A re-estimation of mothers' forgone earnings using Negotiating the Life Course (NLC) data

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1. Introduction

The first wave of the Negotiating the Lifecourse dataset (NLC 1997) was used to obtain estimates of the earnings that women forgo due to having children. The main published work is Chapman, Dunlop, Gray, Liu and Mitchell (2001) in the *Australian Economic Review*, hereafter referred to as CDGLM. A summary of the main CDGLM results, together with further interpretation and discussion, is also reported in *Family Matters* by Gray and Chapman (2001).

These papers make direct comparisons of their findings with earlier work by Beggs and Chapman (1988), who examine a 1986 dataset and find that women with children earn considerably less over a lifetime than women without children. Beggs and Chapman also find large additional effects on lifetime earnings of second and third children. Further, they observe that forgone earnings in 1986 are proportionally less for women at higher levels of education.

The main impact of the CDGLM study is their calculation of much smaller amounts of forgone earnings due to childbearing in 1997 compared to the earlier Beggs and Chapman results. The 'headline' comparison featured in the 2001 papers (and in the media reports at the time) refers to the aggregate lifetime earnings of a woman with middling education, defined as completion of high school only. Allowing for the change in the value of the dollar between 1986 and 1997, the forgone earnings of such a woman over her working life is found to drop from $435,000 in 1986 to $160,000 in 1997, with both measured in 1997 dollar values. Second, and perhaps surprising from casual observation, a second or third child appears to be responsible for very little additional forgone earnings in 1997, unlike the earlier finding of strong effects of additional children in the 1986 data. CDGLM also report finding very little difference in the profiles of

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[1] We began this investigation as preparation for an estimation of forgone earnings using the Household, Income, and Labour Dynamics in Australia (HILDA) survey of 2001. We were unable to replicate the results of Chapman, Dunlop, Gray, Liu and Mitchell (2001) who used the NLC 1997 data. This paper is a documentation of our enquiry into the earlier research. Much thanks to Bruce Chapman and Matthew Gray for their investigative help.

[2] *forgo*/*forego*. The New Shorter Oxford English Dictionary lists *forgo* as meaning 'to abstain, forfeit or renounce' and *forego* meaning 'to precede in place or time' as in the expression 'foregone conclusion'. The first sense is clearly intended in this context, so the spelling is *forgone*. However, in the non-prescriptive manner of modern lexicography, the NSOED also reports *foregone* being used as an alternative spelling.

forgone earnings for women with different levels of education, again in contrast to the earlier Beggs and Chapman results. These findings have generated considerable interest from researchers, the media and policy makers. The authors of the later works attribute these apparently profound differences in women's behaviour to 'the significant increase over the past ten years in the labour force participation of mothers, particularly those with young children' (CDGLM, p.384).

The purpose of the present paper is to re-examine the CDGLM findings using the same NLC 1997 data and to investigate the apparent decline in mothers' forgone earnings between 1986 and 1997. Our research indicates that all three headline features of the CDGLM results are unsustainable: we find the extent of forgone earnings is greater, the further effect of second and third children is much larger, and the relationship of forgone earnings to the woman's educational background is stronger than in their published reports. The reasons for the weak findings in the previous studies are fully documented in this paper.[3]

2. Replicating the 2001 descriptive statistics

We note at the outset that we have been unable to exactly replicate the CDGLM model estimates as reported in their *Tables 3, 5 and A2*.[4] This failure occurs despite the generous assistance of the authors who supplied us with advice, intermediate data files and segments of Stata code. Researchers who are modelling complex survey data like NLC 1997 have to make many decisions about the precise definitions of variables and the treatment of individual cases where the survey data are ambiguous or contradictory. These decisions usually have only a minor impact on the main results, but without a precise and extensive documentation of every step taken in processing the data it is usually impossible to replicate other researcher's results exactly. So it is in this case.

We have managed to replicate many of the summary statistics in CDGLM *Table A1*, to the number of digits presented in that table. In some cases we find that the definitions of created variables provided in *Appendix 1* do not match the summary statistics. After investigation, we

[3] The calculations in this paper are documented in two files that are available on request. The estimation file is in Stata '.do' format and documents all of the inclusion decisions, summary statistics and estimation results. The simulation file is in Microsoft Excel format.

[4] We adopt the convention of using italics for section numbers, table numbers and page numbers of the original papers.

have been able to elicit the actual calculation that was used for some of these variables and we are able to document here the divergence between the definition stated and the calculation that was actually employed. There are other created variables where there is residual ambiguity about the calculation of the variable. There is also some uncertainty about the sample of observations that was used in the estimation.

Our attempt to replicate the variables and the estimation sample are found in Table 1 below. The left side block of columns in this table contains the published results from CDGLM *Table A1* for all women in their sample. The middle block with the grey background is our attempt to replicate the left block, using our most successful reconstruction of the formula used to create each variable and the decisions made about inclusion in the sample. The right hand block is based on the same sample as the second block, but uses the definitions of variables as stated in CDGLM *Appendix A1*. Our findings regarding the coding of variables and the summary statistics of CDGLM are as follows.

