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INTERGENERATIONAL MOBILITY IN BRITAIN: EVIDENCE FROM UNEMPLOYMENT PATTERNS

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I. INTRODUCTION

In this paper we examine the extent to which the 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.[1] 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 his son will subsequently become unemployed?

It is important to distinguish between different mechanisms which might account for such a correlation. The relationship between a parent's and child's unemployment could reflect transmission of tastes, transmission of constraints, or true state dependency.[2] 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 to finance their child's education. That will in turn affect the

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[1] For a summary of this work see Narendranathan and Nickell (1986).

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

child's potential earnings and 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 unemployment 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.[3] 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 chidren'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 premarket experience. This allows us to control for some factors which might cause spurious correlation. To examine the role of unobservable characteristics we simultaneously model the parent's and child's unemployment equations, taking into account correlation in unobservables. The hurdle estimation strategy which we adopt allows us to take account of the fact that three quarters of our sample did not experience a spell of unemployment.

Owing to data limitations much of the recent work on intergenerational mobility has been carried out in the U.S. Recent studies by Gottschalk (1990) and Antel (1992) focused on the welfare participation of daughters and their parents, while work by Solon *et al.* (1988) focused on the relationship between the welfare experiences of siblings. These studies found a strong link between a girl's welfare experience and that of her mother or sister, which remains even after controlling for heterogeneity. For instance, Gottschalk (1990) reported that the probability of the daughter having a child and receiving assistance was twice as high if the parent also received assistance. These studies have tended to concentrate on recipients of Aid to Families with Dependent Children (AFDC), as a result of which the analysis has been restricted to single mothers with low incomes.

The absence of U.K. data spanning more than one generation has restricted the ability of researchers to analyse patterns of intergenera-

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

tional mobility in the U.K. Goldthorpe and Payne (1986) study intergenerational class mobility in England and Wales using information on the occupations of fathers and sons, while Atkinson, Maynard and Trinder (1983) and Dearden *et al*. (1997) provide a detailed discussion on income mobility across generations. However, none of these studies examines the connection between the unemployment behaviour of different generations. In this paper we make use of the National Child Development Survey (NCDS) to analyse unemployment links across generatons. Johnson and Reed (1996) also used the NCDS to tabulate the relationship between the incidence of unemployment among sons and fathers, but they did not attempt to distinguish between competing explanations of the intergenerational link.

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 son's 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.[4] To date there have been five 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 whether the father had been unemployed at any time during 1969 or 1974. We also used a measure of persistent unemployment by looking at parents who were unemployed in both 1969 and 1974. The point estimates were very

[4] Since all children in our sample are born in the same month one may have to take cohort effects into account when generalising to populations born in different periods. However, we believe that the potential for bias is much less than in previous studies where the sample restrictions were even more severe. For instance in Behrman and Taubman (1985) the sample of fathers were drawn from a population of white twins both of whom had served in the armed forces. For further discussion on this see Solon (1989).

similar for this specification although the standard error on father's unemployment was higher. This is because only 1.5 percent of parents were unemployed in both of the years we consider. As a result of the small number of fathers who were unemployed in both years we present only the results for the former specification.[5] For sons we use the number of months the son was unemployed between age 23 and 33. 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. To control for life-cycle differences between parents we also include a measure of father's age in the father's unemployment equation. 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 percent of fathers had been unemployed in either 1969 or 1974. Information on the son's unemployment record between 1981 andf 1991 is provided in Table 2. Two common features associated with count data are evident from this table. Firstly the raw data exhibit overdispersion in the context of the Poisson model normally used to analyse count data. The sample mean of 4.32 months is significantly smaller than the sample variance, which is almost 187 months. This is in contrast to the prediction of the Poisson model, which restricts the population mean and variance to be equal. Secondly three-quarters of our sample experienced no unemployment over this period. Both these features are important and are taken into account in our estimation strategy.

