New Estimates of Mothers’ Forgone Earnings Using HILDA Data

Trevor Breusch
Centre for Social Research, Research School of Social Sciences,
The Australian National University

Edith Gray
Demography and Sociology Program, Research School of Social Sciences,
The Australian National University

Abstract
Women who have children miss out on potential earnings. This happens through a combination of time out of the labour force, reduced working hours and lower paying jobs. We examine mothers’ forgone earnings using HILDA 2001 data and find substantial effects, which vary with the woman’s education and number of children. At a middle level of education (completed year 12 only), women forgo around 31 per cent of lifetime potential income for a first child, an additional 13 per cent for a second child, and a further 9 per cent for a third child. More highly educated women lose less proportionally than the less educated, although their dollar amounts of forgone earnings are higher. There is evidence, in comparison with previous studies, that the proportions forgone are falling with time, but more clearly so for women with higher education. We also find that women who delay motherhood maintain slightly more earnings than early childbearers.

1. Introduction
The economic and social role of women in Australia, as in other developed economies, has changed markedly over the past century, and particularly so in the last twenty to thirty years. The most obvious effects are seen in women’s involvement in the paid labour force, with female participation rates rising from 30 per cent in 1970, to 46 per cent in 1985, and to 55 per cent in the most recent ABS figures for 2002 (ABS, 1971, 1995, 2003). It has been observed that the increase in participation is predominantly due to married women and occurs mostly at the childbearing ages (ABS, 1998). There has also been a great deal of change in patterns of childbearing. The total fertility rate rose from 2.1 in 1934 to a high of 3.6 in 1961 (ABS, 1998). It has since fallen to the lowest point in Australia’s history — 1.73 in 2001 (ABS, 2002). Despite these widespread and rapid changes in women’s involvement in the labour force, substantial differences are found by researchers between the earnings of mothers and women without children. This earnings differential is often termed ‘mothers’ forgone earnings’ or the ‘family gap’.

Address for correspondence: Trevor Breusch, Centre for Social Research, The Australian National University, Canberra ACT 0020. Email: Trevor.Breusch@anu.edu.au
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The interplay of paid work and childbearing is a subject of considerable interest to economists, demographers, and others. There are legions of papers in the economics literature that analyse how women’s labour force participation depends on demographic characteristics, such as the number and ages of children in the household. Typically economists estimate the parameters of female labour supply, either with a direct focus on the effects of children, or with conditioning on children as an important factor when the influence of other factors is measured. The range of social policy questions examined in this body of work is very wide, but two of the more familiar issues are the gap between men’s and women’s pay, and the impact of access to organised child care.

Demographers, on the other hand, are concerned with explaining the causes and effects of changing fertility levels and the relationships of birthrates to economic and social conditions. For instance, it is contended that there is an ‘obvious link between fertility and women’s work… working women have fewer children because of the opportunity costs involved’ (Riley, 1998, p.523). In this context, the costs and benefits of having children are of particular interest. The economic costs of children are typically partitioned into direct costs and indirect (or opportunity) costs, (Robinson and Horlacher, 1971). Direct costs include the additional expenditure paid by parents due to having children, such as extra food, clothing, child care, and educational expenses. Estimates of the direct cost of children are typically based on a budget surplus — or basket of goods — approach (e.g., AIFS, 2000).

The most obvious opportunity cost of children for women is the potential earnings that are forgone when time and energy are expended raising children rather than working in a paid job. The primary mechanism is the mother’s time out of the labour force. This effect is most pronounced when the children are very young, when many women cease work for a period. A mother’s labour participation depends on both personal and societal factors, including household composition, age of the youngest child, educational background, ethnicity and partner’s employment (Brannen, 2000). Family-friendly workplaces also contribute to employment of women with young children. Gornick, Meyers and Ross (1998) find that countries with the least-developed policies (including paid maternity leave, paternity benefits and child-care indicators) had very large reductions in employment for mothers of young children, as compared to countries that lead in employment-supporting policies.

Earned income is also forgone by mothers who work shorter hours when their children are young, so they are available to supervise and care for them some of the time, particularly outside school hours and during school vacations. It has been posited that the main way that work and family are negotiated in Australia is by one parent (predominantly the mother) working part-time (Wolcott and Glezer, 1995). Some mothers engage in employment in less time-demanding jobs (such as casual employment) for the duration of the most intensive time of caring for their children, although these jobs are often associated with more limited access to employment benefits and access to family-friendly workplace policies (Smith and Ewer,
Reduced hours work is not limited to while the children are young: many mothers reduce their amount of paid employment to supervise children through high school years and beyond.

Even a temporary period of detachment from the labour force may cause a permanent reduction in the rate of a mother’s earnings. Much of the observed variation in earnings between people and across time can be explained by differences in general education, job-specific training, experience in the workforce, and tenure in the same position (or with the same employer). These measures are usually grouped together as contributions to the person’s human capital, which in turn is interpreted as the productive resource that influences their rewards in employment. Since employment experience is a form of investment, time out of the labour force will imply a reduced accumulation of capital stock (Mincer and Polachek, 1974). In addition to the hiatus in the accumulation of human capital, time out may result in an actual depreciation of the capital as workplace skills are forgotten or lose their relevance (Mincer and Ofek, 1982). These studies underscore the importance of distinguishing between a person’s age and their actual labour market experience: advancing age without addition to experience is a marker of the depreciation of human capital. The age/experience distinction — which is not often possible in empirical studies — is especially important for groups who are not in continuous attachment to the labour market. The impact of a lower stock of human capital is to reduce the wage rate and hence earnings, perhaps for the rest of the person’s working life.

Periods of part-time employment may be detrimental to lifetime earnings beyond the direct effect of working fewer hours. It is argued that workplace culture is geared to the full-time worker model and is inflexible in recognising alternative career trajectories (Starrels, 1992). One study finds that female part-time workers in managerial positions (or with managerial aspirations) recognise they need to engage in full-time employment to achieve promotions (Still, 1996). The rate of accumulation of human capital will be lower than for full-time workers due to less contact with the workplace. Employers and employees alike may be less willing to invest in education and training when the payoff is endangered by weaker workplace or workforce attachment. The wage gap that is often observed between full-time and part-time workers doing the same job for which they appear to be equally qualified may be the result of sorting, in which those who seek less responsible jobs for personal family reasons also want part-time employment. It is also possible that discrimination by employers is revealed by the association of part-time work with low wages (Waldfogel, 1997).

Forgone Earnings in Australia

Beggs and Chapman (1988) examine data from a 1986 survey and make estimates of the earnings forgone over a working lifetime by women who have children. They find that a woman with a child earns considerably less than one who remains childless, in the range 46–58 per cent less in gross income before the deduction of personal income tax. They observe forgone earnings are proportionally less for women at higher levels of education,
although the dollar values of forgone earnings are higher here because the earnings are higher. Correspondingly, the proportion of income forgone is greatest when education is lowest, although the dollar amounts are in fact less at the lower income levels. They find additional effects on lifetime earnings of a second child of another 6–10 per cent of the income of a woman with no children, and another 4–8 per cent for a third child.

