Sixty Years of Measuring Social Mobility*

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In memory of my former colleague, Sig Prais.

Draft date: 28 April 2015

*I am grateful to Erzsébet Bukodi and John Goldthorpe for insightful comments on an earlier draft of the paper.

Sixty years ago Sig Prais published a seminal paper on measuring social mobility in the *Journal of the Royal Statistical Society* (Prais 1955a), along with an accompanying, non-technical one addressing the same issue in *Population Studies* (Prais 1955b). The former was the foundation for the quantitative analysis of social mobility as a 'stochastic process'. Subsequent papers and books by others have developed this approach (e.g. Kemeny and Snell 1960; Bartholomew 1982). In the present paper I illustrate the key concepts of Prais (1955a) using an application of his ideas to intergenerational educational mobility in contemporary Britain. I then describe some other approaches to measuring social mobility, discuss ways to account for the influence of both parents' education and explore how we may peer into the 'black box' of intergenerational mobility by taking a life course approach for the offspring generation. The final part of the paper takes into account that variation in family background also produces differential growth of segments of the population, thereby providing a population level perspective on social mobility.

1. *Educational mobility*

In the original application by Prais (1955a, 1955b), the methods were illustrated with a table relating the social statuses of fathers and their sons derived from a sample of about 3,500 males, aged 18 and over and resident in England and Wales, interviewed by the Social Survey in 1949. These data formed part of the study edited by David Glass (1954).

Here we analyse data on educational attainments among people sampled in a very large national representative household survey from the United Kingdom: *Understanding Society*. It interviewed nearly 51,000 people in its first wave. Ethnic minority groups are over-sampled. Each person aged 16 or older answers the individual adult interview questionnaire. Questions about each parent's educational qualifications were asked in the first (2009-2010) and second waves (2010-2011) of the study. We focus on people aged 26-65 interviewed in the first wave, and only use the second wave to obtain parents' educational information not collected in the first wave for these respondents. Thus, 'children' in the analyses refers to persons aged 26-65 in 2009-10 (born 1944-1984; old enough to have time to obtain a degree and mainly born since the last world war). Weights to provide a representative cross-section of the UK population of these ages are used in the analyses.

The relevant question about each parent's education is: 'Thinking first about your father's (mother's) educational qualifications, which of these best describes the type of qualifications your father (mother) gained?' The possible responses are given in the first column of Table 1, in which 'did not go to school at all' and 'left school with no qualifications or certificates' are combined in the first category ('No qualification').

Table 1: Parent and child education categories

Parents' educational qualification categories	**Child qualification in comparable parent category**
No qualification	No qualification
Left school with some qualification or certificate	A-level, GCSE or other qualification
Gained post school qualifications or certificates	Higher qualification other than degree
Gained a university degree or higher	Degree

Children's highest qualification information is elicited by a series of questions in the main interview, and it is matched to the parents' categories according to the conventions given in the second column of Table 1. For most of the sample, we have information on both parents' qualifications. To keep the problem in two dimensions, we classify parents by the highest educational level achieved by the two, or by the one whose education we know when the information is missing for the other parent. For simplicity, we denote this as the 'education of the parents.'

We focus on two sets of birth cohorts: children aged 26-45 in 2009-10 and children aged 46-65 in 2009-10. Part of Table 2 shows the educational distributions of the parents in these two cohorts, while part B shows the distributions for their children. The primary change in the child's education distribution between the two cohorts is a large increase in the percentage receiving a degree and a corresponding reduction in the percentage with no qualification. Among their parents, the incidence of all types of educational qualification increased between the two child cohorts.

