# Intergenerational Mobility in Britain : Evidence from unemployment patterns.[1]

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## Abstract

Several papers have examined the intergenerational transmission of well being by looking at the relationship between parents' and children's income. However, by concentrating on those who are working these studies exclude some of the very poorest in society, the long-term unemployed. In this paper we extend the empirical work on intergenerational welfare in the U.K by looking at the links between fathers' and sons' unemployment histories. Using an approach which takes account of both incidence and intensity of son's unemployment we provide further evidence showing that parental background is an important determinant of a child's future welfare. A son whose father was unemployed 20 years earlier is almost twice as likely to be unemployed as a son whose father was not unemployed. Furthermore this dependency remains significant after controlling for a range of sons characteristics including education, ability and family composition.

[1] We would like to thank the ESRC data archive and Peter Shepherd of City University for providing us with the NCDS data and to seminar participants at the Dublin Economics Workshop for comments on an earlier version of this paper.

## I. Introduction

In this paper we examine the extent to which experience of unemployment increases the likelihood of future unemployment. Many studies have examined this issue from an individual perspective. These include studies focusing directly on the work disincentives inherent in the welfare system (Atkinson and Mogensen (1993)) and reduced form studies examining duration dependence within unemployment spells[2]. In this paper we examine dependency on unemployment by focusing on the family dynasty as the unit of analysis rather than the individual. In particular we ask to what extent does a father's participation in unemployment affect the likelihood that their son will subsequently become unemployed.

In carrying out this analysis it is important to distinguish between different mechanisms which might account for this correlation. The relationship between a parent's and child's unemployment could reflect transmission of tastes, transmission of constraints or true state dependency[3]. The transmission of preferences explanation focuses on correlation in tastes such as distaste for unemployment. If tastes are inherited by the child then children of parents who have a lower distaste for unemployment will themselves be more likely to experience unemployment. However removing parents from unemployment will have no effect on the child's participation which is determined by the child's own tastes. Similarly parents with low skill levels may be more likely to experience unemployment. Low-skilled families, as well as being more likely to experience unemployment are also more likely to be low wage earners when working and thus may be unable

[2] For a summary of this work see Narendrnathan and Nickell (1986).

[3] For a discussion of these issues in the context of welfare dependency see Gottschalk (1990) and Antel (1992).

to finance their child's education. This will in turn affect the child's potential earnings as well as their likelihood of experiencing unemployment. This is the transmission of constraints explanation. Both of these mechanisms introduce spurious correlation between a parent's and child's unemploymeny history.

True state dependence occurs when the parent's unemployment status alters the child's outcome directly. Consider a job matching model where search is costly. In this model the probability of accepting a job is the probability of sampling the job times the probability of accepting a job given that it is sampled. Even if the conditional probability of accepting is independent of parental status, children may be more likely to sample their parent's jobs because the cost is lower.[4] If we consider unemployment as one of the options, then children of unemployed parents will be more likely to become unemployed, just as children of teachers will be more likely to become teachers. In this instance, improving parents' employment prospects will have a significant direct effect on their children's future unemployment history.

The different policy implications of these alternative models highlight the need to distinguish between spurious correlation resulting from inherited tastes and constraints and true state dependency. In order to do so it is important to model all possible correlations in characteristics. In this paper we use a data set which contains detailed information on the son's pre-labour market experience. This allows us to control for some factors which might cause a spurious correlation between fathers' and sons' unemployment histories. The hurdle estimation strategy adopted in this paper allows us to take account of the fact that three quarters of our sample did not experience a spell of unemployment. To examine the role of unobservable characteristics we simultaneously model the parent's and child's unemployment equations taking into account

[4] A similar explanation has been used to explain black-white wage differences (Cornell and Welch 1996).

correlation in unobservables. Our results show that father's participation in unemployment has a significant effect on the probability that the son will become unemployed. This remains true even after taking into account characteristics of the child, such as the level of sons' human capital. There is little change in the estimated effect once we model the participation decisions simultaneously but neither the effect of father's unemployment nor the correlation in unobservables is precisely estimated in this case.

