Maternal Employment and Overweight Children: An Australian Study

Keywords: Child obesity, Overweight Children, Maternal employment, Selection bias, Endogeneity, latent factor model, unobservable heterogeneity and Full-Information Maximum Likelihood.

I Introduction

The alarming rise in the number of overweight children in developed nations during a trend of increasing rates of female participation in the labour force has raised concerns about whether longer hours in employment (and away from the child) contributes to poorer health outcomes for children. In Australia, the rate of mothers joining the labour force and with a youngest child aged less than five years old, rose from 36 to 43 per cent between 1986 and 2000 (ABS, 2001). Over a similar period, the prevalence of overweight children almost doubled, and the prevalence of obese children more than tripled (Magarey, Daniels and Boulton, 2001). While these statistics imply a correlation between maternal employment and child obesity, it is unclear if the relationship is a causal one.

In various developed nations, researchers have indeed shown that the more time a mother spends in the formal labour market, the more likely it is for her child to be overweight. In the United States, for example, Anderson, Butcher and Levine (2003) find that this relationship holds for children aged 3 to 11 years and Ruhm (2004) shows that adolescent children of working mothers, on average, experience more weight problems. Similarly, Garcia, Labeaga, Ortega, (2006) discover this link for Spanish children aged 2-15 years, as does Hinke Kessler Scholder, (2007) for English children aged 7-16 years, Phipps, Lethbridge, Burton, (2006) for Canadian children aged 6-11 years and Takahashi, et al., (1999) for Japanese children aged 3 years old.

This paper asks whether mothers who work heavier employment loads increase the likelihood of their child becoming overweight. It uses the first wave of data from the Longitudinal Survey of Australian Children (LSAC), which provides controls on information relating to the child's health, the mother's background and other demographic and socio-economic factors related to the child's household.

However, these traditional controls may be imperfect for capturing all the differences between mothers with different employment situations and this paper aims to explore the unobservable source of differences between mothers who work full-time, part-time and those who stay at home. This contributes to a literature, which has primarily explored whether mothers who work 'additional' hours of employment (such as 10 extra hours) are different in unobservable ways to mothers who do not work as long or if mothers who 'participate' in the labour market are different in unobservable ways to those who stay at home. But a-priori, it is uncertain if mothers who work full-time are different (again in unobservable ways) to mothers who stay at home, nor is it clear if this also applies for part-time mothers.

This paper puts these ideas to test, using a latent factor model to allow for correlations between the error terms and to test and control for potential unobservable heterogeneity. A Full Information Maximum Likelihood (FIML), non-linear, non-normal econometric model is used to jointly estimate the binary outcome equation (whether or not the child is overweight) with a multinomial treatment equation (where maternal employment is divided into full-time, part-time and non-working categories). Exclusion restrictions are adopted to improve identification where the three instrumental variables used are: whether English was the first language the mother was exposed to, whether there is a younger brother present in the household and whether there is a younger sibling present in the household.

II Literature review

There are several health and economic costs associated with a child being overweight or obese. Obesity at a young age is likely to persist into adult life. An overweight 3-year-old child is nearly eight times more likely to be overweight as a young adult than a child of typical development (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). There are also economy-wide implications resulting from childhood obesity. It has been shown that being overweight or obese is negatively related to educational attainment and earnings (Averett and Korenman, 1996; Gortmaker, Must, Perrin, Sobol and Dietz, 1993), dampens productivity growth and reduces labour force participation rates (Murphy, 2005). Obese individuals are also more likely to take sick-leave and twice as likely to have high-level absenteeism (Burton et al, 1998; Tucker, 1998).

A conceptual framework needs to be constructed to understand how a child's weight status can be logically linked to maternal employment. Economic theory, in particular the work of Gary Becker (1965), provides the first step by describing the trade-off between a mother spending time with the child and time in formal employment. Becker (1965) explains how the latter is likely to increase at the expense of the former when the opportunity cost of child-rearing increases. In Australia, as female wages from employment have increased over recent decades in response to higher levels of education acquired by women and shifts in labour market attitudes, Becker's theory may well be prevalent. Australian time-use surveys show that full-time employed mothers spend on average 2 hours and 21 minutes less per day with a child (in their waking hours) than a non-employed mother (Australian Institute of Family Studies, 2008).

When a mother reduces the quantity of time spent with the child, valuable provisions of healthy home-cooked meals or supervised outdoor activities may be readily substituted with take-away foods, restaurant meals or less active indoor activities (Crepinsek and Burnstein (2004), Fertig, Glomm, Tchernis (2006), Cawley and Liu (2007)). These changes to the child's diet and exercise habits can create an imbalance in the calories the child consumes and the energy she/he expends. Over time, this imbalance can result in the child becoming overweight.

However, there may also be other mechanisms at play that are reinforcing or offsetting the previously discussed impact. For example, the quality of time a mother spends with the child may not be compromised as she works more (Bianchi, 2000). Also, the additional income a mother earns from employment can benefit the child's weight if it is spent on purchasing healthier foods or higher quality childcare (Anderson et al., 2003). It would have the opposite effect on the child's weight if the additional income is spent on relatively unhealthy restaurant and fast food meals (Horton and Campbell, 1991 and McCracken and Brandt, 1987). Gregg, Washbrook, Propper, Burgess, (2005) find that different types of child care (in terms of formal and informal) can have different effects on the child's health. Regression analysis can be used to better inform us of the net effect of maternal employment on the likelihood of a child being overweight.

Econometric studies in many parts of the developed world present evidence of a statistically significant and positive relationship between maternal employment and childhood obesity (Anderson, Butcher and Levine, 2003, Ruhm, 2004, Garcia, Labeaga, Ortega, 2006, Hinke Kessler Scholder, 2007, Phipps, Lethbridge, Burton, 2006, and Takahashi, et al.,1999).

One difference between these studies is the way maternal employment is specified. The majority of them use a continuous variable, in terms of the number of hours a mother spends in formal employment. This paper disagrees with using this specification and argues for a categorical variable that divides maternal employment into non-working, part-time and full-time instead. Comparing the effects of not-working and being part-time employed or full-time employed is more appropriate than comparing the effects of hourly changes in maternal employment. The reason involves the interplay of choice and self-selection bias. Australian employees more commonly face the employment choice to not work, work part-time or full-time, rather than choosing the exact hours to work which can vary quite dramatically from week to week. This choice can then create heterogeneity across the employment categories of non-working, part-time and full-time (or broad homogeneity within the categories) based on characteristics of the mother, often unobservable ones (which are the most problematic), such as ability, motivation or preference. When these unobservable characteristics of the mother also have an affect on the child's weight, the problem of self-selection bias arises and results in a biased interpretation of the model coefficients. Since self-selection bias fundamentally arises from deliberate choice, we should control for it according to the way people make their choices in reality.