Table 2: Distribution of educational attainments of parents and children, per cent

	A. Parents' education		B. Child's education	
	Child's age in 2009-10		Child's age in 2009-10	
Education:	46-65	26-45	46-65	26-45
none	46.8	20.2	17.5	6.9
school	20.2	30.6	49.1	48.7
post school	25.8	31.9	12.5	12.7
degree	7.2	17.3	20.8	31.7

The social transition matrix at the core of the analysis by Prais (1955a) is given in Table 3 for the two cohorts' educational transitions. Each row shows how the probability of obtaining that particular qualification varies with the education of the parents. Each column must sum to unity.

Table 3: Educational transition matrix

A. For people aged 46-65 in 2009-10

	Parents' Highest Education			
Child's education	none	school	post school	degree
none	0.260	0.090	0.067	0.014
school	0.525	0.507	0.462	0.262
post school	0.100	0.148	0.172	0.153
degree	0.115	0.255	0.299	0.571

Weighted N=11,572

B. For people aged 26-45 in 2009-10

	Parents' Highest Education			
Child's education	none	school	post school	degree
none	0.164	0.047	0.022	0.009
school	0.564	0.562	0.469	0.234
post school	0.103	0.126	0.165	0.118
degree	0.169	0.265	0.343	0.639

Weighted N=12,955

In this approach, all of the educational mobility information in contained in this matrix. For any matrix of this kind, the educational distribution tends in time to converge to a value that is independent of the original distribution, which is called the *equilibrium distribution*. Table 4 shows this distribution for the two matrices in Table 3.

Table 4: Equilibrium educational distributions*

Education	Aged 46-65 in 2009-10	Aged 26-45 in 2009-10
none	0.071	0.031
school	0.411	0.408
post school	0.150	0.127
degree	0.368	0.434

*Equilibrium vector $\mathbf{x_e}$ solves the equation $\mathbf{x_e}=\mathbf{P}\mathbf{x_e}$, where $\mathbf{P}$ is the appropriate transition matrix in Table 3.

Comparison of the actual distribution of education among children (Table 1, part B) with the equilibrium distribution suggests how the education distribution would change in the future if there are no major changes in the educational mobility process (given by one of the matrices in Table 3). For instance, for the younger cohort, we can expect a substantial increase in the proportion of people obtaining degrees and reductions in the two lowest educational attainment classes.

In the terminology introduced by Prais (1955a), a *perfectly mobile* society would be one in which the probability of obtaining a particular qualification (e.g. degree) is independent of the education of one's parents. There are an infinite number of possible perfectly mobile societies on this definition. Following Prais (1955a), we choose as a basis for comparison with our actual society a perfectly mobile society with the same equilibrium distribution as the actual one. Thus, the transition matrix for the perfectly mobile society associated with the transition matrix for the younger cohort in Table 3 has the probabilities given in the final column of Table 4 in each of its columns.

A measure of social mobility introduced by Prais (1955a) is the average number of generations spent in an educational class, which we can calculate using the diagonal elements of the transition matrix. Table 5 provides these calculations for each educational category from the actual transition matrix in each of the age cohorts (col. 1) and from the matrix of the perfectly mobile society associated with it (col 2.). School qualifications and degree qualifications are the most persistent across generations: on average at least two generations are spent in these classes if the person's parents were in that class.

The average number of generations spent in an educational class is larger for more common educational attainments; e.g. if most people's highest educational qualification is school only, then the offspring of parents who had school qualifications are very likely to remain in this group over many generations. The third column provides a measure of 'relative mobility' that standardises for this tendency, using the equilibrium distribution as the benchmark. It shows that the average number of generations with a degree is about fifty per cent larger in the actual society compared with the corresponding perfectly mobile one, but post-school qualifications (less than a degree) show nearly identical persistence in the actual and perfect mobility societies. That is, the offspring of degree parents are disproportionally likely to obtain a degree themselves. The final column of Table 5 shows the standard deviation of the averages in the first column, which are clearly quite large, indicating considerable heterogeneity in the population.