III. MODEL AND ESTIMATION RESULTS

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

[5] While it may not be sensible to consider transitory changes in income when examining intergenerational earnings mobility (Solon, 1989), the experience of even one spell of unemployment by parents may have long-run consequences for their children.

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. Sons whose fathers had been unemployed in either 1969 or 1974 were twice as likely to be unemployed

TABLE 1
Variable Definition and Means

Variable name	*Variable definition*	*Mean*
U1	Indicator variable indicating son was unemployed between 1981 and 1991	0.24
U2	No. months unemployed between 1981 and 1991	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	0.063
Fint65	Father in intermediate/skilled non-manual social class in 1965	0.27
Fskil65	Father in skilled manual social class in 1965	0.49
Ur69	Unemployment rate in parent's standard region in 1969	2.47
Ur74	Unemployment rate in parent's standard region in 1974	2.62
Fathunem	A dummy variable taking the value 1 if the father was unemployed in 1969 or 1974	0.11
Nwelinc81	Dummy taking value 1 if son has non-welfare-nonlabour income in 1981	0.88
Child81	Dummy indicating son has children in 1981	0.13
Separate81	Dummy variable = 1 if son is separated, divorced or widowed in 1981	0.018
Single18	Dummy variable = 1 if son is single in 1981	0.62
Computer	Dummy variable = 1 if son reports using a computer at home or at work	0.54
Indep7	Dummy variable = 1 if son attended an independent school at age 7	0.017
Indep11	Dummy variable = 1 if son attended an independent school at age 11	0.028
Indep16	Dummy variable = 1 if son attended an independent school at age 16	0.045
Read7	Test score from reading test at age 7 (Standardised)	0.13
Math7	Test score from math terst at age 7 (Standardised)	0.17
Ed181	CSE 2-5/equivalent 1981	0.09
Ed281	O level/equivalent 1981	0.36
Ed381	A level/equivalent 1981	0.27
Ed481	Higher qualification 1981	0.11
Ed581	Degree or higher 1981	0.11
Ur81	Unemployment rate in son's standard region in 1981	8.04
Ur91	Unemployment rate in son's standard region in 1991	7.96

between 1981 and 1991 than sons whose fathers had not been unempl-poyed. Likewise we see that these sons had experienced more than 3 months more unemployment over the first 10 years of their working lives. However, there is little difference between groups in the time spent unemployed conditional on having experienced a spell of unemployment.

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	92.3
15	5	0.51	92.81
16	4	0.41	93.21
17	4	0.41	93.62
18	0	0.00	93.62
19	2	0.51	94.12
20	2	0.2	94.33
21	6	0.61	94.93
22	2	0.2	95.14
23	0	0.00	95.14
24	0	0.00	95.14
25	1	0.1	95.24
26	3	0.3	95.54
27	1	0.1	95.64
28	2	0.2	95.85
$>=29$	41	4.04	100
Mean	4.32		
Variance	187		
Median	0		
Mode	0		
Standard deviation	13.66		

It thus 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 link across generations it is important that we try to understand how poor unemployment prospects are passed on from generation to generation. 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 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 the inclusion of these variables reduces 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 λ_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, 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 $y_i = 0, 1, 2 \ldots$. To examine the impact of regressors in this context it is common to specify the conditional mean $\lambda_i = \exp(X_i'\beta)$ where β is a $(k \times 1)$ 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 Triverdi (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 α 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

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	0.44 (0.05) **108**	0.23 (0.01) **879**
Months spent unemployed between 1981 and 1991	7.41 (1.76) **108**	3.89 (0.44) **879**
Months spent unemployed between 1981 and 1991 given that months are positive	18.17 (3.52) **47**	16.91 (1.59) **202**

using the hurdle model of Mullahy (1986). We assume that the binomial process governing unemployment incidence can be modelled using a density $f_1(y_i|X_i)$ with parameters β_1, while positive counts come from a density $f_2(y_i|X_i)$ with parameters β_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 $[1-f_1(0|X_i)/1-f_2(0|X_i)]\cdot f_2(y_i|X_i)$ 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 β_1 and β_2. Estimation can proceed by first maximising a binary likelihood model and then estimating a truncated count model on the positive counts.