Studies in the literature generally do not find that self-selection bias or unobservable heterogeneity is an issue for the relationship between maternal employment and child’s weight status. However, the literature has only explored if mothers self-select into ‘additional’ hours of employment (or put another way- if mothers who work 10 hours more than other mothers are different in unobservable ways) or self-selection bias into participation in the labour market (as opposed to staying at home). A-priori, it is uncertain and therefore, important to know if there is self-selection bias into full-time or part-time employment; in other words, are mothers who work full-time different to mothers who stay at home in unobservable ways? And what about for part-time mothers? This concept extends Heckman’s (1974) argument that the unobservable factors which motivate a mother to join the labour force may be different in nature and magnitude to the unobservable factors that motivate her to work an extra hour once she is already employed. If there are distinct self-selection bias terms associated with non-working, part-time and full-time employment then these terms need to be separately controlled for or else the usual problems of bias and inconsistency in the regression parameters ensue (Heckman, 1974).

To do this, this paper adopts a latent factor specification for the error terms in the treatment and outcome equations, and jointly estimates these equations to allow for a correlation between the error terms, which tests and controls for the potential unobservable heterogeneity. This econometric methodology was used by Deb and Trivedi (2006) in analysing the impact of health care insurance plan enrolment on health service utilisation in the United States.

III Theoretical Motivation

Economic theory provides an understanding of why maternal employment has increased so dramatically in recent decades and why this is likely to imply a reduction in the quantity of time a mother spends with the child.

In the face of scarcity, households aim to maximise household utility:

$$U = u(C, y) \qquad (1)$$

by finding optimal values of C and y that can be purchased with $PC + y \leq w\overline{T}$. In Equation 1, C refers to the child's health; y denotes all other goods; P is the price associated with producing one unit of child health, w is the wage and $\overline{T}$ is the mother's total available time. For simplicity, it is assumed that a mother divides her time up between t (time with the child) and $\overline{T}$ -t (time spent on work). This trade-off has implications for how a mother allocates her scarce resource of time.

In particular, the mother will maximise the child health production function:

$$C = C(x,t) \qquad (2)$$

by choosing efficient levels of 't' (mother's time devoted to the child) and 'x' (all other market inputs into a child's health) in a way that minimises the costs associated with producing child health:

$$\min\ (rx + wt) \qquad (3)$$

subject to $C(x,t) = 1$

where r is the fixed price of an extra unit of other market inputs and w denotes the opportunity cost of an extra unit of maternal time spent on the child. These marginal costs affect the optimal levels of x and t chosen:

$$x = x^*(w,r)$$
$$t = t^*(w,r)$$

that achieves the minimum cost ‘P’ associated with producing the optimal amount of child health ‘C’. This equilibrium ‘P’ can be expressed as:

$$P = rx^*(w,r) + wt^*(w,r) \qquad (4)$$

and varies across mothers with variations in the opportunity cost of time ‘w’. In addition, as the use of time is subject to diminishing returns, ceteris paribus, mothers with relatively high market wages would be expected to use less time in non-market pursuits.

Using this theoretical framework, the following example will illustrate why higher levels of maternal time are allocated to formal employment from time spent with the child as the opportunity cost of time, ‘w’, increases.

As a mother aims to maximise the utility function, which this example assumes follows quasi-linear preferences:

$$U(c,y) = V(C) + y$$

subject to:

$$PC + y \leq w\overline{T},$$

and after substituting for y, she is essentially faced with:

$$u(C,y) = V(C) + w\overline{T} - PC$$

where the marginal utility of child health can be written as:

$$\frac{\partial u}{\partial C} = V'(C) - P$$, such that V’(C) = P.

Higher wages ‘w’ causes the rational mother to reallocate time to formal employment from time once devoted to child production. This is due to the higher opportunity cost associated with child-rearing as well as through increasing P (using the standard revealed preference argument). An increase in P increases the marginal utility of child health V’(C), and since V’’(C)<0, we can deduce that the child’s health production function, C, will shift inwards resulting in maternal time devoted to the child to decline even further.

While economic theory shows how the rise in the opportunity cost of child-related duties faced by a mother can result in her reallocating time towards maternal employment from time spent with the child, it comes short of explaining the whole picture. For example, the theoretical model did not include leisure as an option for the mother nor does it inform us of the resulting effect on the child’s weight when a mother reduces the amount of time she spends with her child. Furthermore, it ignores other effects such as changes to the quality of time a mother devotes to the child or the income effect (Becker, 1965). Therefore, we turn to econometric modelling to analyse the total net impact.

IV Regression modelling

The observed correlations in a single equation regression model can be muddied by the presence of self-selection bias effects and produce misleading interpretations of the causal impact of maternal employment on childhood obesity. Therefore, this section begins by testing if the mothers in the sample have self-selected themselves into their observed employment choices. In particular, separate tests are conducted for the potentially distinct self-selection bias terms associated with each of the three employment choices. In order to do this, a FIML procedure that jointly estimates a binary outcome with a multinomial treatment and allows for the errors between the two equations to be correlated will be adopted.

Developing the multinomial treatment model

It is assumed in this paper that mothers only face three employment alternatives: non-participation in the labour force, part-time or full-time employment. 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 expresses as

$$U_{ij}^* = \mathbf{z}_i^{'} \alpha_j + \varepsilon_{ij} \tag{5}$$

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 $\varepsilon_{ij} = \sum_{j=1}^{2} \delta_j l_{ij} + \eta_{ij}$, where l_{ij} are latent factors which vary over individuals, i, and are common to their jth employment choice and child outcome equations. Note how separate latent factors are assigned to each employment choice. l_{ij} represent the unobservable characteristics that affect the outcome and also affect selection into treatment. η_{ij} is a random term with mean 0 and is independently, identically distributed (i.i.d.) over individuals and alternatives. l_{ij} and η_{ij} are assumed to be independent. Non-working status will be the base group, i.e. $U_{i0}^* = 0$, in order to identify the parameters.

Notice how the error specification does not allow for the unobservable factors associated with one employment alternative to influence the utility associated with a different employment alternative. Essentially, this restriction of the model invokes the Independence of Irrelevant Alternatives (IIA) assumption and ignores heteroskedasticity.

Imposing the IIA assumption for employment choices can lead to unrealistic estimates of maternal behaviour when different employment alternatives are added or deleted from the choice set. Ignoring the heteroskedasticity can lead to incorrect standard errors and therefore invalidate hypothesis testing. However, the covariance restrictions are necessary for the purpose of identifying the parameters in the joint estimation of the multinomial treatment and child outcome equations. If the multinomial treatment equation was being estimated as a stand-alone exercise, for example, the multinomial probit would be chosen as it relaxes the IIA assumption. However, given the lack of alternative-specific variables in the data and computational limitations, identification would be very fragile if the multinomial probit featured in a simultaneous equation estimation procedure (Keane, 1992).

Deb and Trivedi (2006) describe ε_{ij} from Equation 5 as following a "mixed multinomial logit" (MMNL) structure. Yet ε_{ij} is MMNL in the sense that the distributional assumptions for l_{ij} and η_{ij} are different. η_{ij} is assumed to be i.i.d. and from a logistic density, whereas the latent factors, l_{ij}, are drawn from a standard normal distribution. But i.i.d. is still assumed for l_{ij}.