Table 5: Average number of generations spent in educational class*

A. Aged 46-65 in 2009-10

	1.Actual	2.Perfectly Mobile	3.Actual/PM	4.Std. Dev. actual
none	1.35	1.08	1.255	0.69
school	2.03	1.70	1.193	1.44
post school	1.21	1.18	1.027	0.50
degree	2.33	1.58	1.474	1.76

B. Aged 26-45 in 2009-10

	1.Actual	2.Perfectly Mobile	3.Actual/PM	4.Std. Dev. actual
none	1.20	1.03	1.159	0.48
school	2.28	1.69	1.353	1.71
post school	1.20	1.15	1.046	0.49
degree	2.77	1.77	1.567	2.21

* The average is given by $1/(1-p_{jj})$, where p_{jj} is the diagonal element of the transition matrix for that educational class. Its standard deviation is given by $\sqrt{p_{jj}}/(1- p_{jj})$.

Nearly a quarter of a century later Shorrocks (1978) proposed a *social mobility index* based on the transition matrix. It satisfies a number of desirable properties: *normalisation* (lies between 0 and 1); *monotonicity* (if one of the off-diagonal elements increases at the expense of the diagonal component the index should indicate a higher level of mobility); *immobility* (a transition matrix with ones along the diagonal should have the lowest value of the index); and *perfect mobility* (should be assigned the maximum value of the index). The index is the number of classes minus the sum of the diagonal (the 'trace' of the transition matrix) divided by the number of classes minus one. In the application here, the Shorrocks mobility index is 0.83 for the older cohort and 0.82 for the younger one.[1] In other words, and consistent with the mobility measures in Table 5, educational mobility has remained about the same for these two cohorts.

The measures of mobility in Table 5 and Shorrocks' social mobility index rely only on the diagonal of the mobility matrix. We can also calculate the proportion moving up the educational distribution (relative to their parents) and the proportion moving down. In the older cohort, 50% moved up and 19% moved down; in the younger one, 40% moved up and 23% moved down. Given the rise in educational qualifications, there is a 'mechanical' aspect of these changes: more are 'at risk' of downward mobility in the younger cohort because a larger proportion of their parents have high qualifications than in the older cohort, and fewer

[1] If p_{ii} is the estimate of the i-th diagonal element of the transition matrix, its variance is $p_{ii}(1- p_{ii})/n_i$, where n_i is the sample size in parental origin category *i*. On the assumption that the samples of the origin categories are independent we can easily calculate the standard error of the Shorrocks' index. For the older cohort it is 0.0073 and for the younger cohort it is 0.0053. Thus, the standard error of the difference in the index between the two cohorts is 0.009.

are ‘at risk’ of upward mobility in the younger cohort because a smaller proportion of their parents have low qualifications.

Is social mobility different between the sexes? In light of the small changes between the two broad cohorts, sex differentials are examined for all aged 26-65 in 2009-10 in the Appendix. Overall, there are only small differences in the mobility measures between the sexes.

2. *Social mobility: absolute and relative rates*

When applied to social class mobility, Prais (1955a) suggested that some adjustment to the above approach may be necessary because the occupational structure shifts over generations (e.g. more white collar jobs and fewer blue collar ones). When few parents are in the top occupations and the distribution shifts toward more of such occupations, the chances of upward mobility of children increase. In subsequent generations, as more parents move into the top occupations and fewer are in the bottom occupations, the chances of children’s downward mobility increase and those of upward mobility decrease. As we have seen, a similar argument may be made about the educational distribution.

Sociological researchers make the distinction between *absolute mobility,* which is affected by such occupational shifts, and *relative mobility*: ‘the relative chances of individuals of different class origins arriving at different class destinations considered *net* of all class structural change.’ (Bukodi et al. 2014). Relative mobility is measured by adjusting for the different ‘marginal distributions’ of class (education) in the parents’ and children’s generations (e.g. such as those in Table 1).[2] The ideas can be illustrated with the education mobility matrices in Table 3.