Later estimates by Chapman, Dunlop, Gray, Liu and Mitchell (2001) based on data from a 1997 survey suggest a substantial reduction in the amount of forgone earnings due to childbearing from the time of the earlier 1986 survey. In their calculations, the forgone amount for a first child is 31–35 per cent of net earnings after the deduction of income tax, and the additional effects of a second and third child are extra amounts of 1–3 per cent of the earnings of a woman with no children. It is not easy to make direct comparisons of earnings profiles before and after the deduction of personal income tax without re-analysing the unit record data and knowing enough information about the respondents in the survey to calculate their individual liabilities to income tax. However, a second or third child appears to be responsible for very little additional forgone earnings in 1997, unlike the earlier finding of the effects of additional children in the 1986 data. In addition, in the later study there is very little difference in the profiles of forgone earnings reported for women with different levels of education, again in contrast to the earlier Beggs and Chapman (1988) results.

We have recently re-estimated forgone earnings using the 1997 data of Chapman, et al. (2001), using the same approach but correcting some errors in their methods, and we find strikingly different results (Breusch and Gray, 2003). The broad picture of a reduction in forgone earnings between 1986 and 1997 as painted by Chapman, et al. (2001) is sustained on average, but we find second and third children have much more of an impact on forgone earnings than they report. We also find the education level is a more important determinant than they recognise, particularly when multiple children are involved.

The present paper makes new estimates of forgone earnings for mothers using the second release of the first wave of the Household, Income and Labour Dynamics in Australia (HILDA) data. It follows in the pattern set by Beggs and Chapman (1988) and Chapman, et al. (2001), with whom we compare our findings.

While much of this paper is concerned with estimating and simulating forgone earnings comparable to the earlier studies in Australia, we also examine the impact of timing of first birth on forgone earnings. There has been no Australian research on this question, and the related overseas work is sketchy. One line of investigation suggests that women return to work faster after giving birth when they have longer previous continuous employment experience (McLaughlin, 1982; Glass and Riley, 1998). Such attachment to the labour force may reflect the higher productivity of a larger accumulated stock of human capital or be motivated by interpersonal relations, habit, or financial commitments. Life-cycle change (specifically
fertility) is central to the work on lifetime earnings by Calhoun and Espenshade (1988), and they recommend that research on changes in forgone earnings should account for trends in childbearing. Joshi (1990), in the UK, finds a pattern where forgone earnings are higher with early and late timing of first birth.

2. The HILDA Survey
HILDA is a longitudinal survey of Australian households that has been funded by the Commonwealth Government. It investigates life in Australia, focussing on income, labour market, and family dynamics. We use the second release of the Wave 1 data, collected between August 2001 and January 2002. See, Watson and Wooden (2002) for overview.

The survey used four questionnaires, including a household form, a household questionnaire, a person questionnaire for all household members aged 15 years and over, and a self-completion questionnaire. In wave 1, all components were administered by personal interview except for the self-completion questionnaire.

The reference population is all members of private dwellings with some exceptions. A multi-stage approach is used to select households. There are 11,693 in-scope households of which 6,872 (59 per cent) fully-responded and 810 (7 per cent) partially-responded. Of potentially eligible adults in the households involved, 92 per cent of individuals responded (13,969 respondents). A smaller proportion of individuals completed the self-completion questionnaire (87 per cent).

HILDA is generally representative of the Australian population although there are some differences. Sydney residents are somewhat underrepresented, as are males, unmarried persons and immigrants from a non-English-speaking background.

3. Estimation and Prediction Method
We first estimate a model of earnings and then use it to predict the earnings of women similar to those who are observed in the data. The relationship will depend on various measures of the woman’s human capital (education level, experience in the labour force, tenure in the present job), her age, the numbers and ages of her children, and other background variables that might be important. The predictions are used in simulations of the earnings outcomes for a hypothetical working lifetime, under various ‘scenarios’ of educational background and numbers of children. The different scenarios are compared by summing earnings each year over the simulated lifetime. Forgone earnings are calculated for mothers relative to otherwise similar women who remain childless.

These lifetime scenarios are described in more detail below, but for the moment we note there is an estimation problem associated with zero recorded earnings for someone who is not working at all. We want to find the predicted effects of hypothetically changing some of the characteristics on a typical woman from the population, and not just for those women who are observed to be working at the time of the survey. This is a version
of the well-known ‘selectivity’ problem that arises in estimation of female labour supply functions. This issue here can be considered in purely statistical terms: to predict the results of changing conditions we should consider both the shift from not working to working (or vice versa) as well as the changing level of earnings for someone who has the same employment status at all points in the simulation.

**Estimation and Prediction Strategy**

The statistical model we use has the standard form of a Tobit Type II selection (or Heckman) model consisting of two equations, one for earnings and the other for selection into employment, which can be written as follows:

\[ y_i^* = \beta' x_i + \varepsilon_i \]

and

\[ z_i^* = \gamma' x_i + \eta_i \]

where

\[ \begin{bmatrix} \varepsilon_i \\ \eta_i \end{bmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\varepsilon^2 & \rho \sigma_\varepsilon \\ \rho \sigma_\varepsilon & 1 \end{bmatrix} \right) \]

Here \( y_i^* \) and \( z_i^* \) are latent variables, the former representing ‘potential earnings’ (in this case actually the natural logarithm of potential earnings) and the latter representing something like ‘the propensity to be employed’. The indicator that the person is employed is the event \( z_i^* > 0 \). Earnings \( w_i \) is formed by exponentiating log-earnings and it is observed only when the person is employed. The two parts of the model are tied together through the joint error process, which is represented as a bivariate normal distribution in which the correlation is determined by the parameter \( \rho \). For simplicity the explanatory variables \( x_i \) are written the same in both equations, which implies that each of the coefficient vectors \( \beta \) and \( \gamma \) may need some restriction imposed on it for the other coefficient vector to be well identified. See, Verbeek (2000, p. 207) for an exposition of this class of models.

The predictor for actual earnings in this model, for a person in the whole population irrespective of their current employment status, is the expected value of observed earnings given their characteristics, which takes the form (see Appendix for details)

\[ E[w_i | x_i] = E[w_i | x_i, z_i^* > 0] \cdot Pr(z_i^* > 0) + Pr(z_i^* \leq 0) \]

\[ = \exp(\beta' x_i + \sigma_\varepsilon^2/2) \cdot \Phi(\gamma' x_i + \rho \sigma_\varepsilon), \]

where \( \Phi(.) \) is the cumulative distribution function of the standard normal distribution. The first factor of the last line is the prediction of earnings, given that the person is employed. The component \( \sigma_\varepsilon^2/2 \) is a correction that arises because the linear model applies to the log transformed variable and is related to the mean of the log-normal distribution (Verbeek, 2000, p. 49). The second factor is not quite the same as probability of employment, although the difference will vanish if there is no selection effect (i.e. if \( \rho = 0 \)).
Model Specification

The use of earnings as the measured response combines a price (wage rate) and a quantity (hours worked), which might be examined separately in a more elaborate modelling approach. We do not distinguish whether a change in earnings is due to different hours of employment, a different wage rate in the same job, or a switch of jobs to one with a different level of responsibility and consequent remuneration. Neither do we attempt to capture specific features of the woman’s living arrangements or workplace, such as the availability of childcare either informally with relatives or formally in institutions. Similarly we take as given her partnered status and the economic circumstances of her partner. In making this latter restriction, we are missing some of the subtleties of behaviour that is recognised in models that allow interactions in decision making at the family level (as, for example, in Apps and Rees, 2004).