We base the replication of summary statistics on a sample of 1128 women, which is obtained when just the men and the self-employed women are dropped from the NLC Wave 1 distribution file. CDGLM report summary statistics on 1123 women, so our samples are similar but not exactly the same. We have the same number of employed women as they have (738) but we have 390 unemployed against their 385.

1. Experience (EXP) is defined in *Appendix 1* as 'Years of actual labour market experience since leaving full-time education. Constructed using retrospective questions on labour market experience adjusted for estimated annual working hours in order to take account of the fact that women with children who are employed work, on average, shorter hours.'

From our investigation it appears that the variable is the sum of the number of years employed full-time work plus a fraction of the number of years employed part-time, using the information provided in answers to the work history section of the NLC questionnaire (variables with names Q14AX where X ranges from 55 to 96). We use the fraction 20/35, which gives a close but not exact replication of the published summary statistics.

2. Tenure (TEN) is described as 'Years of tenure with current employer.' The problem with this variable in the NLC survey is the lack of correspondence between those who say they are currently employed (Q77=1 or 2 or 3) and those who answer the question about tenure with current employer (Q100). Any researcher who uses these data to investigate the relationship of tenure to other job characteristics will have to make some reconciliation between these variables. We have made adjustments according to our own judgements and found summary statistics for

tenure that are overall similar to the published CDGLM ones. A complication of the CDGLM study is that some respondents who are coded as not employed have a positive value for the tenure variable, as can be seen in *Table A1*. This contradictory coding makes very little difference to the overall summary statistics, as can be seen from Table 1 below, but it has a significant impact on estimation as discussed in Section 3 below.

3. Age (AGE24 and AGE34) are defined as binary indicator or dummy variables to indicate the woman is aged 24 or less, or 25–34, respectively. These variables are unambiguous and pose no difficulties for replication. CDGLM use this approach to represent the woman's age, following the lead of Beggs and Chapman. As described below, we use a more direct representation of age as years last birthday in our replication.

4. In their calculation of the indicator for Non-English-Speaking Background (NESB), CDGLM includes Singapore as English-speaking, which it is not usually categorised. However, there is only one case and the discrepancy is less than the rounding error in the published summary statistics.

5. Marriage (MAR) includes respondents in cohabiting relationships. We confirm that a straight coding of the appropriate NLC variable (Q20=3 or 4) gives this indicator variable with no inconsistencies.

6. Education is coded as three binary indicator variables (DEGREE/DIPLOMA, TRADE, YR12, base incomplete secondary). A serious error has been made in the computing the categories to describe the three level of education. The descriptive statistics of *Table A1* (shown also in the left hand columns of our Table 1 below) purport that 10 per cent of all women have a degree or diploma, three per cent have a trade qualification, 46 per cent have completed secondary only, while the remainder have incomplete secondary schooling. These are substantial underestimates of the proportion of women who have higher education qualifications.

In fact, thirty-two per cent of women in this sample have a degree/diploma, 18 per cent have a trade, and only 21 per cent have completed secondary education. As evidenced by our success in replication, and reported in the middle (shaded) block of Table 1, the results in CDGLM come from using an incorrect post-school qualification variable. They use Q57, which relates to the highest qualification *of those who have more than one post-school qualification*, and which has to be combined with Q54 to produce a meaningful measure of post-school qualification.

This coding error has the impact of including many of the respondents who actually have a degree, diploma or trade qualification into the categories of completed secondary or incomplete secondary. Hence the extent of higher levels of education in the sample is underestimated.

7. The indicator variable for ever had a child appears to be unproblematic. It is a simple recode of the NLC variable for a positive number of children ever born to the respondent (CEB>0).

8. Ages of children. Five binary dummy variables are created in CDGLM to represent the numbers of children in various age groups. The first created variable represents whether or not the respondent has one child under three years of age, and the second is whether or not they have two or more children under three. The third, fourth and fifth child dummies indicate whether they have one, two, or three or more children in the age group three to 15.

Our investigation indicates that these variables are all incorrectly calculated. The variables in the descriptive statistics of *Table A1* and repeated in the left of Table 1 below use five years as the cut-off age between the two age groups, not three years as stated. This finding is confirmed by our replication in the middle block, which uses under five as the defining characteristic for these variables. So while CDGLM report 18 per cent of women in the NLC data with one child under three years, and six per cent with two such young children, the proportions are actually 14 per cent and one per cent, respectively. The same error is also evident in the variables created to identify women with children 3–15.

There is further ambiguity in the meaning of the upper boundary of the higher age group, which is stated as ‘to 15’ in the definitions of *Appendix 1*. Does it include children who turned 15 last birthday or not? Our replications reveal that age range of the second group in the CDGLM summary statistics is 5–14, not 3–15 as stated. The third block of columns in our Table 1 shows the calculations using the stated definitions, using ages last birthday of 0–2 and 3–15.