One approach to relative mobility is to use the transition data underlying the matrices in Table 3 to calculate so called ‘global’ odds ratios. Each is the ratio of the odds of having a ‘higher’ education level relative to a ‘lower’ one for a ‘higher’ parental education class to the analogous odds for a ‘lower’ class, where the ‘higher’ and ‘lower’ cut-offs are varied. With four education categories there are nine such ratios, which are illustrated in Table 5. For instance, the odds ratio in the middle of panel A of the table is the ratio of odds of attaining qualifications beyond school for children whose parents have a post-school or degree qualification to the odds of attaining qualifications beyond school for children whose parents had at most a school qualification. It is equal to 2.98; that is, the odds of obtaining post-school or degree qualifications are 3 times larger for children of the better educated parents.

[2] Prais was not alone at the time he wrote in failing to take account of change in the marginal distributions of mobility tables in measuring mobility; see Tyree (1973). I am grateful to John Goldthorpe for pointing this out.

Table 5: ‘Global’ odds ratios, two cohorts

	Children’s education comparisons		
Parents’ education comparisons	School or more vs none	Post school or degree vs school or none	Degree vs post school, school or none
A. Aged 46-45 in 2009-10			
School or more vs none	4.77	3.37	3.60
Post school or degree vs school or none	4.49	2.98	3.00
Degree vs post school, school or none	14.84	5.41	5.44
B. aged 26-45 in 2009-10			
School or more vs none	6.61	2.86	2.97
Post school or degree vs school or none	5.72	2.81	2.76
Degree vs post school, school or none	7.53	4.53	4.74

Comparing the corresponding odds ratios for those aged 46-65 and 26-45 in 2009-10, respectively (panels A and B of Table 5), seven of the nine comparisons indicate reductions between the older and younger cohort. On the plausible assumption that the samples from these two cohorts are independent, we can calculate the standard error of the difference for each of the nine cells, and then test for significant changes between the two cohorts.[3] Three of the nine comparisons show significantly different odds ratios between the two cohorts (at the 0.05 level or less), all involving the comparison between parents with ‘school or more’ vs. ‘none’ (the first line in each cohort’s table of ratios); the one in the northwest corner shows an increase in the association between parents’ and children’s education, and the other two show significant reductions, again suggesting that relative educational mobility has changed little overall between the two cohorts.[4]

Another approach to relative mobility is ‘log-linear modelling’ of the frequencies in the table cross-classifying parents’ and children’s education (from which the transition matrices in Table 3 are calculated). In the education example, it attempts to replicate as closely as possible the 32 cells in the 2 tables of cohort data with a few parameters (Erikson

[3] Asymptotically, the log of each of the odds ratios (‘the log-odds ratio’) has a normal distribution with well-defined standard errors (Agresti 2013; pp. 69-74).

[4] The average of the three central global ‘log-odds ratios’ provides an overall measure of association between parents’ and children’s educational outcomes which is estimated with relatively high precision. It has risen from 1.45 to 1.49 between the older and younger cohorts, indicating little change in relative mobility. Cox et al. (2009) show how the standard error of the average may be calculated, taking into account the substantial correlation among the three estimates being averaged.

and Goldthorpe 1992).[5] The two most common simplifications are the 'constant social fluidity' model (CSF), in which associations between parents and children are constant across cohorts, and the log-multiplicative model (UNIDIFF), in which the logarithms of the odds ratios defining the parent-child association increase or decrease by some common multiplicative factor. In the case of our educational mobility example, both of these models are rejected by the data.[6] This is not surprising in light of the fact that two of the global odds ratios showed an increase in the association between parents' and children's education between the older and younger cohorts (the two in the northwest corner of Table 5), while the others declined.

In the most recent analysis of social class mobility covering four birth cohorts (1946, 1958, 1970 and 1980-4), Bukodi et al. (2014) find that when assessing children's social class at age 38, the data accepts the CSF model for men and the UNIDIFF model for women, with the latter indicating higher relative social mobility in more recent cohorts. When assessing children's social class at age 27, there is more relative social mobility in recent cohorts for both sexes. In terms of absolute mobility, upward mobility has become less common and downward mobility more common for both sexes.