The simplified approach is justified on pragmatic grounds that recognise both the limited purpose of the modelling and the limitations of the information contained in the data. The relationship is essentially a reduced form, since it includes factors that would affect either the supply of, or demand for, the woman’s labour, or possibly both. The simplification is justified because all we require is the conditional prediction of the earnings of a woman with some hypothetical characteristics, not a structural interpretation of her economic behaviour.

In some ways the HILDA data set is rich for the present purpose. There are direct observations on labour market experience, so we do not have to use the inferior construct from age and years of schooling that characterises many early studies of labour demand. We can include both age and experience (and also tenure in the present job) in the model as explanatory factors to represent human capital accumulation and its depreciation, with possibly nonlinear effects, and we can base the decisions of which variables to include in the model and their functional form on empirical evidence. If there is multicollinearity from the inclusion of these related variables, then the precision of the estimates will suffer accordingly and this will be revealed by statistically insignificant estimates. In any case, unless the multicollinearity is perfect, there is not much reason for concern, since all we really want from the model is good predictions, not precise estimates of the partial effects of individual variables. If fact, we achieve both.

Some desirable variables are not available. We have noted the importance of availability and cost of childcare to the decision of a mother to engage in paid work. With a single cross section of data, the information that would be useful is the variation in availability and cost from one family to another in the sample. In HILDA, the questions about availability and cost of childcare are only asked of those families who have used, or thought about using, childcare, and the current use and cost of childcare are only asked of those where both major carers are working. There is no indication why some parents did not consider using childcare (was it because the decision had already been made that the mother would not work?). There is also not much information about the potential cost of childcare to a woman
who is currently not working. To use the childcare information in this data set, the childcare outcome would have to be modelled jointly with the labour market outcome.

As with the threat of multicollinearity, unavailability of useful variables need not be a serious problem, because the requirement is conditional prediction not structural explanation. A more finely grained model might lower the residual error variance and thus permit more precise predictions, but the predictions from a simple model are not invalidated by the absence of relevant covariates. The model used here is justified on the grounds that it captures the major features that explain the variation across women in the amount of their earnings and that is because it is consistent with the received literature on modelling female labour market activity.

4. Definitions and Descriptive Statistics

Summary statistics for the variables used in our analysis are given in the first column of table 1. There are 5,061 women in the estimation sample, of whom 3,270 have current wage and salary income. The minimum number of observations on any one variable is 4,731. Most of the variable names in table 1 are self-explanatory, and details of their construction are given in appendix 2. However, it will be useful to clarify the measurement of income and the concept of family we use.

Income data in HILDA are collected separately for each individual in the household. Questions about income cover a wide range of sources and in some cases reflect current income, while in other cases the questions relate to income gained in the last financial year. The categories available on a current basis are wages and salaries, and government benefits, while the last financial year income categories are wages and salaries, government benefits, pensions or allowances, business income, investment income, and other income. The measure of earnings used in our study is current income from wages and salaries, because that is the measure most appropriately related to the other current information in the survey such as the person’s labour force status and current household composition. However, when we measure other available income, the last financial year values have to be used for income components other than salary and wages of the woman and her partner. Thus, gross personal income in our study is a composite of current wages and salaries, and last financial year benefits and pensions, business income, investment and other income.

Our study uses two variables that represent net, post-tax-and-Medicare, income. The focus variable in the study is the woman’s earnings, which we measure as the addition to the family net income that is derived from her wages and salary. This is the response variable ‘Earnings’. We also use the balance of the post-tax income available to the family, derived from all sources other than her earnings, as a background variable called ‘Other family income’. We take the family for this purpose to be essentially the same as the ‘income unit’ defined by the Australian Bureau of Statistics, consisting of the woman, her partner if any and the dependent children who live in the same household. In calculating the other available income
we neglect any earnings of dependent children (who, following the ABS
definition, are 15 years of age or under, or 16–24 years and in full time
education).

Table 1  Sample Summaries and Marginal Effects

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample Mean</th>
<th>Change or Base</th>
<th>∆ Earnings if Employed</th>
<th>∆ Prob Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings if employed</td>
<td>$22,674</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>64.6%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience</td>
<td>14.1 yrs</td>
<td>+1 year</td>
<td>$610</td>
<td>3.2%</td>
</tr>
<tr>
<td>Tenure</td>
<td>3.5 yrs</td>
<td>+1 year</td>
<td>$460</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>37.8 yrs</td>
<td>+1 year</td>
<td>-$213</td>
<td>-2.8%</td>
</tr>
<tr>
<td>Married</td>
<td>66.7%</td>
<td>not married</td>
<td>$2,732</td>
<td>9.3%</td>
</tr>
<tr>
<td>Degree</td>
<td>21.7%</td>
<td>incomplete</td>
<td>$10,672</td>
<td>29.7%</td>
</tr>
<tr>
<td>Trade</td>
<td>19.9%</td>
<td>incomplete</td>
<td>$3,771</td>
<td>14.6%</td>
</tr>
<tr>
<td>Year 12</td>
<td>22.2%</td>
<td>incomplete</td>
<td>$1,688</td>
<td>14.9%</td>
</tr>
<tr>
<td>NESB</td>
<td>13.7%</td>
<td>not NESB</td>
<td></td>
<td>-13.5%</td>
</tr>
<tr>
<td>Ever had children</td>
<td>69.3%</td>
<td>no children</td>
<td>-$4,252</td>
<td>-0.2%*</td>
</tr>
<tr>
<td>Infant</td>
<td>4.4%</td>
<td>Child &gt;14</td>
<td>-$9,190</td>
<td>-55.3%</td>
</tr>
<tr>
<td>Toddler</td>
<td>10.4%</td>
<td>Child &gt;14</td>
<td>-$8,575</td>
<td>-35.4%</td>
</tr>
<tr>
<td>One older child</td>
<td>15.7%</td>
<td>Child &gt;14</td>
<td>-$7,231</td>
<td>-5.6%</td>
</tr>
<tr>
<td>Two or more older children</td>
<td>20.2%</td>
<td>Child &gt;14</td>
<td>-$9,691</td>
<td>-10.6%</td>
</tr>
<tr>
<td>Other family income</td>
<td>$26,812</td>
<td>+$5k</td>
<td>-$128</td>
<td>-0.7%</td>
</tr>
</tbody>
</table>

* Indicates the underlying coefficient is not statistically significant at 5 per cent.