9. P-INC (Partner’s income) presents some problems for researchers seeking to replicate earlier results because the variable has been modified in later releases of the NLC data file due to cleaning and re-processing of the data. As can be seen by comparing the left column with the other columns of Table 1, the levels of the variable in the current dataset are somewhat higher than reported in CDGLM. But this variable has a very small impact in the CDGLM results, and our own research has confirmed its irrelevance, so we have not bothered to replicate the variable used by CDGLM. Instead we have used the new variable PINC from the current release of the data.

10. The attitudinal variables ‘Couple should contribute ... income’ and ‘Husband should ... breadwinner’ are clearly based on the NLC variables Q234A3 and Q267A1.[5] There are several minor errors evident in the CDGLM summary statistics. Their stated figures on the ‘couple should’ question actually relate to the ‘breadwinner’ question, and vice-versa. Further, our reconstructions reveal the coded event in the ‘breadwinner’ variable is evidently ‘strongly disagree/disagree’, not ‘strongly agree/agree’ as they defined it, so the numbers they give are almost the complement of what is stated (the difference is the ‘mixed feelings’ category).

11. Employment status is represented in *Table A1* as the split between the groups rather than as a named variable. As noted earlier, it is not always clear who is employed in the NLC sample because of conflicts between the information contained in the questions on current employment status (Q77), current job tenure (Q100), and working hours (Q110). CDGLM would have had to make reconciliations between these variables, and we are unable to replicate their decisions exactly. However we do agree quite closely with the percentages of employed respondents tabulated by age group and numbers of children in CDGLM *Tables 1 and 2*. The hours worked values reported in *Table 1* are clearly wrong in the ‘Under 25’ age group, where we find the average to be 27.1 hours not 37.0 as reported in the table (and in the text). The number of observations in the ‘35 to 44’ age group is also in error: we have a count of 361 while their stated number of 405 produces a row total that exceeds the total number of women in the NLC sample!

12. Respondent’s net, post-tax, earnings is measured in CDGLM by the NLC variable NET2A. Unfortunately, this variable has been dropped from the released NLC dataset, which now includes a variable WAGE for the gross wage and salary income of respondents (before deduction of income tax and the Medicare levy). Rather than resurrecting a variable that is no longer part of the NLC dataset, we have constructed an estimate of post-tax earnings by applying the tax scales for 1996–7 to the new variable. Our replications of *Tables 1 and 2* (not shown here but available on request) indicate that the new and old net earnings variables are very similar.

<<Table 1 about here>>

[5] The actual questions are ‘It is better for the family if the husband is the principal breadwinner and the wife has primary responsibility for the home and the children’ (Q234A3), and ‘Both the husband and wife should contribute to the household income’ (Q267A1).

3. Re-estimating the model

There is little point in our pressing on to attempt replication of the estimation results based on the faulty data construction noted in the previous section. Instead we will provide our own set of estimates by adopting the *spirit* of the CDGLM project but making our own constructed variables and inclusion decisions. Mostly we work with the variables as *defined* in CDGLM, although in a few places we believe the approach is represented better with a slightly different modelling strategy. We show that very different results are obtained within their framework by the application of their definitions and with reasonable modelling judgements.

It is important for us to document clearly the construction of our variables. Apart from the problems we have already demonstrated with the education variables and with the variables that indicate the presence and ages of young children, there is another problem that has an adverse impact on the CDGLM estimation results. As evident in *Table A1*, some of the cases recorded as unemployed have a positive value for tenure with the present employer, as measured in the variable TEN in their data. This variable is included as an explanatory variable by CDGLM, not only in the earnings equation where it is expected, but also in the employment (or selection) equation where it makes less sense. After all, logically the tenure of an unemployed person is zero (or maybe it is not defined), so a non-zero value for the variable should be a perfect predictor of a person's status as employed. The only reason their estimates do not break down with perfect prediction is that some unemployed people are recorded in the data with a non-zero value for TEN.

It is interesting to observe that in their *Table A2* (reproduced at Appendix) the t-ratio on Lambda is –0.66 (*p*-value of 51%), which indicates a very weak selection effect. However the results for the selection equation are quite different from the univariate (or marginal) probit results of *Table 3*. The probit equation has the expected form of an employment status model in that tenure is omitted. The difference in the results between the selection equation and the marginal probit is not so much attributable to selectivity (which is quite insignificant) but rather to the inclusion of tenure in the selection equation (where it is highly significant both in its level and in its square).

Treatment of model variables

Our employment status measure is based on the NLC variable Q77 'Did you work last week?' We classified a respondent as employed if they worked last week (Q77=1), or if they were on leave (Q77=2 or 3) and had positive hours worked last week (Q110>0).

Respondent's age is a crucial variable in these models. One important role it plays is to adjust for the cohort effect, namely that a woman of a given age today—say 30—has different behaviour in the labour market from another member of the sample who is translated hypothetically into the same situation—say a current 45 year-old when she was fifteen years younger. CDGLM use two dummy variables for women under 25 and under 35. Our modelling suggested that this approach does not represent very well the effects of age in this model. We found a more convincing representation of the age effects by using as explanatory variables age of the respondent in years and its square. We find that the squared variable can be safely omitted from the employment selection equation.

