the potential impacts volunteering work may have on a child being overweight, separate from employment, is reduced. Similarly, English as the first language is a measure of the mother’s language proficiency and may conceivably influence the mother’s knowledge of the benefits of exercise and a healthy lifestyle. Lastly, exposure to English as the first language may be tenuously linked to employment status as Australian immigration requirements largely attract English-speaking and skilled labour into the workforce (Productivity Commission, 2006). These potential problems with the chosen instruments will be explored later.

The instruments used in Anderson et al. (2003), such as, unemployment rate, child care regulations, wages of child care workers, welfare benefit levels and the status of welfare reform in the state can be criticised along the same dimensions. Furthermore, these instruments exhibit very little variation and are more likely to produce inefficient results. Anderson et al. (2003) discard their 2SLS model in further analysis, providing exactly the aforementioned reason.

The choice of confounding covariates used in this analysis is quite different to those used in Anderson et al. (2003). Attributes specific to the child, such as, birth weight, whether the child was breastfed or not, the number of younger and older siblings and the country of birth are included in the model. Unlike Anderson et al. (2003), age and gender are excluded. The sample only consists of 4-5 year old children and gender was found to have no impact on the likelihood of a child being overweight or on the coefficients of the other variables once it was omitted from the model.

Mother-specific variables included in this analysis are the hours of employment, highest level of education achieved, age, and the country of birth. Anderson et al. (2003)

also include the mother's weight status, her AFQT[4] score and two binary indicators for whether the mother's mother and father were present when she was aged 14 years old. The latter variables are not provided by LSAC and maternal weight status is excluded because it is likely to be an endogenous variable. It does not make sense to hold the mother's weight status fixed when hours worked varies and its inclusion can 'mop-up' the effects on child weight status that are legitimately caused by maternal employment (Gregg et al. 2005). Further, ethnicity variables are included to control for genetic factors that may affect the weight status of the mother and/or child.

The attributes of the father, household income and wealth covariates included in the models estimated in this analysis and in Anderson et al. (2003) differ vastly. As NLSY does not contain matched data on the father, his presence and attributes are ignored in the analysis of the latter. Fortunately, LSAC contains detailed information on the father, such as, his employment hours, separate weekly income and age. These are subsequently included in the model. Average family income since the birth of the child is used in Anderson et al. (2003) to proxy for the household's financial capabilities. There are two main problems associated with using this variable and both relate to endogeneity. First, it makes no sense to hold household income fixed when maternal income, a potentially large contributor to household income, rises simultaneously with maternal employment. Second, as it is unknown in Anderson et al. (2003) whether or not the mother is single or partnered, household income is likely to be correlated to the disturbance term. Therefore, biased coefficient estimates will ensue and contaminate the results of the other variables in the model that are correlated to household income. To bypass these pitfalls, we have chosen to include other proxies, such as, the father's separate weekly earnings, a dummy for whether the mother receives a pension from the government or not and also two variables relating to neighbourhood wealth[5].

Results

[4] The Armed Forces Qualification Test (AFQT) is a measure of cognitive ability. It consists of four sections: word knowledge, numeric operations, paragraph comprehension and arithmetic reasoning.

[5] The percentage of households in the current postcode that earn below $1000 in combined income per week (percpc1000) and the percentage of households in the current postcode that only speak English at home (percpcengl).

Estimation results for the 2SLS procedure which accounts for endogeneity in maternal employment are presented in Table 2. A 1-hour increase in the average number of hours worked per week by the mother results in a 0.63 percentage point increase in the probability that a child is overweight. This result is 7 times larger than the estimate obtained in Anderson et al. (2003) and, unlike the latter, is statistically significant with a p-value of 0.0512. The discrepancy is likely to be a result of the vast differences in the covariates and instruments used between the two analyses.