‘Employed’ means there is a positive record for current wage and salary
income. ‘Experience’ is time in the labour force generally, whereas ‘Tenure’
is time with the current employer. ‘Married’ means partnered, including
couples in cohabiting relationships. The three stated educational categories
‘Degree’, ‘Trade’ and ‘Year 12’ record the highest attained level of education,
and so they are mutually exclusive. A fourth category of incomplete high
school is omitted, and this becomes the base in subsequent comparisons.
The acronym ‘NESB’ stands for non-English speaking background; as noted
by Wooden (1994, p.221–222), such people have lower levels of both labour
force participation and employment.

The children categories are not all mutually exclusive, since there are
separate variables for whether the woman has ‘Ever had children’ and for
the presence of children in the younger age categories. ‘Infant’ means under
one year old, ‘Toddler’ means one to two years, while an ‘older child’ is
aged three to 14. For the children in the three to 14 age group, there are
separate categories for the presence of only one, or two or more children,
so these two categories are mutually exclusive. As an example of the
operation of the children variables, a woman with a baby and one child at
primary school will be recorded in three categories, viz. ‘Ever had children’,
‘Infant’ and ‘One older child’, while a woman whose children are all aged
over 15 will be recorded only for ‘Ever had children’.
5. Estimation Results

The model is estimated by the Heckman maximum likelihood procedure in Stata 7, using the option to calculate robust standard errors by the sandwich method. Detailed estimation results are presented in table 2. Both experience and tenure enter the model as their squares as well as in levels, which permits the effects of these variables to be nonlinear. In an initial version of the model, ‘Age’ was specified to enter in the same nonlinear way, but the higher order term was found to be statistically insignificant in the selection equation. Dividing the squared variables by 100 just scales their coefficients; it is done so that a reasonable number of informative digits can be seen within the fields of the table. Other family income is divided by 1000 for the same purpose. Both equations contain some variables that are not in the other equation, which contributes to identification of the separate equations (although identification is not really an issue when the modelling purpose is conditional prediction). The ‘Tenure’ variable is absent from the selection equation for employment, and the NESB variable only appears in the employment equation.

Table 2  Heckman Tobit II Estimation Results

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Earnings Equation</th>
<th>Selection Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100*log(net earnings)</td>
<td>Pr(employed)</td>
</tr>
<tr>
<td>Experience</td>
<td>5.611</td>
<td>17.48</td>
</tr>
<tr>
<td>Experience^2/100</td>
<td>-9.308</td>
<td>-5.24</td>
</tr>
<tr>
<td>Tenure</td>
<td>2.907</td>
<td>6.21</td>
</tr>
<tr>
<td>Tenure^2/100</td>
<td>-7.538</td>
<td>-3.92</td>
</tr>
<tr>
<td>Age</td>
<td>3.582</td>
<td>2.60</td>
</tr>
<tr>
<td>Age^2/100</td>
<td>-6.166</td>
<td>-3.59</td>
</tr>
<tr>
<td>Married</td>
<td>14.84</td>
<td>4.86</td>
</tr>
<tr>
<td>Degree</td>
<td>51.62</td>
<td>16.50</td>
</tr>
<tr>
<td>Trade</td>
<td>21.41</td>
<td>6.57</td>
</tr>
<tr>
<td>Year 12</td>
<td>10.16</td>
<td>3.12</td>
</tr>
<tr>
<td>Ever had children</td>
<td>-19.13</td>
<td>-4.32</td>
</tr>
<tr>
<td>Infant</td>
<td>-28.07</td>
<td>-2.21</td>
</tr>
<tr>
<td>Toddler</td>
<td>-24.12</td>
<td>-4.31</td>
</tr>
<tr>
<td>One older child</td>
<td>-15.98</td>
<td>-4.01</td>
</tr>
<tr>
<td>Two or more older children</td>
<td>-31.42</td>
<td>-7.82</td>
</tr>
<tr>
<td>Other family income/1000</td>
<td>-0.1358</td>
<td>-2.53</td>
</tr>
<tr>
<td>NESB</td>
<td>-0.3583</td>
<td>-5.74</td>
</tr>
<tr>
<td>Constant</td>
<td>871.7</td>
<td>41.26</td>
</tr>
<tr>
<td>Rho</td>
<td>0.0204</td>
<td>0.83</td>
</tr>
<tr>
<td>Sigma</td>
<td>58.47</td>
<td>Censored</td>
</tr>
<tr>
<td>Lambda</td>
<td>-1.193</td>
<td>Uncensored</td>
</tr>
</tbody>
</table>

It is difficult to interpret many of the coefficients in the estimation equations because of the nonlinear effects of some variables. A more accessible summary of the results is given in table 1, which presents the marginal effects of the individual variables, holding all the other variables constant. These effects are measured separately for impact on potential earnings
(which is the same as actual earnings for someone who is employed throughout) and on the probability of being employed. In the case of a continuous variable (such as experience) the effect is measured by incrementing the variable by one unit (one year in this case) from just below the sample mean to just above the sample mean (thus from 14 to 15 years in this case) while holding all other variables at their sample mean values. The one exception is ‘Other family income’ where the measured impact is so small that the effect of a $5,000 increase is reported.

With the binary dummy variables, the marginal effects of a change in category from the base is calculated for both potential earnings and the probability of employment. For the three educational variables the base is incomplete high school, while for the four variables representing the presence of younger children the base is a child who is older than 14. As a ready reference, the central column of table 1 indicates the change that is measured in the marginal effect (for a continuous variable) or the base for the discrete change of state (for a binary dummy variable).

There are few surprises in the estimated marginal effects presented in the last two columns of table 1. Experience and tenure have effects that are positive with plausible magnitudes in both equations. Age has a negative effect in both equations: in the employment equation a year of age almost reverses the effect of a year of experience, but on earnings a year of age reverses only a third of the effect of a year of experience. With a single cross-section of data it is impossible to separate a true effect of aging of the individual (namely depreciation of human capital) from a cohort effect that summarises a whole bundle of social factors, so not too much weight should be put on the interpretation of the age effect.

The education variables have effects that might be expected (presumably they are mostly demand effects but the same variables may influence labour supply as well). Higher education raises both earnings and the probability of employment, and both of these effects increase with increasing educational attainment. Trade qualifications has much the same effect on employment prospects as does completion of year 12, but gives more than twice as much boost to the earnings of someone who is employed. The additional returns to having a degree are very high, indeed, representing nearly 30 per cent higher chance of being in a job and $10,700 extra net earnings for those who are employed, relative to someone who did not complete high school.