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.

Given the normalisation restrictions, then the probability that the mother chooses the jth employment choice assumes a multinomial logit structure defined as:

$$\Pr(\mathrm{d}_{\mathrm{ij}} \mid \mathbf{z}_i, \mathrm{l}_{\mathrm{ij}}) = \frac{\exp(\mathbf{z}_i' \alpha_j + l_{ij})}{1 + \sum_{j=1}^{2} \exp(\mathbf{z}_i' \alpha_j + l_{ij})} \quad , \quad \mathrm{j} = 0, 1, 2. \tag{6}$$

Developing the outcome equation

The dependant variable for the outcome equation is a binary indicator for whether the child is overweight. 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

$$y_i^* = \mathbf{x}_i' \beta + \sum_{j=1}^{2} \gamma_{\mathrm{j}} d_{ij} + \sum_{j=1}^{2} \lambda_j l_{ij} + \eta_i \tag{7}$$

where $\mathbf{x}_i$ is a vector of exogenous characteristics relating to the ith child. The associated parameter vector is β. The binary variables, d_{ij}, representing the mother's observed employment choice allows for a more flexible, non-linear relationship between maternal employment and the likelihood of a child being overweight. Notice that l_{ij} are the exact same latent factors that appeared in the treatment equations. As separate latent factors are assigned to the different employment choices, distinct correlation effects between the unobservable factors in each employment choice equation and the child outcome equation are controlled for. Because only differences in utility matter, the three error correlation parameters are reduced to two estimable parameters. The resulting error covariance parameters, λ_j, indicates the correlation between the unobservable factors in the jth employment decision equation and the unobservable factors in the child's weight status equation. It can be used to test if there are self-selection bias effects associated with the jth employment choice. Deb and Trivedi (2006) call this term the factor loading[1].

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

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

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

[1] See Deb and Trivedi for a discussion on the benefits of specifying the error structure of the model using a factor-loadings specification over a general multivariate normal specification of unobservable heterogeneity.

$$\Pr(y_i \mid \mathbf{x}_{\mathrm{i}}, \mathrm{d}_{\mathrm{ij}}, \mathrm{l}_{\mathrm{ij}}) = \frac{\exp(\mathbf{x}_i^{'} \beta + \sum_{j=1}^{2} \gamma_{\mathrm{j}} d_{ij} + \sum_{j=1}^{2} \lambda_j l_{ij})}{1 + \exp(\mathbf{x}_i^{'} \beta + \sum_{j=1}^{2} \gamma_{\mathrm{j}} d_{ij} + \sum_{j=1}^{2} \lambda_j l_{ij})} \qquad (8)$$

Developing the joint-model

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

$$\Pr(y_i = 1 , \mathrm{d}_{\mathrm{ij}} \mid \mathbf{x}_{\mathrm{i}} , \mathbf{z}_i , \mathrm{l}_{\mathrm{ij}}) = \Pr(y_i = 1 \mid \mathbf{x}_{\mathrm{i}} , \mathrm{d}_{\mathrm{ij}} , \mathrm{l}_{\mathrm{ij}}) \;*\; \Pr(\mathrm{d}_{\mathrm{ij}} \mid \mathbf{z}_i , \mathrm{l}_{\mathrm{ij}}) \qquad (9)$$

where l_{ij} enters both the outcome and treatment equations in the same fashion as the observed covariates. The common factor specification of the error terms is used to form the joint distribution out of the conditional and marginal distributions[2]. This latent factor structure effectively generates correlated errors between the overweight child and maternal employment equations and thus allows for selection on unobservable and observable factors to be separately controlled for. The problem is that we do not observe l_{ij} thus, we assume l_{ij} are i.i.d. draws from a standard normal distribution so their joint distribution, **h,** can be integrated out of the conditional joint density:

[2] See Deb and Trivedi (2006) for a discussion on the benefits of using the latent factor structure over alternative ways of generating correlated errors.

$$\Pr(y_i = 1, d_{ij} \mid \mathbf{x}_i, \mathbf{z}_i) = \int_{-\infty}^{\infty} [\Pr(y_i = 1 \mid \mathbf{x}_i, d_{ij}, \mathbf{l}_{ij}) * \Pr(d_{ij} \mid \mathbf{z}_i, \mathbf{l}_{ij})]\, h(\mathbf{l}_{ij})\, d\mathbf{l}_{ij} \quad (10)$$

However, the integral has no closed-form solution. Therefore, Simulated Maximum Likelihood is used to estimate the parameters of the model, where,

$$\Pr(y_i = 1, d_{ij} \mid \mathbf{x}_i, \mathbf{z}_i) = E[\Pr(y_i = 1 \mid \mathbf{x}_i, d_{ij}, \mathbf{l}_{ij}) * \Pr(d_{ij} \mid \mathbf{z}_i, \mathbf{l}_{ij})]$$

$$\approx \frac{1}{S}\sum_{s=1}^{S} [\Pr(y_i = 1 \mid x_i, d_{ij}, \tilde{l}_{ijs}) * \Pr(d_{ij} \mid z_i, \tilde{l}_{ijs})]. \quad (11)$$

$\tilde{l}_{ijs}$ are the sequence of pseudo-random values drawn from the density **h** in Equation (10) which is assumed to be a multivariate normal. As the covariance matrix is restricted to an identity specification, the impact of each latent factor (for the different employment choices) can be separately identified. Deb and Trivedi (2006) use quasi-random draws based on Halton sequences in order to accelerate the simulations.

The simulated log-likelihood function, given by:

$$\ln L(y_i = 1, d_{ij} \mid x_i, z_i) = \sum_{i=1}^{N} \ln\{\frac{1}{S}\sum_{s=1}^{S} [\Pr(y_i = 1 \mid x_i, d_{ij}, \tilde{l}_{ijs}) * \Pr(d_{ij} \mid z_i, \tilde{l}_{ijs})]\} \quad (12)$$

is maximised using a quasi-Newton algorithm requiring only the first derivatives (Deb and Trivedi, 2006). The Simulated Maximum Likelihood estimator is a consistent estimator. This paper uses 100 simulation draws which is sufficient given its sample size of 4130 (Cameron and Trivedi, 2005).

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).

The joint model is identified in two ways: first, by relying on the non-linear functional form and second, through exclusion restrictions, to be discussed later.

In the next section, definitions of the key variables of interest are defined and descriptive statistics are presented.

V Background

Overweight status

LSAC uses the Body Mass Index (BMI)[3] to construct child-specific measures of weight status which adjust for the age and gender of the child according to the research of Cole, Bellizzi, Flegal and Dietz (2000). The overweight and obese children are merged into the one category of overweight children because only 4 per cent of children in the sample are obese and also this paper's aim is to explore the potential negative externalities of maternal employment on child outcomes in the form of increasing the likelihood of a child being overweight as opposed to merely quantifying how BMI changes[4].