Table 2: 2SLS estimation results; structural equation

Variable	Coefficient	S.E.	P-value
mumemp	0.0063	0.0032	0.0512
pensionmum	0.0555	0.0277	0.0453
pensnmiss	-0.0178	0.0732	0.8074
percpc1000	0.0016	0.0005	0.0007
percpcengl	-0.0023	0.0005	0
incpartner	0	0	0.7838
incpartmiss	0.03	0.0181	0.0971
dademp	0	0.0004	0.9303
dadempmiss	-0.1134	0.0722	0.1164
beyondhs	-0.0376	0.0176	0.0324
beyondtert	-0.0471	0.0306	0.1241
mumeducmiss	0.0209	0.1557	0.8931
bweightz	0.0502	0.006	0
bstfed	-0.0868	0.023	0.0002
ausborn	0.0064	0.0392	0.8698
cofbirthmiss	-0.0256	0.0609	0.6738
nzukbornmum	-0.0167	0.0276	0.5461
oceabornmum	0.2346	0.069	0.0007
eurbornmum	-0.0569	0.0435	0.1908
asiabornmum	-0.0699	0.0259	0.0069
otherbornmum	0.0666	0.0477	0.1621
cofbirthmumiss	-0.0113	0.0398	0.777
anyngsib	0.0382	0.02	0.0562
anoldsib	-0.0068	0.0094	0.4691
agemum	0.0025	0.0017	0.1361
agedad	-0.0005	0.0014	0.7377
constant	0.2005	0.1	0.0452

The coefficient estimates of the other variables in the model have magnitudes, signs and significance levels that follow a-priori expectations. However, discussion of these effects will be postponed until the joint model is estimated.

There is substantial evidence of unobservable heterogeneity. A simple LPM, assuming exogeneity in maternal employment, suggests that a 1-hour increase in the mother's average weekly workload will increase the likelihood of a child being overweight by 0.1 percentage points. This is highly statistically significant with a p-value of 0.011[6]. This result is more than six times lower than the coefficient estimated by the 2SLS procedure, suggesting that the unobservable factors that cause a mother to increase work by 1-hour per week also substantially lower the likelihood of a child being overweight. There is positive selection into the mother's decision to work an extra hour. On the other hand, Anderson et al. (2003) find 'no real signs' of unobservable heterogeneity, stating the reason that the parameter estimates obtained by the fixed effects, IV and simple probit models yield similar results.

This contradiction can be explored with an endogeneity test (Wooldridge, 2006). The predicted values for the residuals of the reduced form equation, once it is substituted into the structural form equation, is statistically significant with a p-value of 0.092. This is evidence that the maternal employment variable is, indeed, endogenous[7]. As previously discussed, the accuracy of the results estimated by a 2SLS model relies heavily on the ability of the chosen instruments to satisfy a set of conditions. Therefore, we now turn to a discussion of the robustness of fstengl and volunt. These two instruments satisfy nearly all of the requirements and appear to be genuinely, quite good.

Together, they yield an F-test statistic of 30.81 with a p-value less than 0.0001. Strong correlation with maternal employment is an important attribute for consistent and efficient estimation (Stock and Watson, 2003). The two overidentification tests, first assuming exogeneity in fstengl, and then in volunt, produce Sargan test statistics of 4.13 and 2.065, respectively. Both tests do not reject the null, suggesting that the instruments are exogenous. Finally, the redundancy test (Wooldridge, 2002) is applied and the p-values

[6]The complete set of results can be obtained on request.

[7] The endogeneity test was not conducted in Anderson et al. (2003) and the comparisons of results were primarily between their fixed effects and single equation probit models. Therefore, the conclusion from my sensitivity analysis is not directly comparable with the conclusions in Anderson et al. (2003).

for the Studentised t-tests corresponding to fstengl and volunt are 0.17 and 0.09, respectively. This suggests that volunt may have an impact on a child's weight status separate from its effect on maternal employment. Recall, however, that 'volunt' was deemed exogenous by the overidentification test. To explore this contradiction, the model using the 2SLS procedure and fstengl as the only excluded instrument is re-estimated. The results are nonsensical. The coefficient of maternal employment becomes -0.4943 and the standard errors for all variables are dramatically inflated; the p-values are all above 0.78 and the majority is above 0.90. Instead of pointing to an inconsistency in the previous findings, the substantively ridiculous results are characteristic of regressions afflicted by multicollinearity. 'fstengl' is weakly correlated with maternal employment when it is the single identifying instrument, separate from volunt, in estimation. Its p-value is 0.937 from the instrument relevance test and thus heavily biases the 2SLS estimates, even more than OLS and regardless of sample size (Bound, Jaeger and Baker, 1995).