The effects of children are also as we might expect. The permanent effect of ever having children on the chances of employment is small and statistically insignificant. Younger children keep women out of paid employment, with an effect that is consistently stronger the younger the child. A woman with an infant is estimated to be less than half as likely to work than an otherwise similar woman whose children are all over 14. Two or more children in the age group three to 14 have almost twice the impact on employment of a single child in the same age range.
The age of children has a less varied effect on the earnings of those who are employed. There is a permanent reduction in earnings of around $4,250 from ever having a child. It is hard to attribute this effect without a more detailed structure to the model, although it may simply indicate lost human capital from periods out of the workforce and imperfections in our measurement of human capital through education, experience and tenure, etc. There is an additional $7,200–9,700 depression in the earnings of an employed woman when a child is under 15, which varies only slightly with the ages of children or with the number of children three to 14. The measured effects are estimated to be stronger when the child is younger and when there are more children, but the differences are small enough to be statistically insignificant. However, the effects that are modelled are additive, so having both an infant and a toddler, or one of these and an older child, will imply around twice the effect of one child on its own. The impact of younger children on the earnings of the employed is presumably a supply effect of the woman choosing to work fewer hours or in a less demanding job so she can care for the younger children, although it may also indicate reduced demand for the services of a worker whose human capital is slipping.

We find a positive marriage (actually partnering) premium, both in the probability of employment and in the earnings of those who are employed. The boost to employment chance of 9.3 percentage points is perhaps not large in comparison to the effects of higher education or of having young children, but it is approximately the same size (although opposite in direction) as the effect of children in the three to 14 age range. The direct impact of being partnered on the earnings of the employed is also positive, and while it is less in magnitude than (say) the return to trade qualifications relative to incomplete high school, it is more than the boost than comes from only completing year 12.

NESB depresses the probability of being employed by 13.5 percentage points, which is of similar magnitude to having a trade qualification or completing year 12 (but in the other direction). Surprisingly, perhaps, while other family income has effects in the expected direction the effects are very small indeed. An additional $5,000 of family income reduces the probability of employment by only 0.7 percentage points, and the direct effect of extra family income on earnings of a woman who remains employed is trivially small.

6. Simulation Method
The Wave 1 HILDA data are limited to a single cross-section record of a number of women with different characteristics, who are observed at (more or less) the same point in time. If we want to know about the lifetime effects that result from certain changes in their circumstances (such as having a child), we have to engage in a hypothetical construction of how the outcomes are different in different circumstances, and how those outcomes change across time. So, for instance, the effect of the woman aging or accumulating workforce experience across a lifetime has to be inferred from the observed behaviour of other women in the sample who have different ages or experience levels, controlling where possible for other differences in their
characteristics. Estimation allows the effects of the different characteristics to be measured; simulation is used to construct lifetime earnings for some illustrative cases. We are particularly interested in comparing women who differ in their childbearing experience, using the estimated model to calibrate the simulations. These simulations are of necessity somewhat artificial and do not represent any particular person in the sample, but nonetheless they serve to describe in a clear and readily understood way the expected outcomes under different scenarios.

Our method of simulation is chosen to be comparable with the approach of Chapman, et al. (2001) and Breusch and Gray (2003). We stratify by three levels of education (degree, year 12 and incomplete high school) and four levels of fertility (no child, one child, two or three children over a lifetime). The woman is allowed to age over her mature working lifetime, which following the earlier work is taken to range from ages 23 to 59. She is assumed to accumulate work experience as she ages, in a way that is described in detail below. Apart from experience, the other variables (marital status, tenure, English-speaking background, and other family income) are set to their sample averages. In the basic simulations, the woman is assumed to have her first child (if she has any) at age 25, a second (if she has one) two years later and a third (if any) two years after that. Later we consider the impacts of a later age of mother at first birth.

Experience might be expected to be lower initially for a woman who has spent more years in education, and then to accumulate at a rate that is directly proportional to the extent of her employment, perhaps moderated by the intensity of that employment. We construct an experience profile as follows. We assume the hypothetical woman acquires an amount of experience in a year that is exactly equal to the probability she is working in that year. Thus a woman with several young children and little education, who on our figures would be predicted to have little chance of being employed, will add correspondingly little to her working experience. On the other hand, one who has no children and a degree, and so is highly likely to be working, will acquire almost a full year of additional experience as she becomes a year older. The initial experience at age 23 for women in each educational category is calculated as the number of years since the assumed completion of education (at ages 21, 18 and 15 for the three levels) multiplied by the average employment rates in the sample for women under age 25 with that level of education.

7. Simulation Results
Simulated lifetime earnings profiles are shown in figure 1 for a woman of the middle education level (completed year 12). These profiles show the predicted net earnings of a woman across her working lifetime, under the four different assumptions of fertility. The heavy solid line at the top is the

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1 Holding tenure constant over a woman’s lifetime in the simulations may not be entirely convincing, but here we follow the earlier research. Tenure is expected to rise with age and experience (which are themselves related). These latter variables are both included in the simulations, so it is just the marginal effect of tenure that is held constant for everybody while the other changes over a working life are simulated.
outcome for a woman who never has children. This curve rises and falls under the combined influence of the woman’s age and experience, according to the parameters of the estimated model and the assumptions that are made in the simulations about the accumulation of experience with age. It can be seen from the estimated coefficients in table 2 that experience is a positive factor initially for both earnings if employed and for employment. However, with the negative coefficients on the squared experience variable, any additional experience brings diminishing effects as experience accumulates. Theoretically, the effect of experience eventually reaches a maximum, after which any further addition to experience has an impact on earnings that is negative. The maximum contribution of experience to earnings if employed occurs at around 30 years of experience, and the maximum of the probability of being employed occurs at 36 years of experience. These are quite large amounts of experience. The former is achieved in the simulations only by women with a lifetime of nearly certain continuous work, and the latter is more than is accumulated by anyone in the simulations. On the other hand, the effect of age on earnings of the employed is negative for most of the woman’s lifetime: the maximum effect is attained at age 29, after which age is an increasingly negative factor. Age is similarly negative in the equation for the probability of employment, although here the effect is linear because the quadratic term has been dropped. The curved shape of the earnings profile is partly due to the positive but diminishing effect of experience and partly due to the mostly negative effects of age in the estimation model. The maximum of the combined effects of experience and age for a median woman with no children can be seen in figure 1 to occur when she is aged 43.

Figure 1  Lifetime Earnings Profiles, by Number of Children Women Completed Year 12 Only

It is also seen in figure 1 that children have a substantial impact on a woman’s earnings. The effects of children are estimated in four age groups, hence there are steps in the earnings profiles for mothers as their children move in and
out of the various age groups. The impact of additional children over the whole lifetime is shown in the shifts down in the profile. By inspection of figure 1, the shifts as children are added to the scenario appear to be progressively smaller in absolute value, although the relative effects of a second or third child are not so clear in the figure. It can also be seen that earnings are very low at a time when a woman has multiple very young children, which occurs mainly because she is very unlikely to be working. The gaps between the curves are closing as the woman ages beyond when her children are young, due to the diminishing marginal effect of higher levels of experience, although there will always be a gap between the top curve and the others due to the permanent effect of the variable ‘Ever had children’.