To round off the section, we return to the Prais (1955a) measures, but now examine *social class* mobility. Panels A and B of Table 6 presents the Prais measures of men's social class mobility using the data from Goldthorpe and Jackson (2007) for two birth cohorts. For completeness, the final column of each panel shows the equilibrium social class distribution, which provides the columns for the transition matrix in the perfectly mobile society. From the 'average number of generations spent in social class' measure, social class mobility appears to have increased between the 1958 and 1970 generations for some social class origins and decreased for others. Using the actual relative to the perfectly mobile measure (Actual/PM), the changes are small. Shorrocks' overall index of social mobility (*SE*) indicates an increase from 0.878 (0.0082) to 0.901 (0.0081) between the 1958 and 1970 cohorts. It is statistically significantly different from zero (the SE of the difference is 0.0115), but small. Thus, the overall conclusion is little change in social class mobility, in line with Goldthorpe and Jackson (2007).

Panel C shows the same measures, but using the social class mobility matrix in Prais (1955a), which is derived from the 1949 Social Survey. While the particular social classes are not strictly comparable to those in panels A and B, there is a broad tendency for lower mobility for the cohorts represented by the 1949 data. Consistent with this interpretation, Shorrocks' index is 0.81 compared with about 0.9 for the more recent cohorts.

[5] Another approach is Goodman's (1979) 'log-multiplicative RC association model', which imposes one hierarchical dimension of origin-destination association.

[6] I thank Tak Wing Chan for running the appropriate models for me.

Table 6: Average number of generations spent in social class

A. 1958 birth cohort

Social class	Actual	Perfectly Mobile	Actual/PM	Std. Dev. actual	Equilibrium Distribution
I	1.93	1.45	1.33	1.34	0.310
II+IVa	1.33	1.24	1.08	0.67	0.190
III	1.12	1.05	1.07	0.37	0.051
IVb	1.35	1.08	1.25	0.69	0.073
V	1.11	1.07	1.04	0.34	0.064
VI	1.31	1.19	1.10	0.63	0.161
VII	1.43	1.18	1.21	0.55	0.151

B. 1970 birth cohort

Social class	Actual	Perfectly Mobile	Actual/PM	Std. Dev. actual	Equilibrium Distribution
I	1.73	1.35	1.28	1.13	0.259
II+IVa	1.46	1.36	1.08	0.82	0.262
III	1.13	1.08	1.05	0.38	0.073
IVb	1.18	1.07	1.10	0.46	0.065
V	1.19	1.13	1.06	0.48	0.114
VI	1.18	1.10	1.07	0.45	0.092
VII	1.39	1.16	1.20	0.74	0.136

C. 1949 Social Survey

Social class	Actual	Perfectly Mobile	Actual/PM	Std. Dev. actual	Equilibrium Distribution
Professional	1.63	1.02	1.59	1.02	0.023
Managerial	1.36	1.04	1.30	0.71	0.042
Higher grade non-manual	1.23	1.10	1.12	0.54	0.088
Lower grade non-manual	1.27	1.15	1.11	0.58	0.127
Skilled manual	1.90	1.69	1.12	1.30	0.409
Semi-skilled manual	1.45	1.22	1.19	0.81	0.182
Unskilled manual	1.38	1.15	1.20	0.72	0.129

3. *Regression-to the mean*[7]

The most common approach to social mobility measurement adopted by research in economics (e.g. Solon 1992) is based on the Galtonian regression equation $y_C=\beta y_P+v$, where y_P is the logarithm of some continuous measure of parents' status, which we shall label as 'income' for simplicity of expression, and y_C is the log of child's income, both expressed as deviations from their respective means; and v captures other influences on the child's income. Then β is the *intergenerational elasticity*. Perfect mobility in this context arises when β=0, and perfect immobility when β=1. The quicker the regression to the mean (lower β), the larger is intergenerational income mobility. By measuring educational attainments in terms of years of education, this approach has also been used to measure intergenerational educational mobility (e.g. Hertz et al. 2007 and Ermisch and Pronzato 2011; the latter uses information on twins to estimate the 'causal impact' of parents' education on that of their children).