A Ramsey RESET test is conducted on the LPM. The squared (yhat2) and cubed (yhat3) values of the fitted linear index are included into the structural form model. The F-statistic for the hypothesis that yhat2 and yhat3 are jointly equal to zero is 0.83 with a p-value of 0.4351. Therefore, the null is not rejected providing evidence that the model does not exhibit functional form misspecification or omitted variable bias.

FIML

The analysis in the previous sub-section relied on the following two assumptions: maternal employment is linearly related to the probability of a child being overweight and that the magnitude and nature of selection on observable and unobservable factors into the decisions to work, work part-time and work full-time are exactly the same. This sub-section will relax these two assumptions. A model, novel to the literature on child outcomes will be introduced; one which, by virtue of its more general specification, aims to provide greater understanding of the relationships between maternal employment and the likelihood of a child being overweight.

Unlike the single equation LPM estimated in the previous sub-section, a multinomial choice specification addresses self-selection bias. By allowing for three separate equations, thus also, disturbance terms for non-working, part-time and full-time, the multinomial choice specification identifies distinct selection bias terms for part-time and full-time employment relative to non-working once the outcome and treatment equations are jointly estimated.

Following the method employed by Deb and Trivedi (2006), a FIML, non-linear, non-normal econometric model is used to jointly estimate a binary outcome equation with a multinomial treatment equation, accounting for selection bias. A latent factor framework is adopted to achieve a parsimonious representation of the correlation between the disturbances of the outcome and treatment equations. Simulated Maximum Likelihood (SML) will be used to estimate the parameters of the joint model.

Developing the multinomial treatment model

A mother is assumed to be faced with three employment alternatives: to not work at all, work part-time or work full-time. The random utility model can be used to characterise the trinomial choice. U_{ij}^{*} denotes the indirect utility associated with the jth employment choice and can be written as

$$U_{ij}^{*} = \mathbf{z}_i^{'} \alpha_j + \varepsilon_{ij} \qquad (3)$$

where j = 0, 1, 2 for non-working, part-time and full-time employment, respectively. U_{ij}^{*} is the sum of a deterministic component, $\mathbf{z}_i^{'} \alpha_j$, and a stochastic component, ε_{ij}. $\mathbf{z}_i^{'}$ is a vector of exogenous and observed characteristics relating to the ith mother and does not vary over alternatives. The associated parameter vector, α_j, varies across the employment alternatives, as required for identification. ε_{ij} can be decomposed and rewritten as ε_{ij} = $\sum_{k=1}^{2} \delta_{jk} l_{ik}$ + η_{ij}, where l_{ik} are latent factors which include unobservable characteristics that vary over individuals and are common to their treatment choice and outcome equations. η_{ij} is a random term with mean 0 and is i.i.d. over individuals and alternatives. l_{ik} and η_{ij} are assumed to be independent. Non-working status will denote the base group, U_{i0}^{*} = 0, in order to identify the parameters.

Deb and Trivedi (2006) describe ε_{ij} as following a "mixed multinomial logit" (MMNL) structure. Yet ε_{ij} is MMNL in the sense that the distributional assumptions for

l_{ik} and η_{ij} are different. η_{ij} is assumed to be i.i.d. and from a logistic density, whereas the latent factors, l_{ik}, are drawn from a standard normal distribution. But i.i.d. is still assumed for l_{ik}.

Further, as the treatment model only allows for individual-varying covariates, a set of normalisation restrictions need to be imposed on the variance-covariance matrix to assist with identification. First, correlation between the disturbances of different alternatives is fixed at 0, i.e. $\delta_{jk}=0 \ \forall \ j \neq k$, for all i. Therefore, the unobservable factors associated with one employment alternative cannot influence the utility associated with a different employment alternative. Essentially, this restriction of the model invokes the IIA assumption and ignores heteroskedasticity. While the Multinomial Probit (MNP) model is attractive for the purpose of modelling employment choice, as it relaxes the IIA assumption, there are limitations in the data, such as, the availability of alternative-specific variables which lessen the appeal and feasibility of MNP. Without alternative-specific variables, identification in the MNP model can be quite fragile (Keane, 1992). The second restriction imposed in Deb and Trivedi (2006) normalises the scale of the choice equations; $\delta_{jj} = 1 \ \forall \ j$.