We examine four alternative models. The first two are the standard Poisson model and negative binomial model applied to all the data. The third is the hurdle model where both the incidence and the positive counts densities are assumed to be Poisson. The fourth is the hurdle model where the densities are assumed to be Negbin 2 with parameters (γ_1, α_1) and (γ_2, α_2) respectively. To determine which of these models 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 be tested for by 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

TABLE 4
Alternative Models for Estimating the Univariate Relationship Between Father's and Son's Unemployment Histories

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-static*
b1. Poisson non-hurdle versus Poisson hurdle: $\chi^2(29)$	8147.8
b2. Negbin 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

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.[6] 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.

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

[6] Since the test of the Poisson model ($\alpha = 0$) lies on the boundary of the parameter space the appropriate critical value for a one-sided 5 percent test is in fact the 10 percent critical value (Lawless 1987).

[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.

TABLE 5

Univariate Estimates of the Father–Son Unemployment Relationship (standard errors in parentheses)

Variable	*Probit*	*Probit incidence*	*Negbin 2 incidence*	*Negbin 2 positive count*
Const	−0.74**	−0.72	−1.16	1.75**
	(0.05)	(0.44)	(0.99)	(0.79)
Fathunem	0.58**	0.55**	1.03**	0.0058
	(0.13)	(0.14)	(0.53)	(0.19)
Nwelinc81		−0.62**	−1.14*	−0.31*
		(0.13)	(0.60)	(0.19)
Child81		0.28*	0.54	−0.36
		(0.16)	(0.36)	(0.33)
Ed181		0.0021	−0.017	−0.36
		(0.21)	(0.41)	(0.33)
Ed281		−0.057	−0.11	−0.37
		(0.18)	(0.36)	(0.31)
Ed381		−0.19	−0.37	−0.66*
		(0.20)	(0.42)	(0.37)
Ed481		−0.073	−0.14	−0.70*
		(0.23)	(0.44)	(0.42)
Ed581		−0.045	−0.09	−0.52
		(0.23)	(0.46)	(0.44)
Separate81		−0.074	0.13	0.46
		(0.33)	(0.56)	(0.48)
Single81		0.42**	0.78**	−0.12
		(0.11)	(0.34)	(0.19)
Computer		−0.21**	−0.39**	−0.19**
		(0.10)	(0.21)	(0.19)
Indep7		−0.41	−0.77	−1.18
		(0.46)	(0.88)	(2.53)
Indep11		−0.10	−0.19	−0.029
		(0.36)	(0.59)	(0.93)
Indep16		0.015	0.04	0.82
		(0.25)	(0.43)	(0.37)
Nsibling		0.021	0.04	0.039
		(0.029)	(0.05)	(0.043)
Math7		−0.051	0.09	0.019
		(0.055)	(0.11)	(0.088)
Read7		0.065	0.12	−0.14
		(0.1061)	(0.12)	(0.10)
Ur81		−0.023	−0.05	0.19**
		(0.037)	(0.06)	(0.059)
Ur91		0.070	0.14	0.0070
		(0.071)	(0.13)	(0.11)
α			1.51	1.08**
			(2.45)	(0.16)
Log-likelihood		−519.68	−519.53	−907.88
N	987	987	987	987

Note:
*Significant at the 10% level.
**Significant at the 5% level.