Maternal employment and Sample Exclusions

---

[3] Defined as weight (in kilograms) divided by the height (in meters) squared.

[4] Nevertheless, the continuous BMI measure will be later used to test the sensitivity of the results.

This paper analyses how the average *intensity* of mother's employment patterns affect the child's weight status. It measures intensity using categorical variables for full-time, part-time employment or not in the labour force (after the birth of the child).

In this section, I explain how this measure of mother's employment intensity is constructed and the sample of mothers (and their children) that are excluded from analysis.

Mothers often transition in and out of the labour market, full-time and part-time employment in a volatile fashion during the period her child is aged 0-5 years. After giving birth, she exits the labour market (to take maternity leave) and after a certain amount of time, she returns to work at a given intensity, which she may or may not vary once her child is a little older or begins primary school. Not only is this volatile for individual mothers, but also there lacks one set pattern across Australian mothers.

We must take these transitioning patterns into account when we analyse how maternal employment affects a child's weight status. For most people, being overweight or obese is the result of a consistent pattern of unhealthy lifestyle choices; it is a prolonged imbalance of calories consumed and calories outputted per day. Therefore, if we are to analyse whether or not maternal employment engenders such patterns we must construct a measure of maternal employment that has been, on average, *consistent* over the child's life. For example, there is little value to concentrating on the employment status during the time of the survey, or any one point in time, as it may well reflect a recent transition rather than portray an average pattern of a mother's employment load.

Instead, I exploit information in Wave 1 of the LSAC survey, on the current employment status of the mother as well as retrospective questions, which give us an idea of her employment status at pregnancy and when she first returned to work after giving birth to the child.

First, I eliminate the very heterogenous group of mothers (790 observations) who were never attached to the labour market at any of those three points in time i.e. they were not employed during pregnancy, nor did they return to work after giving birth, nor were they employed at the time of the survey. Second, for the remaining mothers (who were employed at some stage), I construct three categories of employment: *1/ Full-time employment* characterises mothers who returned to work full-time after giving birth and also answered that they were full-time during the time of the survey (which is when the child was 4-5 years), *2/ Part-time employment* characterises mothers who were employed part-time at any one stage of the child's life (either upon return to work or during the time of the survey) and last, *3/ not-in-the-labour-force* are mothers who did not return to the labour force (after giving birth to the study child) and those who were not working at the time of the survey.

A non-working mother participates 0 hours per week in formal employment, part-time employed mothers work between 1-30 hours per week and full-time employed mothers work 30 or more hours per week. These thresholds were formed after observing the patterns in the maternal employment distribution for the sample. There's a distinct clustering of observations at 0 hours, between 0 and 30 hours and greater than 30 hours[5] (Figure 1).

[5] The sensitivity of these demarcations were tested, such as defining part-time employment as greater than 0 but less than 20 hours (as well as the usual juridical definition of part-time employment as 35 hours per week, as endorsed by the ABS). The results paint a similar story; the signs and the magnitudes of the coefficients of interest are similar. However, the standard errors change slightly such that the robustness of the coefficients of interest become more (no longer) robust compared to the estimates using 30 hours as the cut-off point.

(Insert Figure 1).

Figure 1 also detects outliers in the maternal employment variable. There are 6 women in the sample that report weekly hours worked as exceeding 90 hours. However, upon further inspection of the data it was decided that these observations be left in the sample. The survey question is framed in such a way that captures the total hours worked in all of the mother's formal jobs and includes over-time in both a paid and unpaid sense. For these 6 observations, all of them said that they "owned their own business"[6]. Thus these observations are not considered to be in error but rather honest reflections of the extreme workloads of self-employed mothers.

Independent Variables and Exclusion Restrictions

Attributes specific to the child, such as, birth weight, gender, whether the child was breastfed or not, the number of older siblings and the country of birth are included in the model. Although the sample only consists of 4-5 year old children, an age dummy indicating whether the child was 4 or 5 years old was included to account for the higher likelihood of older children to experience the effects of adiposity rebound[7]. Also, as children in Australia begin kindergarten at age 5, age is likely to be correlated with a mother's employment decisions.

Mother-specific variables include whether the mother is not-working, part-time employed or full-time employed, highest level of education achieved, age, and the country of birth. 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

[6] The proportion of people owning their own business in the sample is only 13 per cent.

[7] This is the onset of the 2nd period of rapid growth in body fat for children (Roland-Cachera, Deheeger, Bellisle, Sempe, Guilloud-Bataille, Patois, 1984)

when hours worked varies and its inclusion can 'mop-up' the effects on the child's weight that originally emanated from maternal employment (Gregg et al. 2005). However, if the mother's BMI reflected her general attitude towards health and lifestyle, for example, which were not induced by her employment load but rather impacted *on it* as well as on her child's lifestyle habits, then omitting the mother's weight status can bias our results. To resolve and test for this, I control for (but later drop[8]) another indicator of health and lifestyle attitudes- 'whether or not the mother was a regular smoker'. Its inclusion had no substantive impact on the coefficients on maternal employment. Other controls include: a set of ethnicity dummies to account for genetic factors and attitudes towards gender roles in the labour market.

Average family income is omitted from the model as it does not make sense to hold household income fixed when maternal income, a potentially large contributor to household income, rises simultaneously with maternal employment. Instead, neighbourhood wealth[9] is included to proxy for variations in wealth and income across households. In a similar vein, paternal employment and paternal income are excluded from the model as they are part of a simultaneous decision-making process with maternal employment[10].

The exclusions restrictions used in this paper consist of three binary instruments: whether English was the first language the mother was exposed to, if there is a younger

---

[8] There is a large number (624) of missing observations for this variable due to non-response.

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

[10] The results are not sensitive to the inclusion of paternal employment and paternal income in the model. Their coefficients were both individually and jointly statistically insignificant.

brother in the household and if there is a younger sister in the household[11]. They can be questioned along several dimensions. The first set of potential problems relate to the endogeneity in the instruments. The decision to have a younger child may be jointly determined with the employment decision and therefore, is potentially just as endogenous. Similarly, English as the first language is a measure of the mother's language proficiency and may conceivably influence the mother's receptiveness to media and social communications of the benefits of exercise and a healthy lifestyle for the child. However, as covariates, such as ethnicity and education are included in the model, the associations will lessen. I will later assess whether these concerns are an issue for analysis by subjecting them to various instrumental variable tests.

The second set of potential problems with the instruments relate to their relevance. 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). Similarly, the gender of the younger sibling may be related to employment status only in a weak fashion.

VI Data and Descriptive Statistics

The analysis in this paper is based on data of children aged 4-5 years from the first wave (the only released wave during the time this study was conducted) of the Longitudinal Survey of Australian Children (LSAC). LSAC 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. The data were collected in 2004 from face-to-face interviews with the 'parent who knew the child best'.