## II. Data

The data used in this paper are taken from the National Child Development Study (NCDS) a longitudinal data set following the lives of all those living in Great Britain who were born between the 3rd and 9th of March 1958. To date there have been 5 follow-up surveys of these individuals. These took place in 1965, 1969, 1974, 1981 and 1991. The information in sweeps 1-3 was provided mostly by the parents of the children and contains data on parents' education, social class, earnings, income and work history. The sweep 5 survey contains detailed self-reported information on the child's labour market status until the age of 33.

We restrict our attention to father-son pairs. In this analysis parental unemployment is measured using both the 1969 and 1974 sweeps, when the children were aged 11 and 16 and the fathers were aged 41 and 46 on average. Our measure of unemployment for parents indicates if the father had been unemployed at any time during 1969 or 1974. For sons we use the number of months the son was unemployed between 1981 and 1991. To create this variable we use diary information provided in sweeps 4 and 5 of the NCDS. This provides a complete month by month record of individuals' work histories over the 10 year period from January 1981 to January 1991.

The explanatory variables used in our analysis include the education levels of both the parent and the child, measures of non-labour non-welfare income of both individuals, measures of family size for both the parent's and the child's own family, proxies for the child's skill level based on the results from ability tests and information on computer literacy and several measures reflecting local economic conditions. These variables are described in more detail in Table 1.

We restrict attention to individuals with complete data on all the variables used and to children who had both own parents present at all surveys until the age of 16. We are left with a working sample of 987 father-son pairs. Of this sample 11% of fathers had been unemployed in either 1969 or 1974. Information on the son's unemployment record between 1981 and 1991 is provided in Table 2. Two common features associated with count data are evident from this table.

Firstly we see that the raw data exhibit overdispersion in that the mean months unemployed is substantially smaller than the variance. The sample mean is 4.32 months while the sample variance is almost 187 months. Secondly we notice that three-quarters of our sample experienced no unemployment over this period. Both these features are important and are taken into account in the estimation strategy which we adopt in this paper.

## III. Model and Estimation Results.

To begin our analysis of the relationship between father's and son's unemployment histories, Table 3 tabulates three dimensions of sons' unemployment conditional on fathers' unemployment status. The first row gives the proportion who had been unemployed between 1981 and 1991, the second row gives the number of months unemployed over this period and the third row gives the number of months unemployed among individuals who had experienced a spell of unemployment. These tabulations establish the main result which we focus on in this paper. Looking at the table we see that sons whose father had been unemployed in either 1969 or 1974 were twice as likely to be unemployed between 1981 and 1991 than sons whose father had not been unemployed.[5] Likewise we see that these sons had experienced over 3 months more unemployment over the first 10 years of their working life. However, there is little difference between groups in the time spent unemployed conditional on having experienced a spell of unemployment. From these data it appears that the impact of parental background on childrens' unemployment history works predominantly through its impact on the incidence of unemployment. The remainder of this paper examines these findings in more detail.

In order to develop policies to break this poverty link across generations it is important that

[5] Johnson and Reed (1996) present similar tabulations for the incidence of unemployment.

we try to understand how poor unemployment prospects are passed on from generation to generation. To do this we first control for several measures which are likely to be important in explaining the son's unemployment history. Included among these regressors are the highest education qualification obtained by the son in 1981, measures of non-labour non-welfare income of the son, indicators of the son's marital status and family size and measures of the local unemployment rate during the spells under consideration. We also take account of whether the child attended an independent school either at age 7, 11 or 16. These education variables should pick up the influence of credit constraints facing the parents when deciding how much to invest in the child's human capital. We also include further measures of human capital such as the results from test scores when the child was age 7 and a variable measuring computer literacy. The degree to which inclusion of these variables reduce the estimated coefficient on father's unemployment gives an indication of their ability to explain the persistence of unemployment.