Given the observable and unobservable attributes associated with the mother, the employment alternative that provides the highest indirect utility will be chosen. d_{ij} is a binary indicator for the mother's observed employment choice and can be expressed as

$$d_{ij} = \begin{cases} 1 & if\ d_i = j, \\ 0 & if\ d_i \neq j, \end{cases}$$

where d_{ij} equals 1 if the jth employment alternative is chosen and 0 otherwise. j = 0, 1, 2 for non-working, part-time and full-time employment, respectively, and j = 0 is the base group.

Therefore, the probability that the mother chooses the jth employment choice can be written as

$$\Pr(d_{ij} \mid \mathbf{z}_i, l_{ij}) = \frac{\exp(\mathbf{z}_i' \alpha_j + l_{ij})}{1 + \sum_{j=1}^{2} \exp(\mathbf{z}_i' \alpha_j + l_{ij})} \quad , \quad j = 0, 1, 2. \tag{4}$$

Developing the outcome equation

The dependant variable for the outcome equation is a binary indicator for whether the child is overweight or not. Similar to the treatment model, the outcome equation is estimated in a random utility framework. y_i^* denotes the unobservable likelihood that the child is overweight and can be written as

$$y_i^* = \mathbf{x}_i' \beta + \sum_{j=1}^{2} \gamma_j d_{ij} + \sum_{j=1}^{2} \lambda_j l_{ij} + \eta_i \tag{5}$$

where $\mathbf{x}_i$ is a vector of exogenous characteristics relating to the ith child. The associated parameter vector is β . d_{ij} represents the mother's employment choice. Compared to the LPM of the previous sub-section, Equation 5 allows for a more flexible, non-linear relationship between maternal employment and the likelihood of a child being overweight.

In addition, the role of each latent factor or the selection on unobservables into non-working, part-time and full-time employment is separately identified. Since l_{ij} is common to the jth treatment and outcome it addresses the self-selection bias associated with the jth employment choice. However, as only differences in utility matter, the three error correlation parameters are reduced to two estimable parameters. The parameter, λ_j, given the normalisation restrictions, represents the effect of unobservable factors, common to the jth employment choice and outcome equations, on the likelihood of a child being overweight, relative to mothers with a randomly assigned jth employment load.

Let y_i be a binary variable equal to one if the child is overweight and 0 otherwise.

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0, \\ 0 & \text{if } y_i^* \leq 0. \end{cases}$$

Assuming η_i is from the logistic density, then, the probability that the child is overweight can be written as

$$\Pr(y_i \mid \mathbf{x}_i, \mathrm{d}_{ij}, \mathrm{l}_{ij}) \quad = \quad \frac{\exp(\mathbf{x}_i^{'}\beta + \sum_{j=1}^{2}\gamma_j d_{ij} + \sum_{j=1}^{2}\lambda_j l_{ij})}{1 + \exp(\mathbf{x}_i^{'}\beta + \sum_{j=1}^{2}\gamma_j d_{ij} + \sum_{j=1}^{2}\lambda_j l_{ij})} \tag{6}$$

Developing the joint-model of multinomial treatment and outcome equations

The joint distribution of treatment and outcome variables, conditional on the exogenous covariates and the common latent factors, can be written as

$$\Pr(y_i = 1, \mathrm{d}_{ij} \mid \mathbf{x}_i, \mathbf{z}_i, \mathrm{l}_{ij}) = \Pr(y_i = 1 \mid \mathbf{x}_i, \mathrm{d}_{ij}, \mathrm{l}_{ij}) \;*\; \Pr(\mathrm{d}_{ij} \mid \mathbf{z}_i, \mathrm{l}_{ij}) \tag{7}$$

where l_{ij} enters the outcome and treatment equations in the same fashion as the observed covariates. The problem of course is that we do not observe l_{ij}. From simulations generated in Stata 9.2 using pseudo-random number generators via an algorithm developed by Deb (2006), a sequence of values that resemble strings of random draws from the standard normal distribution are produced.