of being unemployed in the usual way. For the Probit model we compare $\Theta(Z'\gamma+0.55)$ and $\Theta(Z'\gamma)$, where Z is the set of explanatory variables excluding fathers' employment status, evaluated at the mean, and Θ is the standard normal cumulative distribution function. Using our estimated coefficients we find that the probability of becoming unemployed increases from 0.22 to 0.42 for a son whose father was unemployed. For the Negbin 2 model the relative effect is simply $e^{1.03}$, which equals 2.88. Thus even after controlling for a host of explanatory variable we find that sons of fathers who had been unemployed are between two and three times more 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 affect the unemployment status of the son in the expected way. However, the impact of fathers' unemployment status is no longer significant. The impact of fathers' background on sons' unemployment history thus seems to differ according to 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 have an effect 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. One possible explanation for this is as follows: consider a situation where firms are uncertain about an individual's productivity and use information on their father to help predict it. Suppose further that the occurrence of a spell of unemployment reveals information about an individual. This would reduce the firm's reliance on father's details and so would weaken the intergenerational link among the pool of unemployed.

IV. SIMULTANEOUS MODELLING OF FATHER'S AND SONS' UNEMPLOYMENT

In this section we extend the previous analysis by modelling the correlation in unobservables. Initially we adopted a semi-parametric approach to modelling heterogeneity, allowing for a discrete random component in both the father's and son's unemplolyment equations. The father's and son's equations were then estimated jointly allowing for correlation in the heterogeneity terms.[8] However, the likelihood function for this specification did not appear to be well-behaved, with the final estimates being very

[8] A similar approach was adopted by Gottschalk (1996) in looking at AFDC recipients in the U.S.

sensitive to the starting values chosen.[9] In order to reduce the dimensionality of the problem we adopted a parametric approach where we assumed that the distributions of the errors was bivariate normal. While this may be a more restrictive assumption than that suggested earlier, it has the advantage that it involves the estimation of only one additional parameter, ρ, the correlation between the error terms. This bivariate probit specification leads to the following simultaneous equation model:

$$y_f^* = \gamma' Z_f = \varepsilon_f, \qquad y_f = 1 \text{ if } y_f^* > 0, \quad y_f = 0 \text{ otherwise}$$

$$y_s^* = \beta_1' X_s + \beta_2 v_2 y_f + \varepsilon_s, \quad y_s = 1 \text{ if } y_s^* > 0, \quad y_s = 0 \text{ otherwise}$$

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

Our data consist of observations on y_f (a dichotomous variable indicating parents' unemployment), y_s (a dichotomous variable indicating childrens' unemloyment), and 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 (ε_s and ε_f). Failure to do so could bias our estimate of the 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 observed family specific factors. The exclusion of son's unemployment history from the father's equation guarantees that the system of equations posses a unique implicit reduced form (Maddala, 1983). The model is estimated using full-information maximum likelihood. The likelihood function can be written as:

$$L = \begin{array}{l} \prod_{n_1} \Pr(\varepsilon_f > -\gamma' Z_f, \varepsilon_s > -(\beta_1' X_s + \beta_2' y_f)). \\ \quad \prod_{n_2} \Pr(\varepsilon_f > -\gamma' Z_f, \varepsilon_s < -(\beta_1' X_s + \beta'_2 y_f)). \\ \prod_{n_3} \Pr(\varepsilon_f < -\gamma' Z_f, \varepsilon_s > -(\beta_1' X_s + \beta_2' y_f)). \\ \quad \prod_{n_4} \Pr(\varepsilon_f < -\gamma' Z_f, \varepsilon_s < -(\beta_1' X_s + \beta_2' y_f)) \end{array}$$

where n_1 is the number of cases in which both the parent and child are unemployed, n_2 the number in which the parent is unemployed but the child is not, n_3 the number in which the child is unemployed but the

[9] Even when we allow each of the error distributions only to have two mass points and arbitrarily set one of them equal to zero for both sons and fathers, this approach still involves estimating five new parameters when we include both the estimates of the mass points and the associated probabilities.

parent is not and n_4 the number of cases in which neither the child or the parent is unemployed. In maximising the likelihood we assume that (ε_f, $\varepsilon_s \sim \mathrm{BVN}(0, 0, 1, 1, \rho)$.