It is debatable how best to summarise and compare this kind of information. It is easy to calculate the total dollar amounts over the lifetime, and we do provide a few illustrative calculations for interest. However, while the enormous dollar amounts of lifetime earnings aggregated over more than 30 years make for eye-catching media headlines, we fear they are widely misunderstood. We prefer to give comparisons of a mother’s earnings with a woman who is otherwise similar but who has no children, expressed as a percentage of the earnings maintained or forgone. Percentage calculations are more robust than aggregate dollar amounts because they are less sensitive to small changes in the methodology of the simulations. Especially when it comes to making comparisons between our study and others, it would be unwise to compare anything other than percentages.

Another point of debate is the application of a discount rate to the stream of earnings at different ages over a lifetime, with the objective of making the dollar values comparable at the one point in time. Beggs and Chapman (1989) and Chapman, et al. (2001) variously calculate net present values and net future values at rates of five and eight per cent, and also give simple undiscounted lifetime aggregates. The calculation of a net present value might be appropriate if we were modelling a decision maker standing at the beginning of her working and childbearing life and making choices, but to sustain that view would take more analytical structure than the literature provides. We might just as easily portray the woman at the end of her life measuring the regret in dollar values that are current to her at that time. Of course, if the forgone earnings were in a constant proportion at all stages in the lifecycle, then reporting only percentage comparisons would remove the effects of time preference or changing dollar values. However, it is implicit in the scenarios (as in real life) that fertility has greater impact on earnings at certain ages, so discounting would make some difference to reported results. Nevertheless, without a firm basis for giving present or future values, we report simple lifetime aggregates.

The results of our simulations are presented in the most right hand column of table 3. We have chosen to present the results as maintained earnings not forgone earnings, because this facilitates different comparisons that may interest the reader. For comparison, we have included some results from the Family Formation Survey 1986 reported by Beggs and Chapman (1989) and other results from the Negotiating the Lifecourse (NLC) study 1997 that were first reported by Chapman, et al. (2001). The NLC comparison figures in table 3 are taken from the re-examination of NLC data by Breusch and Gray (2003).
Table 3  Maintained Earnings, by Education Level and Number of Children

Degree

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<td>60</td>
<td>73</td>
<td>72</td>
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<tr>
<td>2 children</td>
<td>44</td>
<td>49</td>
<td>59</td>
<td>62</td>
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<tr>
<td>3 children</td>
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<td>42</td>
<td>48</td>
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Completed Year 12

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<td>52</td>
<td>72</td>
<td>69</td>
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<tr>
<td>3 children</td>
<td>34</td>
<td>39</td>
<td>45</td>
<td>47</td>
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Incomplete High School

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<td>68</td>
<td>60</td>
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<tr>
<td>2 children</td>
<td>36</td>
<td>41</td>
<td>50</td>
<td>42</td>
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<tr>
<td>3 children</td>
<td>32</td>
<td>37</td>
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The first conclusion in comparing the results in the right hand two columns of table 3 is that the maintained (or forgone) earnings in percentage terms are very similar between HILDA and NLC for women of middle education level (completed year 12) who have the average number of children (in our estimation sample the average is 1.7). Maintained earnings in both cases are of the order of 55–60 per cent, or putting it the other way round the forgone earnings is 40–45 per cent. Looking at the effects of numbers of children for a mother at middling education level, we find forgone earnings are around 30 per cent of the earnings of a childless woman for the first child, nearly half that again for the second child and another nine per cent for the third child. This is a slightly larger impact for the first child than we measure in the NLC data, and slightly smaller effects of a second and third child, but the differences are minor indeed.

A common finding in all the previous studies is that women with higher levels of education lose less of their earnings in proportional terms due to motherhood than women at lower levels of education. That finding is repeated here. In fact, the differences due to education level are even more

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2 It should be remembered these numbers are estimates that are subject to some uncertainty. The standard errors of the estimation model are small, so its predictions will be quite precise—especially around the sample mean. There is also variability coming from the simulations where various setup decisions have been made, which if made differently would produce slightly different numbers.

3 Chapman, et al. (2001) report the the additional effects of second and third children as 1.7–2.4 per cent of the earnings of a childless woman (using the zero discount rate). These amounts are erroneously (and implausibly) too small, as we show in Breusch and Gray (2003).
marked in the HILDA data than have been reported in previous Australian studies. For illustration, consider a woman with two children as we compare the three blocks of table 3. At middling education the maintained earnings are the same between NLC and HILDA at 56 per cent. But if we look at the upper block for degree level education, we see that 59 per cent is maintained in the NLC versus 62 per cent for HILDA. And at the lowest educational level the contrast is stronger and reversed: 50 per cent maintained in the NLC data versus only 42 per cent in the HILDA data. The gradient of maintained earnings with respect to education is clearly positive and seems to be getting steeper over time.

It is interesting to attempt a longer-run comparison of our findings with the 1986 data examined in the Beggs and Chapman (1989) study. Percentages calculated directly from that paper for maintained lifetime earnings in the three educational categories (at zero discount rate) are given in the first column of numbers from the left in table 3. There are several difficulties to be faced in comparing these results with the later studies. The changing dollar values between the times of the different studies is not a problem because it is accounted for by our use of percentage comparisons. However, the meaning of a ‘lifetime’ is different, because in Beggs and Chapman (1989) it ranges from 20 years to 60 years, not 23–59 years as in all the other studies reported here. Here, too, our emphasis on percentages will moderate the effects of the different working lives, but it will not remove the incompatibility because the additional years are mostly before children have an impact on simulated earnings. The biggest impediment to meaningful comparison is the earlier focus on gross (pre-income tax) earnings rather than net (post-income tax) earnings of the later studies. Beggs and Chapman (1989) indicate in a footnote they do not have enough information to make individual adjustments of gross earnings to net earnings.

In an attempt to adjust the earliest results to make them (more) comparable to the later ones we make a correction for the effects of income tax. We present an estimate of the percentage maintained net earnings in the second column of numbers from the left of table 3. As expected, the extent of maintained earnings is higher, or equivalently the forgone earnings are lower, when the moderating effect of a progressive income tax regime is accounted for. The procedure we use is to estimate the income tax bill of a person who has taxable income equal to the 1986 percentages of the expected pre-tax earnings of a woman with no children. These calculations are done with 1997 income levels and tax scales (as a matter of convenience), which implies an assumption of constant real tax scales. The biggest problem with the method is that it applies a progressive tax scale to an average (across different people and across years of a lifetime), so it almost certainly underestimates the average tax take. The possibility of other unearned income that would push earnings into a higher tax bracket also points to this being an underestimate of the effect of income tax. The effect of this adjustment is to estimate that the woman in every child-bearing scenario retains an additional four to five per cent of the net earnings of a childless woman in the same educational group. For the reasons given earlier, this adjustment is probably too modest.
The overall picture is an increase in maintained earnings, or equivalently a reduction in forgone earnings, since the 1986 data collection. The changes over time are most marked for a first child and at the highest educational level, where women are estimated to increase their lifetime earnings from 1986 to 2001 by 12 per cent of the earnings of a woman with no children. To put the same calculation differently, the proportion of earnings forgone by mothers in the latest estimates is nearly one-third lower in the 2001 data, than was found in the 1986 data. This direction of change applies at all levels of education and fertility, except for women in the lowest educational group who have multiple children. In these latter cases, maintained earnings as a proportion of the earnings of a childless woman have stayed the same or fallen. This finding that women with little education and multiple children have moved in the reverse direction to others will be amplified by the extent that we have understated the effect of income tax adjustments on the Beggs and Chapman (1989) figures.