Exclusion of cases

Respondents are dropped from our analysis (as they are obviously dropped in the CDGLM study) for a variety of reasons, which include empirical and data quality issues.

Firstly, respondents who are males (Q22=1) or self-employed (Q81=3) are excluded. We follow CDGLM in these decisions. The situation for self-employed respondents is complex and it can be difficult to distinguish between business income and wage or salary income for such people.

Secondly, some respondents are excluded due to missing information on employment status, tenure or wages. Respondents who might otherwise be classified as employed on the criterion described in the first paragraph of the previous section but who have missing data on either years with their employer (Q100) or on wage and salary income (WAGE) are dropped from analysis. There is no way of estimating these crucial variables if they are missing from the data file.

Lastly, we vary from the decisions made by CDGLM in that we remove women aged under 20 from the analysis. This exclusion is based on our experience in estimating models with this data set, where it is apparent that young women under 20 are quite different from older women in terms of their employment behaviour (as they are different in education and childbearing as well). This is, of course, an admission that the model is too simple to capture properly the effects of the interactions of age with these variables especially at the youngest ages. However, since our intention is to conduct an analysis in the spirit of CDGLM and to show that very different results from theirs can be obtained from reasonable modelling within their framework, we proceed with the trimmed dataset.

Our treatment of the squared variables for age, experience and tenure differs from CDGLM, but only for technical reasons that have no consequence in the estimation and simulation of the model. Our definitions of the squared variables are *divided by 100*, which has the effect of shifting the decimal point in the coefficient estimates two places to the right. The advantage is to give reported estimates that have a reasonable number of informative digits within the field that is presented in the tables. For instance, in the published CDGLM results of *Table A1* the coefficient of the squared experience variable EXP^2, an influential variable in the simulations, is reported as –0.001. Now this could represent –0.0005, which has been rounded up to three decimal places, or it could be a number just under –0.0015 and rounded down. So the actual coefficient could be anywhere in an interval that varies by a factor of three! The implications for an earnings profile over a lifetime of accumulating employment experience are profound. It is impossible to replicate the simulations of CDGLM from their published estimation results.

The summary statistics for the sample of data used in our re-estimation of the model are given in Table 2 below.

<<Table 2 about here>>

Estimation results

The results of joint estimation of an employment (selection) equation and an equation for (log) earnings are presented in Table 3. The estimation method is the Heckman maximum likelihood estimator in Stata v.7.

These results are broadly similar to those reported in CDGLM, but they do differ in several important details. In making comparisons, remember that the squared variables (experience, tenure and age) have all been divided by 100, so each of these coefficients is multiplied by 100 compared to CDGLM *Table A2*. Also in the earnings equation the dependent variable is 100 times the natural log of after-tax wages or salary, where the scaling factor has the effect of multiplying all the coefficients in this equation by a further factor of 100. As an example of the effects of these scalings, our coefficient of the tenure squared variable in the earnings equation of –10.056 is indistinguishable from the reported coefficient in CDGLM of –0.001. In this case our estimate is exactly the same as theirs (to the level of detail they report) but there are other coefficients where there are substantive differences.

These differences in estimated coefficients are as anticipated, given the differences in sample inclusion and changes in the definitions of the variables. The earnings variable has been revised in the dataset and we have omitted the 18 and 19 year-olds from the estimation sample. We have also used different representation of the effect of respondent's age, although even there our results preserve the strong negative effect of increasing age in the employment equation and the flatter but still negative effect of age in the earnings equation, both of which are evident in the CDGLM results. Also we remove the controversial inclusion of tenure in the employment equation, which will have impacted on the other coefficients.

We concentrate in this discussion on the coefficients that have important influence on the subsequent analysis, particularly the indicators of education levels and the presence and ages of younger children. Starting with the employment (or selection) equation, we find that correcting the measures of education has the effect of sharpening the difference between those who have completed high school and those who have not, although the effect of having a degree or diploma is similar in our estimates to the earlier ones. We find a weaker and indeed statistically insignificant permanent effect of ever having a child, but stronger effects for the presence of children at the younger ages. In common with CDGLM, we find that the impact of two very young children is very strong, but where they find an effect under twice that of one such child, we find an effect around 2.4 times as great. Unlike the earlier results, we find further effects of children 3–15 that are consistently negative and moderately large (compared to the already reported effects of children in the youngest age group). Also unlike the CDGLM results, we find that increasing the number of children in the intermediate age range has the systematic effect of increasing the probability that the woman is not employed.

The effect of education on earnings for the employed is not as strong in our estimates as in CDGLM, when the comparison is made of those in any of the higher education levels with those in the group that has not completed year 12 (the omitted category for the dummy variables). But the differences in earnings advantage between any of the higher education levels (for example comparing those with degree/diploma with those who have only completed year 12) are strikingly similar in the two sets of estimates.