A popular approach to estimation in the presence of count data is to use a negative binomial model with mean $\lambda_i$ and variance $\lambda_i + \alpha\lambda_i^{2.}$ Making this assumption and letting $Y_i$ denote the random variable indicating the number of months unemployed, then the probability that $Y_i=y_i$ is given by

$$f(y_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_i}\right)^{\alpha^{-1}} \left(\frac{\lambda_i}{\alpha^{-1}+\lambda_i}\right)^{y_i}$$

for $y_i=0,1,2....$ To examine the impact of regressors in this context it is common to specify the conditional mean $\lambda_i=\exp(X_i'\beta)$ where $\beta$ is a (k x 1) vector of unknown parameters. The exponential specification is easy to interpret and ensures that the conditional mean is nonnegative. This model is called the Negbin 2 model and is discussed in more detail in Cameron and Traverdi (1996). The advantage of the negative binomial model is that it accommodates overdispersion of the type illustrated by our data and reduces to the more standard Poisson model in the special case where the overdispersion parameter $\alpha$ equals zero. The negative binomial model can be motivated either as a Poisson model with unobserved heterogeneity parameterised by a gamma distribution or from a particular form of nonstationary stochastic process in which the occurrence of an event increases the likelihood of future occurrences.

Given the large number of sons who experience no unemployment over this period it may be desirable to model the occurrence of zero unemployment separately from those of the positive counts. This can be done using the hurdle model of Mullahy (1986).[6] We assume that the binomial model governing unemployment incidence can be modelled using a density $f_1(y_i|X_i)$ with parameters $\beta_1$, while positive counts come from a density $f_2(y_i|X_i)$ with parameters $\beta_2$. Then the probability of a zero value is $f_1(0|X_i)$, while the requirement that probabilities sum to one leaves the probability of a positive count equal to $[1-f_1(0|X_i)/1-f_2(0|X_i)].f_2(y_i|X_i)$ for $y_i$ equal to 1,2 ,..... The log-likelihood function can be written as

$$\text{Log}\, L = \sum_{y_i=0} \log f_1(0|X_i) + \sum_{y_i>0} [\log(1-f_1(0|X_i])  - \log(1-f_2(0|X_i)) + \log(f_2(y_i|X_i))$$

This log likelihood function is separable in $\beta_1$ and $\beta_2$ and estimation can proceed by first maximising a binary likelihood model and then estimating a truncated count model on the positive counts.

In this paper we examine four alternative models. The first two are the standard Poisson models and negative binomial models applied to all the data. The next model is the hurdle model where both the incidence and the positive counts densities are assume to be Poisson and the fourth

[6] This model has also been recently used by Arulampalam, Booth and Elias (1997) in modelling the wage effects of work-related training.

is the hurdle model where the densities are assumed to be Negbin 2 with parameters ($\gamma_1,\alpha_1$) and ($\gamma_2,\alpha_2$) respectively. To determine which of these model is most appropriate we use a likelihood ratio test. The values of the log-likelihood and the associated likelihood ratio tests are given in Table 4. Because the hurdle model nests the non-hurdle model, the non-hurdle model can tested for using a simple likelihood ratio test. The results for the Poisson and Negbin 2 models are given in rows b1 and b2 of Table 4 respectively. In both cases the non-hurdle model is rejected against the alternative of the hurdle model. Taking the hurdle model as the appropriate specification we then test both the incidence and positive counts components of the Poisson hurdle model against the respective components of the Negbin 2 model. In both cases the likelihood ratio test rejects the Poisson specification in favour of the Negbin 2 model. The rejection of the Poisson specification reflects the overdispersion observed in the data. Thus on the basis of these tests our preferred specification is a Negbin 2 hurdle model, the results of which are presented in Table 5. For comparison we also present the results from a probit specification of the incidence model.On average it appears that the coefficients from the Negbin incidence model are about twice the size of those from the Probit model, although the qualitative results are similar in both cases.[7]

Looking at the results for the incidence models we see that married men are less likely to be unemployed as are individuals skilled in the use of computers. The important finding for this paper however, is that having controlled for observable characteristics we still find a significant positive relationship between fathers' and sons' unemployment histories. These coefficients can be translated into relative effects on the probability of being unemployed in the usual way. For the Probit model we compare $\Phi(Z'\gamma+.55)$ and $\Phi(Z'\gamma)$, where Z is the set of explanatory variables excluding father's employment status, evaluated at the mean and $\Phi$ is the standard normal cumulative distribution

[7] Arulampalam, Booth and Elias (1997) obtained differences of a similar order of magnitude between the Probit and Negbin 2 models of incidence in their analysis of training spells.

function. Using our estimated coefficients we find that the probability of becoming unemployed increases from .22 to .42 for a son whose father was unemployed. For the Negbin 2 the relative effect is simply $e^{1.03}$, which equals 2.88. Thus even after controlling for a host of explanatory variables we find that sons of fathers who had been unemployed are between two and three times as likely to be unemployed than sons of fathers who had not been unemployed.