[11] Mothers are more likely stay at home than work full-time or part-time when her child is a boy but, there's no reason to believe the gender of a younger sibling would have any affect on the child's weight status.

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.

The following sample exclusions were made: 790 observations of mother's who were consistently detached from the labour market (as previously explained), 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. 55 observations pertaining to the overweight indicator for the child[12] and 28 observations pertaining to maternal employment.

Other variables in the regression model contained only very few missing observations. For: 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 treated by simply deleting them from the sample.

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.

[Insert Table 1]

[12] 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.

The mean comparisons between the three employment categories provide a glimpse of the observable differences between non-working, part-time and full-time employed mothers. For example, the proportion of mothers who are in full-time paid work in the sample and who also have completed a degree above the tertiary level is dramatically higher than non-working mothers. Mothers in full-time paid work are also more likely to live in relatively less disadvantaged locations, judging by the percentage of household in the current postcode that earn an income below $1000 per week. If the selection on these observables is ignored in estimation then the coefficients on the categorical maternal employment variables may unduly capture these 'other' effects on the likelihood of a child being overweight.

The same can be said of unobserved effects and in the next section we look at results relating to tests for self-selection bias.

VII Results

Self-selection bias

There is no indication of self-selection bias into full-time or part-time maternal employment compared to non-participation in the labour market. This is evident in Table 2, which shows that the coefficients on the latent factors for full-time and part-time employment (compared to non-participation) are small in size and statistically insignificant. From this, we can infer that there is no correlation in the errors of the outcome and treatment equations i.e. there is no presence of unobservable heterogeneity between full-time and non-participating mothers (nor is there for part-time and non-participating mothers), which is contaminating the relationship between employment load and the child's weight status.

[Insert Table 2]

More specifically, regardless of whether the model is identified through functional form [or exclusion restrictions], the coefficient of the latent factor between the full-time treatment equation and the outcome equation, λ_{ft}, is small in magnitude (-0.056) [-0.114] and not statistically different from 0 (its standard error is 0.741 [0.578]). This is also true of the error correlations for part-time maternal employment where λ_{pt} is small in magnitude (-0.115) [0.133] and the standard errors are large (0.392) [0.458]. This echoes findings in the literature which show that mothers who work more (an extra 10 hours per week) do not differ in unobservable ways to those who work less (Anderson et. al., 2003). However, this paper is the first to show that there is no selection bias into full-time or part-time employment when these two employment loads are separately compared to non-participation in the labour market.

As a result, the coefficients and average marginal effects[13] of a mother changing from non-participation to full-time employment on the likelihood of a child becoming overweight are very similar across the single equation logit model and the joint models (identified by functional form or with exclusion restrictions). This is similar for the part-time maternal employment result. Table 2 displays this stability in the coefficients and AMEs across the three models, where the coefficients (or the effects on the log odds ratio of a child being overweight versus not being overweight) fall in the band of 0.45 - 0.54

[13] Calculated for a reference person and only varying the employment dummy where the reference person is a child who is average aged (57 months), a girl, living in a neighbourhood belonging to the top quartile of affluence, is born in Australia, but not of indigenous or Torres Strait Islander descent, has an average birth weight z-score (-0.03), has an older sibling, whose mother has a bachelor degree, is average aged (35 years), born in Australia and has an average aged father (37.4 years).

per cent (or 8.14 - 10.02 percentage points for the AME) for full-time employment and between 0.13 – 0.34 percent (or 2.21 – 5.95 percentage points) for part-time employment.

The main difference between the results of the joint models and the single equation logit model is the size of the standard errors. For the former, the standard errors are larger due to the inefficiency introduced by including the latent factors and having no real correlation between the errors of the treatment and outcome equations.

Employment Impacts

With no evidence of selection bias, we can rely on the estimates from the single equation logit model. Table 2 shows that there is evidence of a positive, robust and non-linear relationship between maternal employment and her child's weight status. More specifically, when a mother increases her employment load from 0 hours in the labour market to working full-time, the average marginal effect on the likelihood of her child becoming overweight lifts by approximately 8 percentage points and is statistically significant at the 5 per cent level. In contrast, the corresponding part-time effect is only 4 percentage points and this is not statistically significant at the 10 per cent level.

One reason for the different impacts of full-time and part-time employment (compared to non-participation) is that full-time mothers face greater time-constraints and more inflexible working hours such as early starting hours or late finishing hours, which constrains their ability to undertake critical measures that maintain a healthy weight for the child such as, eating a nutritious breakfast that is high in protein to avoid snacking later in the day or having a healthy home-cooked dinner as opposed to high caloric take-away options. There may also be less time for the mother to supervise or transport the child to outdoor organised sporting activities.

The interpretation of the marginal effects of the other variables in the model is fairly involved due to the recursive nature of the model (Greene, 2003). There is a direct effect on the outcome produced by its presence in the outcome equation, however, there is also an indirect effect transmitted through employment. Nevertheless, the signs and importance of certain variables can still be interpreted. Tables 3, 3a, and 4 show the full set of results for the joint model (identified by functional form and with exclusion restrictions) and the single equation logit model, respectively.

Children who are breastfed and lighter at birth have 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, et al., 2001).

The coefficient on age is positive and statistically significant suggesting that the adiposity rebound effects are more prevalent for the 5-year old cohort.

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.

Households with higher incomes and wealth are less likely to have children experiencing overweight issues as suggested by the positive signs and statistically significant coefficients of the two income and wealth proxies: the percentage of households in the current postcode that only speak English at home and the percentage of households in the current postcode that earn less than $1000 per week.

Instrumental Variable Tests

The three instruments: whether or not English was the first language the mother was exposed to and if there is a younger brother (and sister) in the family, were subjected to a series of informal tests (due to the lack of formal tests in a non-linear setting) and were found to be genuinely quite good. First, the instruments are relevant. When tested jointly, the instruments are shown to be robust in the multinomial treatment equation yielding a Chi-squared statistic of 80.90. Strong correlation with maternal employment is an important attribute for consistent and efficient estimation (Stock and Watson, 2003). Second, there is evidence that the instruments are exogenous. For the redundancy test (Wooldridge, 2002), the instruments were substituted into the single equation logit model, controlling for full-time and part-time employment, as well as all other relevant covariates, the three instruments were all individually statistically insignificant (yielding p-values of 0.16 and 0.62 and 0.71 for the mother's exposure to English as the first language dummy, and the presence of a younger brother or younger sister dummies, respectively). These instruments are also jointly statistically insignificant (yielding a Chi-squared statistic of 2.48 and p-value of 0.48). These favourable test results can give us greater confidence in the ability of the instruments to improve identification of the joint model.

VIII Robustness analysis

I test the robustness of the findings above in a number of ways. First, I use the entire sample of mothers i.e. without excluding those who were continuously detached from the labour market. Again, there is no evidence to suggest that unobservable heterogeneity exists; the correlation between the error terms of the outcome and treatment equations yield coefficients that are small in magnitude and/or statistically insignificant (λ_{ft} and λ_{pt} equal 0.067 and 0.470, with standard errors of 0.646 and 0.526, respectively).