To obtain the unconditional joint density of outcome and treatment, the joint distribution of l_{ij} must be integrated out of the conditional joint density, i.e.

$$\Pr(\mathrm{y}_i = 1, \mathrm{d}_{ij} \mid \mathbf{x}_i, \mathbf{z}_i, \mathrm{l}_{ij}) = \int_{-\infty}^{\infty} [\Pr(\mathrm{y}_i = 1 \mid \mathbf{x}_i, \mathrm{d}_{ij}, \mathrm{l}_{ij}) * \Pr(\mathrm{d}_{ij} \mid \mathbf{z}_i, \mathrm{l}_{ij})]\, h(\mathrm{l}_{ij})\, d\,\mathrm{l}_{ij} \tag{8}$$

However, the integral has no closed-form solution. Therefore, Simulated Maximum Likelihood is used to estimate the parameters of the model. These simulations are conducted in Stata 9.2 with an algorithm provided by Deb (2006) that uses Halton sequences and a quasi-Newton algorithm to maximize the simulated likelihood function.

The Simulated Maximum Likelihood estimator, $\hat{\theta}_{SML}$, is a consistent estimator. A sufficient number of simulation draws for the sample size of 4130 used in this paper is 100 (Cameron and Trivedi, 2005).

FIML is more efficient than the two-step method and suffers from less problematic and fragile estimation which occurs in the latter due to multicollinearity; it is a result of introducing several bias-correction terms in the polychotomous choice sample selection model (Schmertmann, 1994).

The variance of $\hat{\theta}_{SML}$ is obtained using the sandwich form estimator. Since a simulated joint density is estimated in place of the true joint density function the information equality does not hold and therefore, it is inappropriate to use the outer product form or the inverse Hessian matrix to estimate the asymptotic variance (Greene 2003).

Results

The same two instruments, fstengl and volunt, are used in this analysis. The instrumental variable tests conducted in the previous sub-section are constructed specifically for linear models. Thus their use in this chapter is to provide only informal indications of the appropriateness of the instruments. The relevance test for fstengl and volunt yield a LR-test statistic of 78.105, suggesting the instruments are robust in the multinomial treatment equation. For the redundancy test, fstengl and volunt are substituted into the single equation logit model, controlling for full-time and part-time employment, and were found to yield p-values of 0.204 and 0.100, respectively. This suggests that these instruments do not strongly affect the likelihood of a child being overweight, separate from the effect of maternal employment.

Table 3 provides the estimated coefficients on the variables used in the joint binary and multinomial model along with their standard errors and p-values. As only differences in utilities matter, the coefficients in the treatment equations represent the effect of a change in the exogenous variables on the log-odds (log (P_{ft}/P_{nw}) and (log (P_{pt}/P_{nw})), where 'ft', 'pt' and 'nw' denote full-time, part-time and non-working, respectively (Appendix A, Table A.1 and A.2). The results in the outcome equation are of primary interest, however, and will be the focus of discussion. The dependant variable is

$\log(P_1 / P_0)$, where P_1 and P_0 denote the probability that a child is overweight and not overweight, respectively.

One major substantive finding of the joint model is evidence of a non-linear relationship between the likelihood of a child being overweight and maternal employment. After controlling for selection bias, moving from non-working to full-time employment causes the odds of a child being overweight relative to not being overweight to increase by exp(1.0302)=2.80, or more than 180%. The coefficient on full-time employment (ftmother) is positive and significant with a p-value of 0.063. However, the coefficient on part-time employment (ptmother) is not only negative, but also statistically insignificant with a p-value of 0.93. Contrary to the findings in the previous sub-section and in the literature, this result suggests that a mother who merely joins the workforce or moves from non-working to working less than 30 hours per week, does not have a damaging impact on the child's weight.

Another substantive finding of the joint model is that, λ_{ft} and λ_{pt}, the error correlation point estimates for full-time and part-time employment equations, respectively, are starkly different. While λ_{ft} is estimated to be -0.94 and with a p-value of 0.1240, λ_{pt} is estimated to be 0.16 and has a relatively high p-value of 0.6830. The large confidence interval fails to precisely detect self-selection bias into full-time employment in the significance test (p-value equals to 0.1240), however, this should not lessen the need for a selection bias correction, especially considering the very large point estimate of -0.94. In fact, as λ_{ft} lies close to the extreme value of -1, which is on the boundary of the parameter space, it suggests that the selection into full-time employment and the outcome regression are accomplished by near-identical processes. Therefore, the unobservable factors that increase the probability of a mother working full-time, decreases the likelihood of a child being overweight relative to that of a randomly assigned full-time employed mother. Yet the error correlation point estimate for part-time employment is not only relatively minute but its p-value is much larger and therefore, suggests that there is no selection bias into the part-time employment decision.