By construction, v is assumed uncorrelated with y_P (i.e. $E(vy_P)=0$). This 'moment condition' entails that $\beta=\text{cov}(y_C, y_P)/\text{var}(y_P)$, where cov indicates covariance and var denotes variance. Its estimator is its sample counterpart. The value of β will reflect the distribution of income in the parents' and children's generations. The Pearson correlation coefficient standardises the distribution in the two generations in a particular way: $\rho= \beta\text{SD}(y_P)/\text{SD}(y_C)$, where SD indicates standard deviation. When the variance is the same in the two distributions, $\rho=\beta$. For a given ρ, the larger the variance of income in the child's generation relative to that in the parents' generation, the higher the value of the intergenerational elasticity. Thus, when income inequality is increasing across generations, there is a tendency for β to increase.

The variance is, however, only one feature of the income distribution. Differences in marginal distributions between the two generations would be fully controlled by the 'Spearman rank correlation' rather than ρ (because both marginal distributions would be standard uniform distributions). It is the Pearson correlation coefficient between the ranked (rather than the 'raw') variables. A perfect Spearman correlation results when the two variables are related by any monotonic function, in contrast to the Pearson correlation, which only gives a perfect value when they are related by a linear function.[8] Rank-based measures are discussed in the next section.

One important challenge in the estimation of β arises because the income concept should be a 'lifetime' or 'permanent' one, which is measured with error from any one snapshot for each generation. This is less of a problem for the child's income because measurement error is reflected in v. Classical measurement error in the parents' income (in the sense that the error is not correlated with the true value of parents' income) produces a downward bias in the estimate of β—*attenuation bias*. Averaging parents' income over many

[7] For a comprehensive discussion of income mobility and its measurement, see Jäntti and Jenkins, forthcoming.
[8] The Spearman rank correlation is 'non-parametric' in this sense, but also in the sense that its exact sampling distribution can be obtained without requiring knowledge (i.e., knowing the parameters) of the joint probability distribution of the two variables.

years tends to reduce the bias, although many data sets do not possess such multiple measurements.

A second estimation challenge relates to when in the life course the child's income is observed. Both generations' incomes need to be observed when their career progression is sufficiently advanced. In most data, there is usually little problem with the parents' income in this respect, but this issue often arises with the child's income—*life cycle bias*.

Estimates of β (and sometimes ρ) have been used to compare intergenerational earnings or income mobility between countries and over time in particular countries. For example, Bjorklund and Jäntti (2009) find lower β's (higher mobility) for Scandinavian countries compared to the USA and Western Europe, and Lee and Solon (2009) find that intergenerational elasticities of income in the USA did not change significantly between the 1950 and 1970 birth cohorts.

4. *Rank-based measures*

While the intergenerational elasticity approach (log-log model) has some desirable theoretical properties (Solon 2004), it suffers from two empirical shortcomings, pointed out by Chetty et al. (2014a). First, it omits observations with zero income in the observation period, and this situation is more likely among children of low income parents, thereby tending to overstate mobility. Second, the relationship between log child and log parent income is highly non-linear, with lower intergenerational elasticities below the 10^{th} percentile and above the 90^{th} percentile of the parents' distribution.

To address these problems Chetty et al. (2014a) develop a rank-rank specification of the relationship between child's and parents' incomes. They rank children based on their income relative to other children in the same birth cohort (including those with zero income), and they rank parents of these children based on their income relative to other parents with children in these cohorts. Their data is US federal income tax records. For instance, for US citizens in the 1980-82 birth cohorts they measure the children's income as mean total family income in 2011 and 2012 (when they were aged about 30) and parents income as mean family income between 1996 and 2000 (when the children were aged 15-20).