Our results are all quite robust to the model specification we have adopted. Some of the decisions, such as dropping the quadratic age term from the employment equation, have no effect at all on the percentages of forgone earnings, since the coefficient of this variable if included is small and statistically insignificant. Dropping the quadratic age term in the employment equation — which is larger and clearly significant — does have quite substantial effects on the remaining coefficients of age and experience, but the predictions from the model are almost identical, and the lifetime simulations remain the same as those we report. The findings of this paper are robust to even major changes in the specification of the model: in other versions of the model we included attitudinal variables in the manner of Chapman, et al. (2001) and Breusch and Gray (2003), but the difference in the simulated forgone earnings due to respecification of the model is at most two percentage points throughout.

To interpret the dollar amounts that underlie the reported percentages, recall the calculation is for 37 years of a working lifetime from ages 23 to 59. For the woman with middle level educational attainment in our simulations, the expected lifetime earnings without children is $788,000. With one child the amount falls to $541,000, or an amount forgone of $247,000. A second child corresponds to an additional forgone amount of $103,000, and a third child an additional $70,000.

8. Age at First Birth
One assumption in all the scenarios of the previous section is that the first child is born when the woman is 25 years of age. In this section we explore the consequences of varying that assumption from 25 to 30 and 35 years. There are two opposing forces working to change the lifetime forgone earnings when motherhood is delayed. We have seen that the combined effects of age and experience cause earnings to rise with age up to a maximum (at age 43 in the simulations in the case of a woman with no children and middle level education) and then decline. By having a child later, at say age 35 instead of 25, the woman is absent from the paid workforce or working reduced hours at the ages when her earnings would
have been at their highest. The impact of child rearing on her rate of earnings will be greater if she is doing it mid-30s to mid-40s when her earnings would have been higher, compared to a decade earlier in her life.

On the other hand, delayed motherhood has two implications that reduce the impact on lifetime earnings. One is simply that the woman is a mother for less of her otherwise working life (taken in the simulations to extend to the fixed age of 59). The estimation model allows for a permanent impact of motherhood on earnings through the variable ‘Ever had children’. This effect is estimated to be negative and of moderate size, and that is what accounts for the gap between the earnings of mothers and childless women at the upper ages in the simulations of figure 1. By having a child at 35 instead of 25 she has a decade less of this permanent impact.

The other issue is attachment to the work force. The experience of working adds to the chances that a woman will be working in any given circumstances, at least up to early middle age in our simulations. There is possibly also an attachment mechanism operating in the estimated effect of experience on the earnings outcome of someone who is employed (presumably through her working more hours or at a higher rate of pay in a more responsible job, although our model does not distinguish). The result is that if we simulate two women who are otherwise identical except for their ages when they have a child, we will predict that the older woman with more work experience is less likely to stop work, will return to work faster and suffer less of a negative impact on her earnings.

**Figure 2. Lifetime Earnings Profiles by Mother’s Age at Birth Women Completed Year 12 Only**

These effects can be seen in the lifetime earnings profiles of figure 2, again for a woman of middle level education. The upper heavy solid curve is the case of a childless woman, and is the same as the corresponding curve in figure 1. The lighter solid line represents the earnings profile for a woman
who has a child at age 25. Again this line is the same as in figure 1. The other two lines in figure 2 represent the profiles of women who have their children at ages 30 and 35, and are easily distinguished by the ages of onset of the forgone earnings. As we have already noted, the size of the drop in the earnings profile related to having a very young child is seen to be greater when it occurs at 35 rather than 25. The effect of attachment we described earlier can also be seen in the higher profile in the middle 30s of a woman who had her child at 30 rather than 25, and in the lower 40s of one who had her child at 35 rather than 30. But evidently in figure 2 the dominant impact of delayed age of first birth is the reduced portion of the working lifetime that is affected by the impact of motherhood on earnings.

We noted earlier for a woman with middle level education and one child born when the woman is aged 25, the maintained lifetime earnings is 69 per cent of that of an otherwise similar woman who remains childless. If the birth occurs when the mother is aged 30, the maintained proportion rises to 72 per cent, and when the mother’s age is 35 it rises further to 76 per cent. While these are not large differences, in comparison to the effect of the mother’s level of education, or even the impacts of second or third children, they do represent substantial dollar amounts. Each one per cent of the estimated lifetime earnings of such a woman with no children is around $8,000.4

9. Conclusion

Women’s participation in paid employment has increased markedly in recent decades. At the same time there has been a dramatic decrease in the total fertility rate and changes in the patterns of childbearing in relation to the mother’s age and level of education. In this paper we use the data in the first wave of the HILDA survey to make new estimates of the earnings that women forgo when they have children. We calculate the hypothetical earnings over a complete lifetime by the use of simulations that are calibrated from the parameters of a fitted model. The scenarios describe different combinations of the woman’s childbearing history and her education level.

We find that women of middling education forgo around 31 per cent of their potential income for a first child, an additional 13 per cent for a second child, and a further nine per cent for a third child. We consider these percentage calculations to be more robust than the actual dollar amounts, but for the record the dollar estimates are $247,000 for a first child, an additional $103,000 for a second child, and a further $70,000 for a third child.

The percentages of income forgone are all found to be lower for highly educated women, where a woman with a university degree and two children manages to forgo less than 40 per cent of the lifetime earnings of a childless

4 The question may be more interesting for highly educated women. We find a similar pattern, with each delay of five years in the timing of birth reducing the mother’s forgone earnings by additional amounts of around 3 per cent of the earnings of a childless woman who is otherwise similar. Highly educated women have less to gain from delayed motherhood (in percentage terms) because they maintain more of their potential earnings, anyway.
woman with the same education. The picture is reversed for lesser educated women, where forgone earnings are all high in percentage terms relative to the potential. A woman with two children is estimated to forgo nearly 60 per cent of the lifetime earnings of a childless woman who has the same incomplete high school education.

We also examine the impact on earnings of the age at which the woman has a child. We find that forgone earnings are less when the birth occurs later, but the differences are not great. With a single child in a lifetime, only three to four per cent more of potential lifetime earnings flows from delaying childbearing by five years.