The effects of the other variables in the model behave as expected. A child who is breastfed and lighter at birth has a significantly smaller chance of being overweight at 4-5 years old. This result is overwhelmingly consistent and robust in the econometric and paediatric literature (Anderson et al., 2003; Ruhm, 2004; Gilman, Rifas-Shiman, Camargo, Berkey, Frazier, Rockett, Field and Colditz, 2001). Only the coefficients for Oceanic-born mothers and Asian-born mothers are significant in the set of ethnicity variables and reflect the influence of genetic make-up on the likelihood of a child being overweight.

From initial inspection, paternal-specific characteristics, such as, income and employment appear to have very limited influence on the likelihood of a child being overweight, which is similar to the finding in the LPM. The coefficient estimates are both individually statistically insignificant with p-values of 0.242 and 0.530, respectively. However, the LR statistic for a joint test of paternal employment and paternal income gives 86.25 which is highly statistically significant and yields a p-value of 0. This suggests that the paternal effect is indeed important, however, the data is simply not rich enough to disentangle the effects of paternal employment from paternal income. The implication of this result is that the estimates obtained in Anderson et al. (2003) potentially suffer omitted variable bias problems as a result of excluding paternal characteristics from the model specification.

There is evidence of beneficial impacts on the child's weight associated with higher incomes and household wealth. The variables paternal income and the percentage of households in the current postcode that only speak English at home, yield negative coefficient estimates, and the percentage of households in the current postcode that earn less than $1000 per week has a positive coefficient, which suggests that higher incomes or residing in relatively wealthier neighbourhoods will decrease the likelihood of a child being overweight. The two latter variables are highly statistically significant, both yielding p-values less than 0.0001. These results are concordant with the expectation that higher incomes increase the financial ability of families to pursue a healthier and often therefore, more expensive diet and lifestyle; a product of the income effect (Becker, 1981).

Table 3: The Joint Model. Dependant variable: log (P_1 / P_0) where '1' and '0' refer to overweight and not overweight respectively

Variable	Coefficient	S.E.	P-value
ftmother	1.0302	0.5536	0.0630
ptmother	-0.0292	0.3330	0.9300
pensionmum	0.2092	0.1306	0.1090
pensnmiss	-0.1476	0.5177	0.7760
percpc1000	0.0119	0.0040	0.0030
percpcengl	-0.0141	0.0037	0.0000
incpartner	-0.0001	0.0000	0.2420
incpartmiss	0.1976	0.1323	-0.0617
dademp	0.0019	0.0030	0.5300
dadempmiss	-1.0594	0.7050	0.1330
beyondhs	-0.1745	0.1092	0.1100
beyondtert	-0.1266	0.1616	0.4330
mumeducmiss	0.4129	1.0556	0.6960
bweightz	0.3647	0.0669	0.0000
bstfed	-0.5328	0.1616	0.0010
ausborn	0.1688	0.2882	0.5580
cofbirthmiss	-0.1529	0.4788	-1.0913
nzukbornmum	-0.1784	0.2050	0.3840
oceabornmum	1.1836	0.4376	0.0070
eurbornmum	-0.5654	0.3359	0.0920
asiabornmum	-0.6134	0.2468	0.0130
otherbornmum	0.3950	0.3338	-0.2592
cofbirthmu~s	-0.1437	0.2833	-0.6990
anyngsib	0.1381	0.0910	0.1290
anoldsib	-0.1083	0.0549	0.0490
agemum	0.0218	0.0127	0.0870
agedad	-0.0058	0.0100	0.5610
constant	-1.4900	0.7342	0.0420
λ_{ft}	-0.9400	0.6114	0.1240
λ_{pt}	0.1586	0.3890	0.6830

For ease of interpretation, Average Marginal Effects (AME) of part-time, and full-time employment are estimated and presented in Table 4. For comparison, AME are calculated for the joint model which accounts for selection bias (Column 1, Table 4) and the single-equation logit model that assumes part-time and full-time employment are exogenous variables (Column 2, Table 4). The difference in the estimated AME of the two models described above represent linear approximations of the magnitude of selection bias into part-time and full-time employment, respectively (Column 3, Table 4). A large difference is further indication that the selection effect is a significant one. The AME estimated under the exogeneity assumption does not represent the causal effect of an increase in maternal employment on the likelihood of a child being overweight as both the causal treatment and selection effects are incorporated into the estimated parameters.