Again, we find that in the single-equation logit model, only the full-time effect on child's weight status is statistically significant (at the 5 per cent level) and not so for part-time employment. The coefficient on the full-time employment variable is slightly lower at 0.318 (with a standard error of 0.141) than the estimate obtained in the main results, which can be attributed to the inclusion of a more heterogenous base of continuously non-participating mothers. The coefficient for part-time is 0.113 with a standard error of 0.099.

Another robustness test that we can use is to vary the way that we specify the child's weight status variable by converting the binary variable to a continuous specification i.e. use the child's BMI and test if there are self-selection bias effects associated with full-time and part-time employment. A two-step model which estimates a linear regression model on a selected subset of observations, where selection is modelled as a multinomial logit[14] is used (Bourguignon, Fournier and Gurgand, 2001). In Stata, this model is coded using the 'Selmlog' command. The Selmlog procedure is estimated three times; once for each of the samples of non-working, part-time and full-time mothers. The first step which involves the multinomial selection equation remains the same for the three models. Effectively, this procedure interacts the treatment effect with all the variables in the model and there is heterogeneity in the self-selection bias effects across employment choices within each of the three samples.

[14] The Dubin-McFadden (dmf(1)) correction method is used.

Table 5 echoes the findings of the main results where the coefficient on the full-time variable is 0.138 and statistically significant at the 10 per cent level, therefore, when a mother increases her formal employment load from 0 hours to full-time, she increases the child's BMI by 0.138 units.

The error correlation coefficient between the full-time equation in the treatment model and the outcome equation based on the non-working mother and part-time working mother samples are again statistically insignificant.

VIIII Conclusion

This paper found no evidence of self selection bias into full-time or part-time employment when compared to non-participating mothers. Without the presence of unobservable heterogeneity contaminating the relationship between maternal employment and the child's weight status, we can confidently rest on the laurels of logit and interpret the relationship through its eyes.

For the typical child, harmful effects on their weight were mainly seen when mothers worked full-time hours in paid employment. Participating in part-time employment is found to have no effect on the likelihood of a child being overweight.

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 and full-time, an even more general 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 the results will have underestimated the impact of commencing part-time or full-time employment.

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 an unrealistic assumption. Another drawback of the multinomial logit model is that heteroskedasticity is not controlled for. But the alternative methodologies that address these issues are more demanding in terms of the structure of the data as well as computationally.

Third, with the 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 conjecture about the linkages. Therefore, there are limits to the policy implications that can be drawn from these empirical results. Yet, it has been highlighted that the full-time maternal employment effect may in fact be much larger than has been previously reported in the literature. This perspective invites further investigation into the effects of maternal employment as a potential underlying cause of the dramatic rise in childhood obesity rates in Australia.

References

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

Australasian Society for the Study of Obesity 2004, *Australasian Society for the Study of Obesity*, Australia, viewed 15 October 2006, <http://www.asso.org.au/home>

Australian Bureau of Statistics 2001, *ABS*, Australia, viewed 15 September 2006 http://www.abs.gov.au

Australian Institute of Family Studies 2007, AIFS, Australia, viewed 20 May 2008 http://www.familiesaustralia.org.au/publications/pubs/AIFS-FamiliesWeek.pdf

Averett, S., & Korenman, S. 1996, 'The Economic Reality of the Beauty Myth', *Journal of Human Resources*, vol. 31, no. 2, pp. 304-330.

Becker, G. S. 1965, 'A theory of the Allocation of Time', *Economic Journal*, vol. 75, no. 299, pp. 493-517.

Bianchi, Suzanne M. 2000. "Maternal Employment and Time with Children: Dramatic Change or Surprising Continuity?" Demography vol. 37, no 4, pp. 401-414.

Blau, F. & Grossberg, A. 1992, 'Maternal Labor Supply and Children's Cognitive Development', *Review of Economics and Statistics*, vol. 74, pp. 474-481.

Bouchard, C. 1997, 'Genetics of Human Obesity: Recent Results from Linkage Studies', *Journal of Nutrition*, vol. 127, no. 9, pp. 1887-1890.

Bourguignon, F., Fournier, M., and M. Gurgand, 2007, Selection bias corrections based on the multinomial logit model: Monte Carlo Comparisons, Journal of Economic Surveys, vol. 21, no.1, pp.174-205.

Burton, W. N., Chen, C., Schultz, A. B. & Edington, D. W. 1998, 'The Economic costs associated with body mass index in a workplace', *Journal of Occupational and Environmental Medicine*, vol. 40, no 9, pp. 786-792.

Cameron, A. C. & Trivedi, P. K. 2005, *Microeconometrics: Methods and Applications*, Cambridge University Press, NY.

Cawley, J. and Liu, F. 2007, "Maternal Employment and Childhood Obesity: A Search for Mechanisms in Time Use Data". NBER Working Paper No. W13600

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*, vol. 320, pp. 1240-1243.

Crepinsek, M. and N. Burstein. 2004. “Maternal employment and children’s nutrition”. Electronic Publications from the Food Assistance and Nutrition Research Program. Economic Research Service.

Deb, P. & Trivedi, P. K. 2006, ‘Specification and simulated likelihood estimation of a non-normal treatment-outcome model with selection: Application to health care utilization’, Econometrics Journal, vol. 9, pp. 307-331.

Dietz, W. H. 1997, ‘Periods of risk in childhood for the development of adult obesity -What do we need to learn?’, *Journal of* Nutrition, vol. 127, no. 9, pp. 1884-1886.

Dietz, W. H. 1998, ‘Childhood weight affects adult morbidity and mortality’, *Journal of Nutrition*, vol. 128, pp. 411-414.

Dietz, W. H. & Bellizzi, M. C. 1999, ‘Introduction: the use of body mass index to assess obesity in children’, *American Journal of Clinical Nutrition*, vol. 70, pp. 123-125.

Fertig, A., Glomm, G., & Tchernis, R. 2006, ‘The Connection between Maternal Employment and Childhood Obesity’, *Centre for Applied Economics and Policy Research, Working Paper.*.

Frühbeck, G. 2000, ‘Childhood obesity: Time for action, not complacency’, *British Medical* Journal, vol. 320, pp. 328-329.

Garcia, E., J. Labeaga, and C. Ortega. 2006. “Maternal employment and childhood obesity in Spain.” FEDEA, Working Paper.

Gilman, M. W., Rifas-Shiman, S. L., Camargo, C. A. Jr., Berkey, C. S., Frazier, A. L., Rockett, H. R., Field, A. E., & Colditz, G. A. 2001, ‘Risk of overweight among adolescents who were breastfed as infants’, *Journal of the American Medical Association*, vol. 285, pp. 2461-2467.