The effects of children in the earnings equation are also fairly similar between our estimates and CDGLM. We estimate a somewhat weaker permanent effect of ever having a child than reported in the earlier work and slightly stronger effects of children in the youngest age group, although the differences here are slight. These are similar comparisons to what we reported in the employment equation, but here the contrast with the earlier results is not so marked. In common with CDGLM, we find consistently negative effects on earnings of children in the intermediate age group 3–15. Our measures of these effects are stronger than they report (possibly due to the variables being mismeasured in the earlier work), particularly for those who have two or more such children. The coefficients of children aged 3–15 are at best borderline significant by the usual statistical criteria, although our results are less weak in this respect than the earlier ones.

Another point of comparison concerns the selection effect, called the coefficient of ‘Lambda’ in the CDGLM results and ‘rho’ in Table 3 below. This is the coefficient which, if zero, indicates that the model can be partitioned into two unrelated equations for employment and earnings. In the CDGLM results the estimate of the coefficient of Lambda is –0.025 with a t-ratio of –0.61, so it is clearly small and statistically insignificant. This finding implies that consistent and efficient estimation of the two equations in the model can be made separately, by probit for the employment equation and ordinary least squares for (log) earnings of the employed. In our estimates the same coefficient is –0.127 with a t-ratio of –0.77, so a similar conclusion of insignificant selection effect would be reached.

In summary, while our earnings equation is more sharply defined than the corresponding equation in CDGLM, the principal difference between the two sets of estimates is in the more pronounced effects of higher education and younger children that we find in the employment equation. We attribute some at least of these differences to our corrections to the codings of the education categories and of the variables indicating the presence of children in the younger age groups. Our estimation results are reported in Table 3 below.

<<Table 3 about here>>

4. Simulation using the new estimates

It is difficult to assess the forgone earnings due to having children directly from coefficients of an estimated model. The device used by CDGLM is to simulate the lifetime earnings of some illustrative cases of 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.

We follow the method of CDGLM, which involves assigning values to the explanatory variables in the model to describe the various possibilities. We stratify by three levels of education (degree/ diploma, completed 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 age 23 to age 59. Apart from labour force experience, the other variables (marital status, tenure, English-speaking background, partner's income and the social attitudes) are set to their sample averages[6].

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[6] Holding tenure constant over a woman's lifetime in the simulations may not be entirely convincing, but here we follow the earlier research. It is not *impossible* for a woman of 23 at the start of the simulations to have the sample average tenure of 3.7 years, although it is implausible, particularly at higher levels of education. 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.

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.

CDGLM do not explain how they establish the profile of the woman's labour force experience over her lifetime for use in the simulations. In their intermediate results that we have been privileged to see, experience varies with both her education level and her childbearing history. 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 be assumed to 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 be assumed to 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 25 years old with that level of education.

It is also unclear in the published papers how the prediction of earnings is done, although the illustrative calculations and the explanations in the text of CDGLM suggest that the wrong formula is used. The model that is employed in our replications is the same as in the earlier work. It has the standard form of a Tobit Type II selection (or Heckman) model for log-earnings and selection into employment:

$$\begin{aligned} y_i^* &= \beta' x_i + \varepsilon_i \\ z_i^* &= \gamma' x_i + v_i \end{aligned} \qquad \text{where} \qquad \begin{bmatrix} \varepsilon_i \\ v_i \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\varepsilon^2 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & 1 \end{bmatrix} \right)$$

and

$$y_i = \begin{cases} \exp(y_i^*) & \text{if } z_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

Here y_i^* and z_i^* are latent variables, the former representing something like 'potential earnings' (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 y_i is formed by exponentiating log-earnings and it is observed only when the person is employed. See Verbeek (2000, p.207) for details 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 the person's characteristics, viz.

$$
\begin{aligned}
E\left\{y_i \mid x_i\right\} &= E\left\{y_i \mid x_i, z_i^* > 0\right\}.\Pr(z_i^* > 0) + 0.\Pr(z_i^* \le 0) \\
&= \exp\left\{\beta' x_i + \sigma_\varepsilon^2/2\right\}.\Phi(\gamma' x_i + \rho\sigma_\varepsilon)
\end{aligned}
$$

The term in the first factor of the last line involving the variance arises in the mean of a log-normal distribution. As noted in Verbeek (2000, p.49) omission of this factor can lead to serious prediction errors in a regression model with a log transformation on the dependent variable. The second factor is not quite the same as probability of employment, $\Pr(z_i^* > 0) = \Phi(\gamma' x_i)$, although the difference here will be small when the selection effect is weak (i.e. when $\rho \approx 0$), as it is in both our estimates and the reported CDGLM results.

Simulation results

CDGLM give calculations of lifetime earnings, both in current dollar terms and as a percentage of the earnings of a woman who has no children. They also provide the dollar value calculations as a simple sum over the lifetime and as a discounted present value using a discount rate of 5%. We prefer to give percentage comparisons of simple sums with no discounting. The percentages are less eye-catching as media headlines than enormous lifetime dollar amounts of earnings aggregated over 30 years or more, but we fear the dollar values are widely misunderstood. Another reason to prefer percentages is that they are less sensitive to small changes in the methodology of the simulations than aggregate dollar amounts.