The estimates from the Negbin 2 model for the positive counts provide a different story. In this case we see that as well as marital status and computer skills the education variables and the local labour market conditions also effect the unemployment status of the son in the expected way. However the impact of fathers' unemployment status is no longer significant. The impact of father's background on sons' unemployment history thus seems to differ whether we look at measures of incidence or measures of intensity conditional on experiencing a spell. For individuals who experience a spell of unemployment fathers background has no direct effect on employment prospects, though it may effect it through other channels such as education. However, father's background has a direct effect on the probability of becoming unemployed even when controls are included for ability and education. Therefore in a certain sense we can think of unemployment as providing an equalising force across social classes. One way it might do this is by increasing the information set available to potential employers. Thus the old boys' network may be important but less so if employers have extra information on the child, namely the fact that they are currently unemployed. What is important once you are unemployed are more reliable indicators of productivity such as education.

## IV. Simultaneous Modelling of Fathers and sons unemployment

To examine the extent to which the correlation between fathers' and sons' unemployment incidence reflects correlated unobserved heterogeneity or true state dependence we extend the modelling exercise of the previous section. Focusing on the probit specification of the incidence model we specify the following simultaneous equation model :

$$y_f^* = \gamma' Z_f + \varepsilon_f , \qquad y_f = 1 \text{ if } y_f^* > 0, \quad y_f = 0 \text{ otherwise}$$
$$y_s^* = \beta_1' X_s + \beta_2 y_f + \varepsilon_s , \qquad y_s = 1 \text{ if } y_s^* > 0, \quad y_s = 0 \text{ otherwise}$$

where $(\varepsilon_f , \varepsilon_s) \sim BVN(0,0,1,1,\rho)$.

Our data consist of observations on $y_f$ (a dichotomous variable indicating parents' unemployment), $y_s$ (a dichotomous variable indicating childrens' unemployment), and on the exogenous variables $Z_f$ and $X_s$. To take account of the possible endogeneity of $y_f$, we allow for correlation in the unobserved terms ($\varepsilon_s$ and $\varepsilon_f$). Failure to do so could bias our estimate of state dependency. If, for example, we assume that parents and children share similar motivation and that more motivated individuals are less likely to become unemployed, then our measure of state dependency would be biased upwards, reflecting in part the correlation in unobserved family specific factors. The exclusion of son's unemployment history from the father's equation guarantees us that the system of equations possess a unique implicit reduced form (Maddala (1983)). The model is estimated using full-information maximum likelihood. The likelihood function can be written as:

$$L = \begin{array}{l} \prod_{n_1} \Pr(\varepsilon_f > -\gamma' Z_f , \ \varepsilon_s > -(\beta_{1'} X_s + \beta_{2'} y_f )). \prod_{n_2} \Pr(\varepsilon_f > -\gamma' Z_f , \ \varepsilon_s < -(\beta_{1'} X_s + \beta_{2'} y_f ) ) \\ \prod_{n_3} \Pr(\varepsilon_f < -\gamma' Z_f , \ \varepsilon_s > -(\beta_{1'} X_s + \beta_{2'} y_f )). \prod_{n_4} \Pr(\varepsilon_f < -\gamma' Z_f , \ \varepsilon_s < -(\beta_{1'} X_s + \beta_{2'} y_f ) ) \end{array}$$

where $n_1$ is the number of cases where both the parent and child are unemployed, $n_2$ the number where the parent is unemployed but the child is not, $n_3$ the number where the child is unemployed but the parent is not and $n_4$ the number of cases where neither the child or the parent is unemployed. In maximising the likelihood we assume that $(\varepsilon_f , \varepsilon_s) \sim BVN(0,0,1,1,\rho)$.

In the parent's unemployment equation we include measures of the father's education and social class, a control for the number of children in the parent's household, a measure of the father's age and a set of variables measuring local labour demand conditions. These variables consist of 1969 and 1974 measures of unemployment rates in the parent's standard region. We would expect the higher local unemployment rates to be associated with a higher probability of parental unemployment.