The relationship between child and parent percentile ranks turns about to be almost perfectly linear in their US tax records data: $r_C = \alpha + \gamma r_p + e$. The slope parameter γ is a measure of *relative mobility*.[9] For instance, their estimate of γ is 0.34 for the 1980-82 birth cohort. The expected rank for a child coming from a family with rank p ($E[r_C \mid r_P = p]$) is a measure of *absolute mobility at rank p*. It tells us how the children's outcome differs between high and low income families, which is useful for geographic and temporal comparisons. Furthermore, 'rank-rank slope estimates are robust to measuring parent and child income at different ages and using multiple years to measure income, indicating that the estimates do not suffer from significant life cycle or attenuation bias' (Chetty et al. 2014b, p.142).

[9] While related, γ is not identical to the Spearman rank correlation coefficient, which is equal to $1-\{6\sum(r_{pi}- r_{Ci})^2/n(n^2-1)\}$, where n is sample size.

With respect to trends in the US, the analysis in Chetty et al. (2014b) indicates no trend in the slope parameter over the 1971-82 birth cohorts, and extensions to later cohorts by other means indicate stability through the 1993 birth cohort. They also find that estimates of the intergenerational elasticity (β) with their rich data are stable, or possibly declining slightly, despite increases in income inequality because 'the marginal distributions of parent and child incomes have expanded at roughly similar rates' (p.143).

A comparison with Denmark also indicates a nearly linear rank-rank relationship there (Chetty et al. 2014a). But the slope is nearly half that in the US at 0.18, consistent with previous cross-national comparisons of intergenerational elasticities (Bjorklund and Jäntti 2009). If the ranks were defined for a common income distribution for the US and Denmark, it would be possible to make absolute mobility comparisons using the $E[r_C | r_P=p]$ measure.

5. *Influences of each parent's status*

In the analysis of income mobility we can add together the parents' incomes, but when social origin is represented by categories, some other 'aggregation' of parents' 'classes' is necessary. In the analysis of educational mobility above, we took the 'parent's education' to be the higher of the two parents' educations. A similar approach (the 'dominance method'; Erikson 1984) is taken in analysis of social class mobility, or, alternatively, only father's social class is used to represent social class origin. Beller (2009) extends the class mobility analysis to include both parents' class position, also incorporating a 'homemaker' category for mothers who do not have paid employment.[10] Here we explore whether there are other models with a few parameters that can capture the influence of both parents in education or mobility.

With four education categories, there are sixteen possible parental education combinations (assuming we observe both parents' education levels). The dominance (highest education) method introduces twelve constraints. An alternative approach is the so called 'diagonal reference model' (DRM; e.g. Sobel et al 2004). Here we apply it to modelling the log odds that a child obtains a degree qualification.

The father has education level R, with categories $r=1,\ldots,4$ and the mother has education level C with categories $c=1,\ldots,4$. The log-odds ('logit') that their child obtains a degree is assumed to be given by:

$$\log(\pi_{rc} /(1- \pi_{rc})) = w\log(\pi_{kk} /(1- \pi_{kk})) + (1- w)\log(\pi_{kk} /(1- \pi_{kk})) ,$$

where π_{rc} is the probability of a child, whose father has education level r and whose mother has education level c, obtaining a degree; π_{rr} and π_{cc} are the probabilities that a child with educationally homogamous parents, at levels r and c respectively, obtains a degree; and w and $1 - w$ are the weights of the father's and the mother's education in determining a child's degree attainment, with $0<w<1$. In words, the logit of their child obtaining a degree for educationally heterogamous parents is constrained to be a weighted average of the logits of

[10] She uses Goodman's (1979) 'log-multiplicative RC association model' to study the issue, but we take another approach here.

the relevant homogamous parents. The intuition here is that homogamous parents are 'pure types', and they serve as reference points for parents who have different levels of education. The DRM model here imposes 11 constraints on the parameters.