Gortmaker, S. L., Must, A., Perrin, J. M., Sobol, A. M. & Dietz, W. H. 1993, ‘Social and economic consequences of overweight in adolescence and young adulthood’, *The New England Journal of Medicine*, vol. 329, no. 14, pp. 1008-1012.

Greene, W. H. 2003, *Econometric Analysis*, 5th ed, Pearson Education, NJ.

Gregg, P., Washbrook, E., Propper, C., & Burgess, S. 2005, 'The Effects of a Mother's Return to Work Decision on Child Development in the UK', *Economic Journal*, Royal Economic Society, vol. 115, no. 501, pp. 48-80.

Growing Up in Australia: Longitudinal Study of Australian Children (LSAC) 2005, *Australian Institute of Family Studies (AIFS)*, Australia, viewed 30 October 2006 <http://www.aifs.gov.au/growingup/>

Heckman, J. J. 1974, 'Shadow Prices, Market Wages, and Labor Supply', *Econometrica*, vol. 42, no. 4, pp. 679-694.

Hinke Kessler Scholder, S.V. 2007, 'Maternal employment and Overweight Children: Does timing matter?', The Centre for Market and Public Organisation (CMPO), CMPO Working Paper Series. No. 07/180.

Horton, S. and C. Campbell. 1991. "Wife's employment, food expenditures and apparent nutrient intake: evidence from Canada." American Agricultural Economic Association. Vol. 73, no. 3, pp.784-794

Keane, M. P. 1992, 'A note on identification in the multinomial probit model', *Journal of Business and Economic Statistics*, vol. 10, no. 2, pp. 193-200.

Magarey AM, Daniels LA, Boulton TJ. 2001, 'Prevalence of overweight and obesity in Australian children and adolescents: reassessment of 1985 and 1995 data against new standard international definitions'. *Medical Journal of Australia,* Vol. 174, pp. 561-565.

McCracken, V. and J. Brandt. 1987. 'Household consumption of Food-Away-From-Home: Total expenditure and by type of food facility." American Agricultural Economic Association. Vol. 69, no. 2, pp.274-284.

Murphy, J. 2005, 'Health promotion, lifestyle modification strategies for delaying and possibly preventing diabetes', *The Department of the Treasury*, Treasury Working Papers.

Power, C., Lake, J. & Cole, T. 1997, 'Measurement and long-term health risks of child and adolescent fatness', *International Journal of Obesity and Related Metabolic Disorders*, vol. 21, pp. 507-526.

Phipps, S., L. Lethbridge, and P. Burton. 2006. “Long-run consequences of parental paid work hours for child overweight status in Canada.” Social Science Medicine, vol. 62, pp. 977-986

Productivity Commission 2006, *Productivity Commission*, Australia, viewed 8 October 2006, http://www.pc.gov.au

Roland-Cachera, M.F. & Deheeger, M. & Bellisle, F. & Sempe, M. & Guilloud-Bataille, M & Patois, E. 1984. ‘Adiposity rebound in children: a simple indicator for predicting obesity.’ The American journal of Clinical Nutrition, vol. 39, pp. 129-135.

Ruhm, C. J. 2004, ‘Maternal Employment and Adolescent Development’, *National Bureau of Economic Research*, Working Paper Series, vol. 10691.

Stock, J. H. & Watson, M. W. 2003, *Introduction to Econometrics,* Addison-Wesley, CA.

Strauss, R. 1999, ‘Childhood obesity’, *Current Problems in Pediatrics*, vol 29, pp. 1-29.

Takahashi, Eiko, Katsumi Yoshida, Hiroki Sugimori, et al. 1999. “Influence Factors on the Development of Obesity in 3-Year-Old Children Based on the Toyama Study.” Preventive Medicine, vol 28, pp. 293-296.

Tucker, L. A. & Friedman, G. M. 1998, ‘Obesity and Absenteeism: an epidemiologic study of 10,825 unemployed adults’, *American Journal of Health Promotion*, vol. 12, no. 3, pp. 202-207.

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

Figure 1 Distribution of Maternal Employment

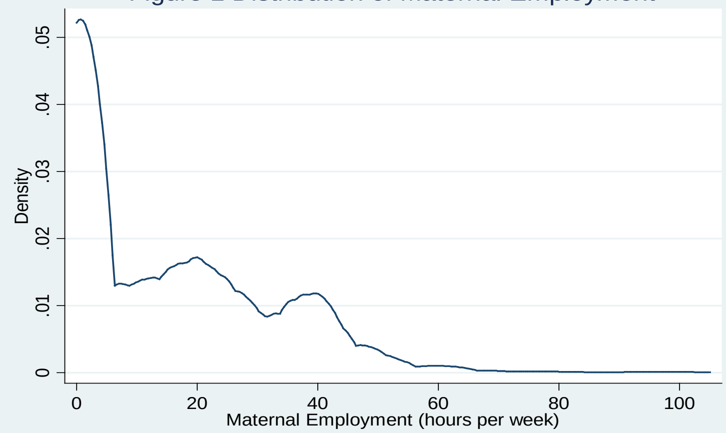

Table 1: Descriptive Statistics			
	Full-time	**Part-time**	**Not in labour force**
% Overweight	0.234	0.204	0.188
Child's BMI	16.420	16.348	16.237
Age of Child (in months)	57.107	56.935	56.797
1 if child is female	0.502	0.488	0.495
1 if SEIFA Disadvantage index for neighbourhood is in the 2nd quartile (least affluent neighbourhood is the base)	0.249	0.252	0.232
1 if SEIFA Disadvantage index for neighbourhood is in the 3rd quartile	0.294	0.278	0.270
1 if SEIFA Disadvantage index for neighbourhood is in the 4th quartile (most affluent neighbourhood)	0.276	0.301	0.214
1 if mother has completed a postgraduate degree	0.101	0.069	0.021
1 if mother has completed a graduate degree	0.078	0.070	0.051
1 if mother has completed a bachelor degree	0.158	0.194	0.101
1 if mother has completed a diploma	0.099	0.100	0.069
1 if a mother has completed a certificate	0.232	0.261	0.226
1 if a mother has some 'other' degree	0.016	0.013	0.014
1 if a mother is still studying	0.021	0.019	0.023
Birth weight Z-score	-0.115	-0.015	-0.129
Age of mother	35.813	34.803	34.595
Age of father	38.206	37.340	37.855
1 if child was being breastfed at 1 month	0.794	0.833	0.762
1 if the child is of Aboriginal or Torres Strait Islander descent	0.045	0.024	0.057
1 if child is born in Australia	0.938	0.967	0.942
1 if mum is born in an Oceanic country excluding Australia and New Zealand	0.010	0.007	0.018
1 if mum is born in either Western or Eastern Europe	0.076	0.077	0.067
1 if mum is born in the Middle-East, Africa, Americas or the Carribean	0.010	0.004	0.041
1 if mum is born in Asia (including South Asia and Central Asia)	0.113	0.051	0.099
1 if mum is born in any other country (where Australia and New Zealand is the base)	-38.992	-38.171	-38.633
Number of older siblings in the household	0.597	0.551	0.650