This model is identified if $\rho$=0 or if there is a variable included in the parent's equation which is omitted from the son's equation. Since we wish to test the hypothesis that $\rho$=0 we must rely on exclusion restrictions to identify the system. Obtaining such restrictions is difficult. In an earlier draft of this paper we tried to use information on the father's region before 1969. It seemed reasonable to assume that this would be significant in explaining fathers' unemployment but would not explain sons' behaviour over and above its effect on the father. Unfortunately, although these early regional variables were significant in the parents equation when entered alone they became insignificant when the later region variables were included. We therefore rely on these later regional effects to identify the model. In particular we include the unemployment rate in the father's region in 1969 and 1974 as explanatory variables in the father's equation but not in the sons. For this to be a valid identifying restriction it must be the case that having controlled for local labour market conditions in 1981 and 1991, as well as father's unemployment status, then the local labour market conditions when the child was aged seven should not explain the son's unemployment. This assumption may be questionable. Fathers' education and fathers' social class are also excluded from the sons equation. Although fathers' education and fathers' social class are statistically insignificant in the son's equation when the other variables are included, the economic rational for these restrictions may be even more questionable that the region variable.

The Full Informational Maximum Likelihood results are given in Table 6. With the exception of the father's unemployment variable the results for the son's equation are similar to the univariate probit. In the father's equation, fathers in skilled professions are less likely to be unemployed, as are fathers with fewer children and fathers from areas with favourable local labour market conditions. In terms of explaining the persistence of unemployment across generations the two key estimates are those on father's unemployment and $\rho$. To the extent that unobservables which are correlated across generations are important in generating our finding we would expect the estimate on father's unemployment to decline and to observe a positive estimate on $\rho$. However our estimate of $\rho$ is small and negative and the coefficient on fathers unemployment increases slightly. Unfortunately neither coefficient is precisely estimated. We expect that this reflects the identification difficulties which we discussed earlier. Since the NCDS is focused on the child and contains relatively little data on the parents it is difficult to progress much further on this issue using the NCDS. Obtaining more a more precise estimate of $\rho$ is a challenge for future work.

## IV. Conclusion

In this paper we examine the extent to which unemployment encourages dependency among future generations. We do this by looking at the correlation between the unemployment histories of fathers and sons. We find that sons who had fathers who were unemployed were almost twice as likely to experience unemployment than sons whose father was not unemployed. Furthermore these sons could expect to have spent over 3 months longer unemployed over the first 10 years of their working lives. However, much of this effect works through the increased incidence of unemployment rather than longer durations. These results reinforce the findings based on the intergenerational transmission of earnings and highlight the importance of family background in explaining a child's future labour market prospects. While we are not able to determine precisely the channels through which this transmission works we are able to eliminate several. For instance controlling for several dimensions of the son's education does not eliminate the greater tendency for sons from disadvantaged backgrounds to experience unemployment. The same is true for other measures of human capital such as results from test scores and computer skills. Identifying policies which would be successful in breaking this link is a future challenge to both researchers and policy makers.

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**Table 1**
**Variable Definition and Means**

| Variable Name | Variable Definition | Mean |
|---|---|---|
| U1 | Indicator variable indicating son was unemployed between '81 and 91 | .24 |
| U2 | # months unemployed between '81 and '91 | 4.42 |
| Fathed | Father's Years of Education | 10.41 |
| Fathage | Father's age | 46.41 |
| Nsibling | No of siblings | 2.07 |
| Fprof65 | Father in Professional Social Class in 1965 | .063 |
| Fint65 | Father in Intermediate/Skilled non-manual social class in 1965 | .27 |
| Fskil65 | Father in Skilled Manual Social Class in 1965 | .49 |
| Ur69 | Unemployment Rate in parents standard region in 1969 | 2.47 |
| Ur74 | Unemployment Rate in parents standard region in 1974 | 2.62 |
| Fathunem | A dummy variable taking the value 1 if the father was unemployed in 1969 or 1974 | .11 |
| Nwelinc81 | Dummy taking value 1 if son has non-welfare-nonlabour income in 1981 | .88 |
| Child81 | Dummy indicating son has children in 1981 | .13 |
| Separate81 | Dummy variable =1 if son is separated, divorced or widowed in 1981 | .018 |
| Single81 | Dummy variable =1 if son is single in 1981 | .62 |
| Computer | Dummy variable=1 if son reports using a computer at home or at work | .54 |
| Indep7 | Dummy variable=1 if son attended an independent school at age 7 | .017 |
| Indep11 | Dummy variable =1 if son attended an independent school at age11 | .028 |
| Indep16 | Dummy variable =1 if son attended an independent school at age16 | .045 |
| Read7 | Test score from Reading Test at age 7 | .13 |