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 unemloyment rates in the parent's standard region. We would expect 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 children'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.[10] We rely on later regional effects to identify the model: 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. Father's education and father's social class are also excluded from the son's equation. Although father's education and father's social class are statistically insignificant in the son's equation when the other variables are included, the economic rationale for these restrictions may be even more questionable than the region variable.

The Full Information Maximum Likelihood results are shown in Table 6. 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. With the exception of the father's unemployment variable, the results for the son's equation are similar to the univariate probit. In explaining the persistence of unemployment across generations, the two key estimates are those on father's unemployment and ρ. 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 ρ. However, our estimate of ρ is small and negative and the coefficient on father's unemployment increases slightly. Unfortunately neither coefficient is precisely estimated. We suspect that this is a further reflection of the identification difficulties which we

[10] Initially 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 parent's equation when entered alone, they became insignificant when the later region variables were included.

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 a more precise estimate of the intergenerational correlation in unemployment patterns in the presence of unobserved heterogeneity 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 fathers were not unemployed. Furthermore, these sons could expect to have spent over 3 months longer unemployed between the age 21 and 31. However, much of this effect works through the increased incidence of unemployment rather than longer duration. These results reinforce the findings based on the intergnerational transmission of earnings and highlight the importance of family background in explaining a child's future labour market prospects.

The second part of the paper attempts to distinguish between competing explanations for the relationship between parents' and childrens' unemployment histories. We make a distinction between spurious correlation and true state dependence. With state dependence it is the fact that the father experienced a spell of unemployment which alone increases the probability of the son experiencing unemployment. While it is important to distinguish between alternative transmission mechanisms in developing policies, it is not clear *a priori* which of these mechanisms should be viewed as most problematic for society. While true state dependence implies the existence of poverty traps in the system, spurious correlation may reflect equally troublesome issues such as discrimination. To see this, assume that employers discriminate against individuals belonging to a certain group when making hiring decisions. Parents who are members of this group will find it difficult to obtain work, as will their children, since both will be discriminated against. However, removing fathers from unemployment without tackling discimination will have no direct effect on sons, since they will still encounter discrimination when they enter the labour market. What is needed is a policy which tackles the source of the unemployment problem directly, in this case a policy aimed at reducing discrimination. We would label this as spurious correlation. However, few people would argue that an intergeneratinal link in unemployment driven by discrimination is any less of a problem than one driven by poverty traps in a benefit system.

While we are not able to determine precisely the channels through which the intergenerational transmission process works, we are able to

TABLE 6
Bivariate Probit Estimates of Father–Son Unemployment Relationship
(standard errors in parentheses)

Father's equation		*Son's equation*	
Dependent variable	*Estimate (Std. error)*	*Dependent variable*	*Estimate (Std. error)*
Constant	−1.09 (0.63)	Contant	−0.72 (0.45)
Fathed	−0.039 (0.05)	Fathunem	0.63 (0.83)
Nsibling	−0.14** (0.03)	Newline81	−0.62** (0.13)
Fathage	−0.004 (0.01)	Child81	0.28* (0.16)
Fprof65	−0.34 (0.34)	Ed181	0.002 (0.22)
Fint65	−0.56** (0.19)	Ed281	−0.06 (0.19)
Fskil65	−0.30** (0.14)	Ed381	−0.20 (0.21)
Ur69	−0.11 (0.12)	Ed481	−0.08 (0.24)
Ur74	0.24** (0.11)	Ed581	−0.05 (0.24)
		Separate81	0.07 (0.30)
		Single81	0.42** (0.11)
		Computer	−0.21** (0.10)
		Indep7	−0.41 (0.44)
		Indep11	−0.10 (0.31)
		Indep16	−0.16 (0.24)
		Nsibling	0.02 (0.04)
		Math7	−0.05 (0.06)
		Read7	0.06 (0.06)
		Ur81	−0.02 (0.04)
		Ur91	0.07 (0.07)
		ρ	0.04 (0.44)
N	987	987	

See Notes to Table 5.