The application of a discount rate to obtain 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, the fact that we are limiting our reporting to 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 just percentage calculations based on simple lifetime aggregates.

<<Table 4 about here>>

We have chosen to present the results as retained earnings not forgone earnings, because this facilitates different comparisons that may interest the reader. The results of our simulations are presented in the most right hand column of Table 4. For comparison, we have included the results of CDGLM taken directly from their *Tables 7, 8, 9* in the second column from the right of Table 4. The other two columns of numbers refer to comparisons with the results of Beggs and Chapman (1989) and will be discussed below.

The first conclusion in comparing the results in the right hand two columns of Table 4 is that the retained (or forgone) earnings in percentage terms is very similar in the two sets of calculations for women of middling education level having an typical number of children (the average in our estimation sample is 1.7). Further we find the effects of different education levels to be pretty much the same as reported in CDGLM. We find a slightly steeper gradient of percentage retained earnings with education level in our estimates, particularly for women with more than one child, but the differences from the earlier findings are not marked. The similarities are not surprising given that overall the estimated effects of education are quite similar despite the miscoding of the education variables in the earlier research.

Where our results differ most markedly from those reported in the earlier papers is in the effects of second and third children. In CDGLM, the *extra* loss of earnings due to having three children over one child is estimated as only 4–5% of the lifetime earnings of a similar woman who has no children. By contrast, in our re-calculations the amount of extra forgone earnings for the additional two children is 25–30% of the earnings of a woman who remains childless. Some of this difference, at least, can be attributed to the stronger effects of younger children on employment participation in our estimates.

It is interesting but difficult to compare our findings with the Beggs and Chapman (1989) study. Percentages calculated directly from the numbers in *Table 11* of that paper for retained lifetime earnings in the three educational categories (at 0% discount rate) are given in the first column of Table 4. There are several difficulties to be considered 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 in Beggs and Chapman, because there it ranges from 20 years to 60 years, not 23–59 years as in CDGLM and in our replication. 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 focus in Beggs and Chapman (1989) on gross (pre-income tax) earnings rather than net (post-income tax) earnings of the later studies. As they indicate in their *Footnote 2*, they do not have enough information to make individual adjustments of gross earnings to net earnings.

In an attempt to adjust the Beggs and Chapman results to make them (more) comparable to the later ones we attempt a correction for the effects of income tax. We present an estimate of the percentage retained *net* earnings in the second column of numbers from the left of Table 4. As expected, the extent of retained 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 is 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 4–5% 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 broad picture of Table 4 bears out one of the main results of CDGLM: the extent of forgone earnings has fallen markedly from the 1986 survey used by Beggs and Chapman to the 1997 NLC Wave 1 survey. This finding is most secure for women at higher educational levels and with fewer children. On the other hand, on our corrected figures it seems there is no change in eleven years for women in the lowest educational category who have three children. To the extent that our procedure for adjusting the Beggs and Chapman calculations for income tax is an underestimate, the position of women with little education may have gone in the opposite direction.

Contrary to the second main finding of CDGLM, the effects of second and subsequent children appear to be stronger than ever. In the Beggs and Chapman data the additional net earnings forgone by a woman with three children over a woman with one child is 10–18% of the earnings of a woman with no children, compared to our finding of 25–30%. Both of these results are in strong contrast to the implausibly low CDGLM figure of 4–5%.

5. Other Problems

We have seen that the CDGLM study is marred by a series of errors in the data coding, in the econometric modelling and in the prediction formula. There are other problems in the execution of the simulations, which lead to highly inflated dollar sums being given for lifetime earnings. The effect can be seen most clearly in lifetime earnings profiles of CDGLM *Figure 2*. The notable feature in this figure is the absence of any drops in the simulated earnings profiles at ages 25 and 35, when the dummy variables should no longer indicate the person is below that age. To put it another way, everyone in the simulations is given the earnings premium of an under-25-year-old, whether they are 22 or 42!

Treating everyone as if they are under 25 generates an enormous inflation in the estimates of lifetime expected earnings. In the employment equation of CDGLM the coefficient of the AGE24 indicator is 0.724 (and 0.790 in the marginal probit estimates), so that if someone who is 42 is predicted to have, say, a 60% chance of being employed, then another person who is 22 and otherwise identical will be predicted to have an 83.6% chance of being employed. On this account alone, the predicted expected earnings from this model is much higher when the person is under 25 (or is assumed to be in that age group even when they are not).

This problem is exacerbated by a similar error in simulating the equation for the earnings of those who are employed. The coefficient of the AGE24 dummy variable in the earnings equation is 0.411. This implies that if a worker is 42 and predicted to earn $20,000, then another worker who is otherwise identical except that she is assumed to be 22 will be predicted to earn $30,200. This is an increase in expected earnings of 51% even comparing people who are employed in both cases.

This discussion of earnings profiles creates an interesting conundrum. If the CDGLM earnings profiles are all wildly inflated, the estimates of forgone earnings due to childbearing are also presumably too high, since they are just the difference in the areas under two such profiles. How then could they produce the headline result that forgone earnings have *fallen* between 1986 and 1997?