| | | |
|---|---|---|
| | (Standardized) | |
| Math7 | Test score from Math Test at age 7 (Standardized) | .17 |
| Ed181 | CSE 2-5/equivalent 1981 | .09 |
| Ed281 | Olevel/equivalent 1981 | .36 |
| Ed381 | Alevel/equivalent 1981 | .27 |
| Ed481 | Higher qualification 1981 | .11 |
| Ed581 | Degree or Higher 1981 | .11 |
| Ur81 | Unemployment Rate in sons standard region in 1981 | 8.04 |
| Ur91 | Unemployment Rate in sons standard region in 1991 | 7.96 |

**Table 2**
**Frequency of months spent unemployed by sons between 1981 and 1991**

| months unemployed | Number | frequency | cumulative frequency |
|---|---|---|---|
| 0 | 738 | 74.77 | 74.77 |
| 1 | 15 | 1.52 | 76.29 |
| 2 | 18 | 1.82 | 78.12 |
| 3 | 21 | 2.13 | 80.24 |
| 4 | 13 | 1.32 | 81.56 |
| 5 | 11 | 1.11 | 82.67 |
| 6 | 14 | 1.42 | 84.09 |
| 7 | 12 | 1.22 | 85.31 |
| 8 | 11 | 1.11 | 86.42 |
| 9 | 8 | 0.81 | 87.23 |
| 10 | 10 | 1.01 | 88.25 |
| 11 | 10 | 1.01 | 89.26 |
| 12 | 18 | 1.82 | 91.08 |
| 13 | 6 | 0.61 | 91.69 |
| 14 | 6 | 0.61 | 92.30 |
| 15 | 5 | 0.51 | 92.81 |
| 16 | 4 | 0.41 | 93.21 |
| 17 | 4 | 0.41 | 93.62 |
| 19 | 5 | 0.51 | 94.12 |
| 20 | 2 | 0.20 | 94.33 |
| 21 | 6 | 0.61 | 94.93 |
| 22 | 2 | 0.20 | 95.14 |
| 25 | 1 | 0.10 | 95.24 |
| 26 | 3 | 0.30 | 95.54 |
| 27 | 1 | 0.10 | 95.64 |
| 28 | 2 | 0.20 | 95.85 |
| 29 | 1 | 0.10 | 95.95 |
| 30 | 2 | 0.20 | 96.15 |
| 31 | 1 | 0.10 | 96.25 |
| 33 | 3 | 0.30 | 96.56 |
| 34 | 1 | 0.10 | 96.66 |
| 35 | 1 | 0.10 | 96.76 |
| 36 | 2 | 0.20 | 96.96 |
| >=37 | 30 | 2.94 | 100.00 |
| | 967 | | |

Mean:4.32
Variance:187

**Table 3**
**Relationship between father's unemployment status and son's unemployment status**
**(standard errors in parentheses; cell numbers in bold)**

| | Father unemployed in 1969 or 1973 | Father not unemployed in either 1969 or 1973 |
|---|---|---|
| Proportion of sons unemployed between 1981 and 1991 | .44<br>(.05)<br>**108** | .23<br>(.01)<br>**879** |
| Months spent unemployed between 1981 and 1991 | 7.41<br>(1.76)<br>**108** | 3.89<br>(.44)<br>**879** |
| Months spent unemployed between 1981 and 1991 given that months are positive | 18.17<br>(3.52)<br>**47** | 16.91<br>(1.59)<br>**202** |