Table 2: Comparison of Results Across Models and Test for Self Selection Bias				
N=3222	**Coefficient**	**SE**	**Marginal Effect**	**λ (SE)**
Logit				
Full-time	0.449**	0.204	8.135	N/A
Part-time	0.235	0.174	4.020	N/A
Joint Model				
Full-time	0.508	0.675	9.315	-0.056 [0.741]
Part-time	0.339	0.376	5.948	-0.115 [0.392]
Joint Model (with IV)				
Full-time	0.54	0.552	10.019	-0.114 [0.578]
Part-time	0.133	0.433	2.212	0.133 [0.458]
*** significant at 10%; ** significant at 5%; *** significant at 1%**				

Table 3a: The Joint Model: Identified by Functional Form		
Variable Definition	**Coefficient**	**S.E.**
1 if the mother is full-time employed	0.508	-0.675
1 if the mother is part-time employed	0.339	-0.376
Age of Child (in months)	-0.004	-0.018
1 if child is female	0.262***	-0.091
1 if SEIFA Disadvantage index for neighbourhood is in the 2nd quartile (least affluent neighbourhood is the base)	-0.091	-0.141
1 if SEIFA Disadvantage index for neighbourhood is in the 3rd quartile	-0.232*	-0.141
1 if SEIFA Disadvantage index for neighbourhood is in the 4th quartile (most affluent neighbourhood)	-0.341**	-0.144
1 if mother has completed a postgraduate degree	0.151	-0.190
1 if mother has completed a graduate degree	-0.136	-0.193
1 if mother has completed a bachelor degree	-0.074	-0.145
1 if mother has completed a diploma	-0.286	-0.177
1 if a mother has completed a certificate	-0.041	-0.126
1 if a mother has some 'other' degree	0.281	-0.353
1 if a mother is still studying	0.407	-0.348
Birth weight Z-score	0.357***	-0.047
Age of mother	-0.078	-0.065
Age of mother squared	0.002*	-0.001
Age of father	-0.014	-0.011
1 if child was being breastfed at 1 month	-0.456***	-0.119
1 if the child is of Aboriginal or Torres Strait Islander descent	0.767***	-0.267
1 if child is born in Australia	0.246	-0.269
1 if mum is born in an Oceanic country excluding Australia and New Zealand	0.262	-0.472
1 if mum is born in either Western or Eastern Europe	-0.194	-0.179
1 if mum is born in the Middle-East, Africa, Americas or the Carribean	0.334	-0.603
1 if mum is born in Asia (including South Asia and Central Asia)	-0.473	-0.303
1 if mum is born in any other country (where Australia and New Zealand is the base)	0.314	-0.209
Number of older siblings in the household	-0.362***	-0.103
constant	0.240	-1.577

Table 3: The Joint Model : Idenitified by Exclusion Restrictions		
Variable Definition	**Coefficient**	**S.E.**
1 if the mother is full-time employed	0.540	0.552
1 if the mother is part-time employed	0.133	0.433
Age of Child (in months)	-0.004	0.018
1 if child is female	0.262***	0.091
1 if SEIFA Disadvantage index for neighbourhood is in the 2nd quartile (least affluent neighbourhood is the base)	-0.090	0.141
1 if SEIFA Disadvantage index for neighbourhood is in the 3rd quartile	-0.235*	0.141
1 if SEIFA Disadvantage index for neighbourhood is in the 4th quartile (most affluent neighbourhood)	-0.338**	0.144
1 if mother has completed a postgraduate degree	0.158	0.192
1 if mother has completed a graduate degree	-0.129	0.193
1 if mother has completed a bachelor degree	-0.053	0.143
1 if mother has completed a diploma	-0.279	0.177
1 if a mother has completed a certificate	-0.034	0.126
1 if a mother has some 'other' degree	0.281	0.357
1 if a mother is still studying	0.449	0.348
Birth weight Z-score	0.361***	0.048
Age of mother	-0.084	0.065
Age of mother squared	0.002*	0.001
Age of father	-0.015	0.011
1 if child was being breastfed at 1 month	-0.452***	0.117
1 if the child is of Aboriginal or Torrest Straight Islander descent	0.780***	0.264
1 if child is born in Australia	0.271	0.27
1 if mum is born in an Oceanic country excluding Australia and New Zealand	0.233	0.471
1 if mum is born in either Western or Eastern Europe	-0.195	0.179
1 if mum is born in the Middle-East, Africa, Americas or the Carribean	0.310	0.598
1 if mum is born in Asia (including South Asia and Central Asia)	-0.500*	0.297
1 if mum is born in any other country (where Australia and New Zealand is the base)	0.314	0.21
Number of older siblings in the household	-0.351***	0.103
constant	0.506	1.613

Table 4: Single Equation Logit Model		
Variable Definition	Coefficient	S.E.
1 if the mother is full-time employed	0.449**	0.204
1 if the mother is part-time employed	0.235	0.174
Age of Child (in months)	-0.004	0.018
1 if child is female	0.263***	0.09
1 if SEIFA Disadvantage index for neighbourhood is in the 2nd quartile (least affluent neighbourhood is the base)	-0.089	0.14
1 if SEIFA Disadvantage index for neighbourhood is in the 3rd quartile	-0.231*	0.14
1 if SEIFA Disadvantage index for neighbourhood is in the 4th quartile (most affluent neighbourhood)	-0.339**	0.143
1 if mother has completed a postgraduate degree	0.158	0.188
1 if mother has completed a graduate degree	-0.131	0.192
1 if mother has completed a bachelor degree	-0.064	0.137
1 if mother has completed a diploma	-0.280	0.175
1 if a mother has completed a certificate	-0.036	0.123
1 if a mother has some 'other' degree	0.281	0.353
1 if a mother is still studying	0.411	0.345
Birth weight Z-score	0.357***	0.047
Age of mother	-0.079	0.063
Age of mother squared	0.002*	0.001
Age of father	-0.014	0.01
1 if child was being breastfed at 1 month	-0.455***	0.116
1 if the child is of Aboriginal or Torrest Straight Islander descent	0.759***	0.259
1 if child is born in Australia	0.255	0.265
1 if mum is born in an Oceanic country excluding Australia and New Zealand	0.254	0.468
1 if mum is born in either Western or Eastern Europe	-0.195	0.179
1 if mum is born in the Middle-East, Africa, Americas or the Carribean	0.333	0.592
1 if mum is born in Asia (including South Asia and Central Asia)	-0.478*	0.287
1 if mum is born in any other country (where Australia and New Zealand is the base)	0.315	0.208
Number of older siblings in the household	-0.353***	0.099
constant	0.323	1.564

Table 5: Regression. Dependent variable: continuous BMI		
Variable Definition	**Coefficient**	**S.E.**
1 if the mother is full-time employed	0.138*	0.074
1 if the mother is part-time employed	0.075	0.059
* p<0.1; ** p<0.05; *** p<0.001		