The answer would appear to reside in an incorrect comparison of two hypothetical income flows that are discounted at different rates. Taking just the leading case of the first child for a woman in the middle education category, the CDGLM calculation for forgone lifetime earnings is $374k with no discounting (a discount rate of 0%) and $162k when expressed as a net present value at a discount rate of 5%. This is net earnings in 1997 dollar values. The nearest Beggs and Chapman *Table 11* numbers are $336k and $132k, respectively, both representing gross earnings in 1986 dollars. The challenge is to transform the earlier figures to match the later ones.

The Consumer Price Index rose from 73.5 in June 1986 to 120.3 in June 1997, so the Beggs and Chapman figures when converted to 1997 dollar values are $550k and $216k. As we noted earlier, it is difficult to estimate accurately the effect of personal income tax, but a 21% tax rate seems a reasonable approximation. (There is a wide band of incomes for which the marginal rate of income tax in 1986 was in fact 20% with an additional 1% contribution going to Medicare.) At this conversion of gross to net, the Beggs and Chapman figures become $435k and $171k. The most likely explanation for the CDGLM attribution of the number of $435k is that it is the former figure: the forgone earnings calculated without discount. The comparable figure in the CDGLM results is the $374k number, not the $162k, so the finding of a massive drop in forgone earnings between the two dates is apparently based on a simple error of comparing two flows that are discounted at *different* rates.

6. Conclusions

We re-examine the investigations of forgone mothers' earnings reported in Chapman, Dunlop, Gray, Liu and Mitchell (2001) and Gray and Chapman (2001). We report several errors in the construction of key variables and in the conduct of the predictions and the simulations.

We find that the main result of a decline in forgone earnings between 1986 and 1997 is sustainable, at least for the 'typical' case of an average number of children to a mother with middling education. However the effects of education level and additional children are both underestimated in the earlier work, the latter quite seriously. The dollar values that are calculated from the simulations (and were reported in the mass media) are not at all accurate (and would not be very meaningful even if they were accurate) so we have chosen instead to report all comparisons as percentages.

Table 1. Replication Results: Variable Means and Standard Deviations.

	CDGLM		Replication		Re-estimation	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Experience	12.61	8.02	12.72	7.73	12.72	7.73
Experience^2	233.17	250.28	221.4	243.1	221.4	243.1
Tenure	3.88	5.67	3.82	5.73	3.78	5.73
Tenure^2	47.16	121.71	47.4	121.3	47.1	121.6
Age 18–24	0.14	0.35	0.137	0.344	0.137	0.344
Age 25–34	0.32	0.47	0.318	0.466	0.318	0.466
Married/cohabiting	0.64	0.48	0.642	0.480	0.642	0.480
Degree/diploma	0.10	0.31	0.105	0.306	0.322	0.467
Trade&equivalent	0.03	0.18	0.032	0.176	0.179	0.384
Year 12	0.46	0.50	0.456	0.498	0.217	0.413
NESB	0.08	0.27	0.081	0.272	0.082	0.274
Ever had a child	0.69	0.46	0.688	0.464	0.688	0.464
1 child aged under 3 years	0.18	0.38	0.177	0.382	0.142	0.349
2 children aged under 3 years	0.06	0.24	0.060	0.238	0.010	0.098
1 child aged 3–15 years	0.19	0.39	0.189	0.392	0.190	0.392
2 children aged 3–15 years	0.14	0.35	0.145	0.352	0.169	0.375
3 children aged 3–15 years	0.06	0.24	0.063	0.243	0.090	0.286
Partner income	22893	24320	25081	28208	25081	28208
Couple should contribute ... income	0.66	0.47	0.660	0.474	0.686	0.464
Husband should ... breadwinner	0.69	0.46	0.686	0.464	0.316	0.465
Observations	1123		1128		1128	

Note: The left side block of columns contains the published results from CDGLM for all women in their sample. The middle block with the grey background is our attempt to replicate the left block. The definitions of variables needed to produce these results are discussed in the text. The right hand block is based on the same sample as the second block, but with the variables constructed by applying the definitions stated in CDGLM, *Appendix A1*.

Table 2. Summary statistics: Women aged 20–55.