**Table 4**

| **Model** | **Log-Likelihood** |
|---|---|
| *Non-Hurdle Models* | |
| a1. Poisson | -7355.37 |
| a2. Negbin 2 | -1492.98 |
| *Hurdle Models* | |
| a3. Poisson Incidence | -897.75 |
| a4. Poisson positive counts | -2383.72 |
| a5. Negbin 2 Incidence | -519.53 |
| a6. Negbin 2 positive counts | -907.88 |
| | |
| **Tests** | **LR-statistic** |
| b1. Poisson Non-Hurdle versus Poisson Hurdle: $\chi^2(29)$ | 8147.8 |
| b2. Negin 2 Non-Hurdle versus Negbin 2 Hurdle : $\chi^2(30)$ | 131.4 |
| b3. Poisson Incidence versus Negbin 2 incidence | 756.4 |
| b4. Poisson Positive counts versus Negbin 2 positive counts | 2951.7 |
| | |
| | |

**Table 5**
**Univariate estimates of the father-son unemployment relationship**
**(standard errors in parentheses)**

| Variable | Probit | Probit Incidence | Negbin 2 Incidence | Negbin 2 Positive counts |
|---|---|---|---|---|
| Const. | -.74** (.05) | -.72 (.44) | -1.16 (.99) | 1.75** (.79) |
| Fathunem | .58** (.13) | .55** (.14) | 1.03** (.53) | .0058 (.19) |
| Nwelinc81 | | -.62** (.13) | -1.14* (.60) | -.31* (.19) |
| child81 | | .28* (.16) | .54 (.36) | -.36 (.33) |
| ed181 | | .0021 (.21) | -.017 (.41) | -.36 (.33) |
| ed281 | | -.057 (.18) | -.11 (.36) | -.37 (.31) |
| ed381 | | -.19 (.20) | -.37 (.42) | -.66* (.37) |
| ed481 | | -.073 (.23) | -.14 (.44) | -.70* (.42) |
| ed581 | | -.045 (.23) | -.09 (.46) | -.52 (.44) |
| separate81 | | -.074 (.33) | .13 (.56) | .46 (.48) |
| single81 | | .42** (.11) | .78** (.34) | -.12 (.19) |
| computer | | -.21** (.10) | -.39** (.21) | -.19** (.19) |
| indep7 | | -.41 (.46) | -.77 (.88) | -1.18 (2.53) |
| indep11 | | -.10 (.36) | -.19 (.59) | -.029 (.93) |
| indep16 | | .015 (.25) | .04 (.43) | .82 (.37) |
| nsibling | | .021 (.029) | .04 (.05) | .039 (.043) |
| math7 | | -.051 (.055) | .09 (.11) | .019 (.088) |
| read7 | | .065 (.061) | .12 (.12) | -.14 (.10) |
| ur81 | | -.023 (.037) | -.05 (.06) | .19** (.059) |
| ur91 | | .070 (.071) | .14 (.13) | .0070 (.11) |
| α | | | 1.51 (2.45) | 1.08** (.16) |
| Log-Likelihood | | -519.68 | -519.53 | -907.88 |
| N | 987 | 987 | 987 | 987 |

* significant at the 10% level

** significant at the 5% level

**Table 6**
**Bivariate Probit estimates of father-son unemployment relationship (standard errors in parentheses)**

| **Variable Name** | | | N=987 |
|---|---|---|---|
| | | Son's Equation | |
| Constant | (.63) | Constant | (.45) |
| Fathed | (.05) | Fathunem | (.83) |
| nsibling | ** | Nwelinc81 | ** |
| fathage | (.01) | | .28 (.16 |
| | -.34 | ed181 | (.22) |
| | -.56 (.19) | | -.06 |
| fskil65 | ** | ed381 | (.21) |
| | -.11 | ed481 | (.24) |
| | .24 (.11) | | -.05 |
| | | separate81 | (.30) |
| | | | .42 (.11) |
| | | | -.21 (.10) |
| | | | -.41 |
| | | indep11 | (.31) |
| | | | -.16 |
| | | nsibling | (.04) |
| | | | -.05 |
| | | read7 | (.06) |
| | | | -.02 |
| | | ur91 | (.07) |

| | | | |
|---|---|---|---|
| | | ρ | -.04<br>(.44) |

* significant at the 10% level
** significant at the 5% level