Table 4: Average Marginal Effects of employment: likelihood of child overweight and selection bias

Variable	FIML model; controls for selection bias	Single-equation model; assumes exogeneity	Selection bias
ftmother	0.1864	0.0358	-0.1506
ptmother	-0.0047	0.0079	0.0126

Again, there is a clear non-linear effect of maternal employment on the likelihood of a child being overweight. As a non-working mother commences full-time employment, it causes the likelihood of a child being overweight to increase by 18.64 percentage points. The part-time AME, of -0.47 percentage points, is more than 19.1 percentage points lower than the AME of full-time employment.

There are several and interrelated explanations for the non-linear effect. First, full-time mothers face greater time-constraints; they have less available time to spend with their child during the day. For example, the daily office-arrival and departure times associated with full-time employment are relatively inflexible, full-time mothers may be absent or rushed during times of the day that are critical to satisfying the dietary or exercise requirements associated with maintaining a healthy weight for the child. For example, the child may be more likely to skip breakfast and therefore, snack on unhealthy foods later in the day. Or rather than playing outdoor sports after school, the child and the mother, anxious for her child's safety, yet unable to supervise her child due to work, opt for less-active indoor activities, such as, watching television or playing computer games. Alternatively, inferior substitutes, such as, child care and foods that require less time-intensive preparation may be consumed more frequently and intensively. These are lifestyle changes of fundamental consequence and their catalyst is full-time maternal employment.

The large selection bias term into full-time employment highlights the mistake of assuming exogeneity in the full-time employment variable. Its effect on the likelihood of a child being overweight is grossly underestimated to the effect of 15.1 percentage points, when compared to the true impact. On the other hand, the magnitude of selection bias into part-time employment is only 0.013 and as λ_{pt} was found to be highly statistically insignificant[8], it suggests that the selection on unobservable factors that influence the mother to choose part-time employment do not affect her child's weight status.

The discrepancy between the nature of selection bias into full-time and part-time employment highlight the importance of the trinomial specification for the treatment. In this case, as the 2SLS procedure specified maternal employment as a continuous variable, in a single equation, self-selection bias into the different employment categories are not separately controlled for. Consequently, the 2SLS predictions overestimate the impact of a married mother changing from non-working to full-time employment [9] and even more severely for when the married mother changes from non-working to part-time employment[10], on the likelihood of a child being overweight. Ignoring the self-selection problem, even after controlling for endogeneity, can still produce biased and inconsistent results.

Section V: Conclusion

The main substantive finding of this paper involves the causal, non-linear effect maternal employment has on the likelihood of a child being overweight. Commencement of part-time employment is found to have no effect whereas commencement of full-time employment for a non-working mother has a significant and damaging impact. Failing to acknowledge the separate self-selection bias terms will produce misleading interpretations of the impacts of maternal employment.

There are several ways to improve the analysis conducted in this paper. First, instead of dividing maternal employment into the three groups of non-working, part-time

[8] Although it is more appropriate to use standard errors associated with the AME to judge statistical precision, the estimated standard errors associated with the estimates of the error correlations still provide rough, often similar results.
[9] The mean of the hours of employment for the subcategory of full-time employment is approximately 41 hours. Therefore, 0.63*41 gives approximately 25.83 percentage points.
[10] The mean of the hours of employment for the subcategory of part-time employment is approximately 15 hours. Therefore, 0.63*15 gives approximately 9.45 percentage points

and full-time, an even more flexible model can be estimated by incorporating more categories. For example, unemployed status has been collapsed with non-working status but there may be unobserved differences between the mothers that belong in these respective groups. A quadnomial treatment model, for example, would allow for more error correlation parameters between the disturbances of the treatment and outcome equations to be estimated. If there is unfavourable selection into unemployed status then my results will have underestimated the impact of commencing part-time or full-time employment. However, with the aim of a more general model specification comes the need for more computational prowess. The trinomial treatment estimated in this paper is already computationally intensive.

Second, instead of the Multinomial Logit model that invokes the IIA assumption, a model that allows for a more flexible variance-covariance structure such as the Multinomial Probit or Mixed Multinomial Logit can be used. Part-time employment is a closer substitute to full-time employment than non-working status, making IIA quite a heroic assumption. Another drawback of the multinomial logit model is that heteroskedasticity is not controlled for. But again, the alternative methodologies are more demanding in terms of the structure of the data as well as computationally.