Appendix 1
Derivation of the Prediction Formula
Consider the model of section 3, which consists of one equation for the logarithm of potential earnings \( y_i^* \) (which is the log of actual earnings for those who are employed) and another equation for the employment status. Recall \( z_i^+ > 0 \) is the event the person is employed and hence the condition that actual earnings is observed. The standard and familiar result from the literature on incidental truncation in a Tobit Type II model is the prediction (or regression) of the dependent variable in the subset of the population for whom it is observed, viz.

\[
E[y_i^* | x_i, z_i^+ > 0] = \beta' x_i + \rho \sigma \lambda(y' x_i)
\]

where \( \lambda(u) = \phi(u)/\Phi(u) \) and where \( \phi(.) \) and \( \Phi(.) \) are the standard normal density function and cumulative distribution function, respectively (e.g., Verbeek (2000, p.208)). However this is not what is wanted for our predictions, both because it predicts log earnings not earnings, and because it applies only to the subset of the population who are employed. The result we want is \( E\{w | x\} \) where \( w \) is actual earnings,

\[
w_i = \begin{cases} 
\exp(y_i^*) & \text{if } z_i^+ > 0 \\
0 & \text{otherwise .}
\end{cases}
\]

Now consider a variable \( u \) distributed as \( N(\mu, \sigma^2) \). A standard result from the log-normal distribution that appears when predicting from a log-linear model (see, e.g., Verbeek, p.49) is

\[
E\{\exp(au)\} = \exp[\mu a + a^2 \sigma^2/2]
\]

Write the density function of \( u \) as \( f(u) \), so the density function of \( u \) given \( u > 0 \) is \( f(u)/\Pr(u > 0) \) for \( 0 < u < \infty \). It follows for any constant \( a \) that
where the second line is obtained by completing the square in the exponent and collecting terms. Notice the first factor in the last line is the expectation without the restriction to \( u > 0 \).

Now we deal with the case of incidental truncation. To simplify notation, the conditioning on \( x_i \) will not be shown explicitly. Define, \( h = y_i^* - \rho \sigma_i \), which is distributed as \( \mathcal{N}(\mu_h, \sigma_h^2) \), where \( \mu_h = \beta'x_i - \rho \sigma_i \gamma'x_i \) and \( \sigma_h^2 = \sigma_e^2(1 - \rho^2) \). Note that is distributed independently of \( z_i^* \), so we may write

\[
E\left[ \exp(y_i^*) \middle| z_i^* > 0 \right] = E\left[ \exp(h + \rho \sigma_i z_i^*) \middle| z_i^* > 0 \right] \\
= E\left[ \exp(h) \right] E\left[ \exp(\rho \sigma_i z_i^*) \middle| z_i^* > 0 \right] \\
= \exp\left( \mu_h + \sigma_h^2/2 \right) \exp\left( \rho \sigma_i \gamma'x_i + \mu^o \sigma_i^2/2 \right) \frac{Pr(z_i^* > -\rho \sigma_i)}{Pr(z_i^* > 0)} \\
= \exp\left( \beta'x_i + \sigma_i^2/2 \right) \frac{Pr(z_i^* > -\rho \sigma_i)}{Pr(z_i^* > 0)} .
\]

Then we have for the prediction of actual earnings \( w_i \) given the characteristics \( x_i \),

\[
E[w_i \mid x_i] = E\left[ \exp(y_i^*) \middle| z_i^* > 0 \right] \cdot Pr(z_i^* > 0) + 0. Pr(z_i^* \leq 0) \\
= \exp\left( \beta'x_i + \sigma_i^2/2 \right) \cdot Pr(z_i^* > -\rho \sigma_i) \\
= \exp\left( \beta'x_i + \sigma_i^2/2 \right) \cdot \Phi(\gamma'x_i + \rho \sigma_i).
\]

This is the prediction formula given in the text.
Appendix 2

Construction of Variables

Earnings
Definition: Addition to family net income from the woman’s earnings.

Construction: Based on HILDA variable AWSCEI for current wages and salary and ATIFEFP/N for financial year total income including impuations but excluding windfalls. Calculated jointly with ‘Other family income’, which is described below. Family income is the sum of the incomes of the woman and her spouse, ignoring any separate income of dependent children. A synthetic income measure is constructed for all adults from current wages and salary and financial year other income. Income tax and Medicare liabilities are calculated by the schedules for 2000-01, taking into account family structure and taxable incomes, with allowance for non-taxable income components and for the tax offsets available to low income and aged persons. The calculation of net family income from gross is done twice: once for the stated incomes and once excluding the woman’s wages and salary. The difference between the two values is the addition to family net income from the woman’s earnings.

Other Family Income
Definition: Net family income, derived from sources other than the woman’s earnings.

Construction: Calculated by the second pass described under ‘Earnings’ above.

Employed
Definition: Binary (1,0) dummy whether person is employed or not.

Construction: Coded ‘Employed’ = 1 when respondent receives a current wage or salary, AWSCEI>0.

Experience
Definition: Reported years of labour market experience since leaving full-time education.

Construction: Using variables AEHTJBYR and AEHTJBMT, experience is years in paid work, or the proportion of a year worked if the respondent is employed for less than a year since leaving full-time education.

Tenure
Definition: Years of tenure with current employer.

Construction: Based on variables AJBEMLYR and AJBEMLWK. Tenure is the number of years with the current employer, or the proportion of a year employed if the respondent is with that employer for less than a year. Set to zero for respondents who are not employed.
Age
Definition: Age in years.

Construction: Uses variable AHGAGE.

Married
Definition: Binary (1,0) dummy, where the classification of ‘married’ includes respondents in cohabiting relationships.

Construction: Based on HILDA derived variable AMRCURR, where ‘legally married’ and ‘de facto’ are classified as ‘married’, else not married. Coded so ‘Married’ = 1 if married.

Education
Definition: Highest level education achieved is coded as three binary (0,1) dummy variables (Degree, Trade, Year 12). The base for all three variables is incomplete secondary education.

Construction: These variables are coded using the derived variable AEDHIGH ‘Highest education level achieved’. Respondents are classified ‘Degree’ = 1 for a bachelor degree or higher; ‘Trade’ = 1 for an advanced diploma, diploma or certificate III+; or ‘Year 12’ = 1 for certificate I or II, or for completed Year 12. Classified as completed Year 12 for this purpose if AEDHIGH is ‘Certificate not defined’ and AEDHISTS is ‘completed or is currently attending Year 12 or equivalent’.

NESB
Definition: Binary (1,0) dummy variable for non-English-speaking background (NESB) or not.

Construction: NESB is based on AANENGF ‘Is English the first language you learned to speak as a child’. Respondents who answered ‘No’ are classified as ‘NESB’ = 1. We note that this question is not asked of respondents born in Australia although they may come from a non-English-speaking family.

Ever Had Children
Definition: Binary (1,0) dummy variable for whether respondent has ever had a child (that is, ever fathered/given birth to/adopted) or not.

Construction: Coded as 1 when positive ‘Total children ever had’, ATCHAD> 0.

Ages of Children
Definition: Ages of children who live with the respondent more than half the time are coded as four binary (1,0) dummy variables (Infant, Toddler, One older child, Two or more older children). ‘Infant’ is a child or children aged less than one year. ‘Toddler’ is a child or children aged one or two. ‘One older child’ refers to one child aged three to 14, while ‘Two or more older children’ indicates two or more children aged three to 14.
Construction: The four dummy variables are created using the ARCAGE (1 to 13) series of variables. They are coded as 1 when there is a child or children in the stated age category.

References