	Not employed		Employed		All women	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Experience	10.56	7.12	14.46	7.46	13.10	7.57
Experience^2/100	1.62	2.11	2.65	2.53	2.29	2.44
Tenure	0	0	5.69	6.16	3.70	5.66
Tenure^2/100	0	0	0.70	1.41	0.46	1.19
Age 20–24	0.09	0.28	0.10	0.31	0.10	0.30
Age 25–34	0.36	0.48	0.32	0.47	0.33	0.47
Married/cohabiting	0.71	0.45	0.64	0.48	0.67	0.47
Degree/diploma	0.22	0.41	0.40	0.49	0.34	0.47
Trade&equivalent	0.18	0.38	0.19	0.39	0.19	0.39
Year 12	0.21	0.41	0.18	0.39	0.19	0.40
NESB	0.11	0.31	0.06	0.24	0.08	0.27
Ever had a child	0.86	0.35	0.65	0.48	0.72	0.45
1 child aged under 3 years	0.26	0.44	0.09	0.28	0.15	0.35
2 children aged under 3 years	0.03	0.17	0.00	0.04	0.01	0.10
1 child aged 3–15 years	0.25	0.43	0.18	0.38	0.20	0.40
2 children aged 3–15 years	0.22	0.42	0.16	0.36	0.18	0.38
3 children aged 3–15 years	0.14	0.35	0.07	0.25	0.10	0.29
Partner income/1000	25.20	26.61	26.70	29.39	26.18	28.46
Couple should contribute ... income	0.54	0.50	0.75	0.43	0.68	0.47
Husband should ... breadwinner	0.48	0.50	0.24	0.43	0.32	0.47
Age	36.18	8.65	37.02	9.18	36.73	9.01
Age^2/100	13.84	6.44	14.55	6.90	14.30	6.74
Employed					0.65	0.48
Net Earnings	0	0	21020	10393	13676	13068
Observations	355		661		1016	

Table 3. Estimation Results: Heckman MLE for Employment and Earnings.

	Employment Equation		**Earnings Equation**	
	Coefficient	t-value	Coefficient	t-value
Experience	0.171	7.27	8.390	5.22
$Experience^2/100$	-0.326	-4.91	-11.907	-3.00
Tenure			3.078	3.20
$Tenure^2/100$			-10.056	-2.67
Age	-0.046	-4.72	-6.565	-2.46
$Age^2/100$			4.963	1.41
Married/cohabiting	-0.081	-0.59	-2.468	-0.39
Degree/diploma	0.563	4.56	43.752	6.92
Trade&equivalent	0.284	2.08	23.446	3.73
Year 12	0.219	1.61	13.689	1.82
NESB	-0.436	-2.71	11.849	1.66
Ever had a child	0.086	0.47	-15.989	-1.96
1 child aged under 3 years	-1.033	-6.21	-16.333	-1.39
2 children aged under 3 years	-2.493	-4.51	-64.691	-3.09
1 child aged 3–15 years	-0.285	-2.02	-9.084	-1.22
2 children aged 3–15 years	-0.499	-3.17	-18.761	-1.87
3 children aged 3–15 years	-0.589	-3.31	-17.026	-1.29
Partner income/1000	0.005	2.19	-0.199	-1.62
Couple should contribute ... income	0.588	6.00		
Husband should ... breadwinner	-0.333	-3.28		
Constant	0.352	1.23	1052.227	25.78
Rho			-0.127	-0.77
Number of censored observations			347	
Number of uncensored observations			659	
Log likelihood			-4033.463	

Table 4. Retained Earnings: Various Cases.

Scenario	B&C 1986 (% of gross)	1986 (% of net)	CDGLM 1997 (% of net)	Re-do 1997 (% of net)
		Degree/diploma		
1 child	54	60	69	73
2 children	44	49	67	59
3 children	36	42	65	48
		Completed year 12		
1 child	47	52	66	72
2 children	39	44	65	56
3 children	34	39	62	45
		Incomplete high school		
1 child	42	47	65	68
2 children	36	41	62	50
3 children	32	37	60	38

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Appendix

***Table A2*. Determinants of Net Annual Earnings, Heckman Estimation: Results from CDGLM (2001, p.387).**

	Selection Equation		**Earnings Equation**	
	Coefficient	t-value	Coefficient	t-value
EXP	0.072	2.59	0.070	5.34
EXP^2	-0.001	-1.51	-0.001	-3.68
TEN	0.660	5.50	0.030	2.94
TEN^2	-0.020	-5.76	-0.001	-2.29
AGE24	0.724	3.12	0.411	3.60
AGE34	0.415	2.90	0.309	4.21
MAR	-0.302	-1.77	-0.035	-0.47
DEGREE/DIPLOMA	0.587	2.92	0.551	9.10
TRADE (per cent)	1.190	3.91	0.359	3.47
YR12 (per cent)	0.097	0.75	0.255	5.04
NESB	-0.133	-0.65	0.164	1.96
Ever had a child	-0.457	-2.63	-0.268	-4.44
1 child aged under 3 years	-0.434	-2.99	-0.142	-1.30
2 children aged under 3 years	-0.815	-2.00	-0.625	-3.57
1 child aged 3 to 15 years	0.323	2.18	-0.083	-1.14
2 children aged 3 to 15 years	0.278	1.72	-0.070	0.89
3 children aged 3 to 15 years	0.318	1.74	-0.120	-1.10
P-INC ($)	0.010	2.48	-0.001	-0.78
Couple should contribute to the household income (per cent)	0.308	2.43		
Husband should be the main breadwinner (per cent)	0.448	3.87		
Constant	-1.773	-5.87	8.904	56.61
Lambda [Rho]			-0.025	-0.61
Number of censored observations			385	
Number of uncensored observations			679	
Wald $chi^2(18)$			334.33	
Log likelihood			-873.60	