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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REFERENCES

Antel, J. (1992). 'The Intergenerational Transfer of Welfare Dependency', *Review of Economics and Statistics*, Vol. 3, pp. 467–73.

Arulampalam, W., Booth, A. and Elias, P. (1997). 'Modelling Work-Related Training and Training Effects using Count Data Techniques', CEPR Discussion Paper No. 1582.

Atkinson, A., Maynard, A. and Trinder, C. (1983). *Parent's and Children: Incomes in Two Generations*, London: Heinemann.

Atkinson, A. and Mogensen, G. (1993). *Welfare and Work Incentives: A Northern European Perspective*, Oxford University Pres.

Barr, N. (1993). *The Welfare State*, Oxford University Press.

Behjrman, J. and Taubman, P. (1985). 'Intergenerational Earnings Mobility in the United States: Some Estimates and a Test of Becker's Intergenerational Endowments Model', *Review of Economics and Statistics*, Vol. 67, pp. 144–51.

Blundell, R. and Smith, R. (1993). 'Simultaneous Microeconometric Models with Censored or Qualitative Dependent Variables', in Maddala, G. and Rao, C. (eds.), *Handbook of Statistics: Volume 14*.

Cameron, A. and Triverdi, P. (1996). 'Count Data Models for Financial Data', in Maddala, G. and Rao, C. *op. cit.*

Cornell, B. and Welch, I. (1996). 'Culture, Information and Screening Discrimination', *Journal of Political Economy*, Vol. 104, pp. 542–71.

Dearden, L., Machin, S. and Reed, H. (1997). 'Intergeneratinal Mobility in Britain', *Economic Journal*, Vol. 107, pp. 47–66.

Goldthorpe, J. and Payne, C. (1986). 'Trends in Intergenerational Class Mobility in England and Wales, 1972–1983', *Sociology*, Vo. 20, pp. 3–24.

Gottschalk, P. (1990). 'AFDC Participation Across Generations', *American Economic Review*, Vol. 80, pp. 367–71.

Gottschalk, P. (1996). 'Is the correlation in welfare participation across generations spurious?' *Journal of Public Economics*, Vol. 63, pp. 1–25.

Heckman, J. (1978). 'Dummy Endogenous Variables', *Econometrica*, Vol. 46, pp. 931–59.

Jenkins, S. (1987). 'Snapshots versus Movies: Life-Cycle Biases and the Estimation of Intergenerational Earnings Inheritance', *European Economic Review*, Vol. 31, pp. 1149–58.

Johnson, P. and Reed, H. (1996). 'Two Nations: The Inheritance of Poverty and Affluence', IFS Commentary No. 53.

Lawless, J. (1987). 'Negative Binomial and Mixed Poisson Regression', *The Canadian Journal of Statistics*, Vol. 15, pp. 209–25.

Maddala, G. (1983). *Limited Dependent Variables*, Cambridge University Press.

Mullahy, J. (1986). 'Specification and Testing of some Modified Count Data Models', *Journal of Econometrics*, Vol. 33, pp. 341–65.

Murphy, A. (1997). 'Dummy Endogenous Variables in Probit Models', Mimeo, University College Dublin.

Narendranathan, W. and Nickell, S. (1986). 'Estimating Parameters of Interest in a Job-Search Model', in Blundell, R. and Walker, I., *Unemployment, Search and Labour Supply*, Cambridge University Press.

Solon, G. (1989). 'Biases in the Estimation of Intergenerational Earnings Correlation', *Review of Economics and Statistics*, Vol. 71, pp. 172–74.

Solon, G., Corcoran, M., Gordon, R. and Laren, D. (1988). 'Sibling and Intergenerational Correlations in Welfare Program Participation', *Journal of Human Resources*, Vol. XXIII, pp. 389–95.

Winkelmann, R. and Zimmermann, K. (1995). 'Recent Developments in Count Data Modelling: Theory and Application', *Journal of Economic Surveys*, Vol. 9, pp. 1–24.