Third, with the soon-to-be-released second wave of LSAC data many possible extensions can be explored. Panel data will allow for a wide-variety of econometric methodologies that control for endogeneity to be employed and introduce avenues for analysis that are impossible with cross-sectional data.

Last, more research is needed to fully uncover the transmission mechanism from maternal employment to child weight outcomes. This paper could only hypothesise. Therefore, there are limits to the policy implications that can be drawn from the empirical results. Nevertheless, the findings presented in this paper provide focus for the next step in the puzzle of uncovering the underlying cause(s) of the child obesity epidemic.

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Table A.1: Joint model parameters and estimated error correlations

Dependant variable: log (P_{ft} / P_{nw}) where 'ft' and 'nw' stands for full-time and non-working respectively.

Variables	Coefficient	S.E.	P-value
pensionmum	-1.4782	0.1200	0.0000
pensnmiss	0.0893	0.6068	0.8830
percpc1000	-0.0033	0.0042	0.4300
percpcengl	0.0093	0.0038	0.0140
incpartner	-0.0005	0.0001	0.0000
incpartmiss	-0.2858	0.1505	-0.5808
dademp	0.0016	0.0035	0.6510
dadempmiss	-0.2407	0.6294	0.7020
beyondhs	0.8358	0.1207	0.0000
beyondtert	1.4817	0.1773	0.0000
mumeducmiss	0.0029	1.7170	0.9990
bweightz	0.0561	0.0471	0.2340
bstfed	0.1787	0.1857	0.3360
ausborn	0.7978	0.3216	0.0130
cofbirthmiss	0.5694	0.4681	-0.3481
nzukbornmum	-0.1231	0.2222	0.5790
oceabornmum	-0.4515	0.5158	0.3810
eurbornmum	-0.4335	0.3481	0.2130
asiabornmum	-0.0112	0.2378	0.9620
otherbornmum	-0.4714	0.4036	-1.2625
cofbirthmu~s	-0.4962	0.3529	-1.1879
anyngsib	-1.2014	0.1068	0.0000
anoldsib	-0.4367	0.0647	0.0000
agemum	0.0145	0.0142	0.3080
agedad	-0.0129	0.0116	0.2660
fstengl	0.1429	0.1935	0.4600
volunt	-0.8043	0.1087	0.0000
constant	-0.1033	0.7246	0.8870

Table A.2: Joint model parameters and estimated error correlations

Dependant variable: log (P_{pt} / P_{nw}) where 'pt' and 'nw' stands for part-time and non-working respectively.

Variables	Coefficient	S.E.	P-value
pensionmum	-0.7541	0.1037	0.0000
pensnmiss	-0.2048	0.4917	0.6770
percpc1000	0.0047	0.0033	0.1580
percpcengl	0.0084	0.0032	0.0090
incpartner	-0.0001	0.0000	0.0560
incpartmiss	-0.0620	0.1234	-0.3038
dademp	0.0136	0.0026	0.0000
dadempmiss	-0.2539	0.4917	0.6060
beyondhs	0.6520	0.0962	0.0000
beyondtert	1.0501	0.1536	0.0000
mumeducmiss	0.6439	0.9170	0.4830
bweightz	0.0366	0.0418	0.3820
bstfed	0.3477	0.1648	0.0350
ausborn	0.8123	0.2841	0.0040
cofbirthmiss	-0.6755	0.5128	-1.6806
nzukbornmum	-0.4423	0.1908	0.0200
oceabornmum	-1.5816	0.7746	0.0410
eurbornmum	-0.1082	0.3214	0.7360
asiabornmum	-0.7954	0.2281	0.0000
otherbornmum	-0.2772	0.3314	-0.9268
cofbirthmu~s	-0.3173	0.3013	-0.9077
anyngsib	-0.5571	0.0741	0.0000
anoldsib	-0.3186	0.0492	0.0000
agemum	0.0181	0.0121	0.1340
agedad	-0.0064	0.0099	0.5150
fstengl	0.5343	0.1740	0.0020
volunt	0.0764	0.0953	0.4230
constant	-2.7428	0.5945	0.0000