Table 7 shows the estimated parameters for the DRM for a child's degree attainment for the two birth cohorts. For both birth cohorts, the estimate of the father's weight is not significantly different from one-half. That is, equal importance is given to father's and mother's education in their influence on their child's odds of getting a degree. Compared to the general model, which has a different parameter for each parental education combination, the DRM is rejected at conventional significance levels by a chi-square likelihood ratio test (11 d.f.). But if we use the Bayesian Information Criterion (BIC), which penalises models with more parameters, we would select the DRM over the general model: for each birth cohort, the DRM has lower value of the BIC than the general model. The Akaike information criterion, which penalises models with more parameters less severely than the BIC, favours the general model.

Table 7: Diagonal Reference Model for log odds of child obtaining a degree

Homogamous Parents' education	Age 26-45		Age 46-65	
	Parameter	SE	parameter	SE
constant	-1.451	0.044	-1.967	0.040
logit degree	2.771	0.087	2.980	0.128
logit post school	1.109	0.067	1.452	0.078
logit school	0.634	0.063	1.166	0.073
father's weight	0.521	0.024	0.511	0.031
Reduction in BIC cf. general model	63.14		73.31	
Chi-square test cf. general model (11df)	40.18*		29.75*	

*Significant at 0.01 level or less

The DRM model performs better than the dominance (highest education) model on the BIC. It may, therefore, be an acceptable way to combine the two parents' education levels in affecting the log odds of the child's educational attainment. In our particular example, the parental weights turned out to be roughly equal.[11] Thus, consistent with Beller (2009) for class mobility in the USA, both parents' education matter for the child's educational attainments.

A third type of constrained model may be called the 'independent effects' model, in which the impact of each parent's education level on the log odds of the child obtaining a degree is the same no matter what the level of the other parent's education. It is not nested in the models considered so far, as it does not constrain the parameters from the general model,

[11] Similar results are obtained when we estimate an ordered logit using all levels of the child's education; while the DRM is rejected by a likelihood ratio test, it is favoured by the BIC compared to both the dominance model and the general model, particularly relative to the former. Also the father's and mother's education weights are equal.

but rather aggregates the independent variables. But we can compare it with the other models using the BIC and AIC. The DRM performs best on the BIC, but the independent effects model (with 7 parameters) is quite close in terms of the BIC score. On the AIC, the general model always performs best.

6. Influences of parental background over the life course

The social mobility analysis up to this point has contrasted origins and destinations in terms of education, social class or income. It has not analysed how parental background affects outcomes through the life course. Figure 1, from Ermisch et al. (2012), provides a schema with which to think about the process. It illustrates that parental socio-economic status (SES) may be associated with any stage or outcome of the child development process, and any outcome at an earlier life stage may be related to later outcomes all the way up to adulthood. For example, parental education or income ($Parental_{SES}$) may be related to birth weights in the birth year, or to test scores and socio-emotional behavior in early childhood, which in turn, may be associated with various outcomes at any of the subsequent developmental stages. Ultimately, offspring adult socioeconomic status is the outcome of a whole series of parental and other inputs to children's development from the birth year forward. This schema is consistent with Cunha and Heckman's (2007) dynamic multi-stage model of skill development, in which intermediate outcomes at each stage not only affect subsequent outcomes but may also affect the productivity of inputs at subsequent stages. For example, children who were not read to as preschoolers may find it more difficult to learn to read at school. This initial disadvantage can then be reinforced if a poor secondary education limits one's choices and opportunities in terms of preparation for higher education. On the other hand, if this same child were fortunate enough to attend better schools, this may offset some of the initial disadvantage.

As an example to illustrate the analytical issues, consider the impact of parental background, as measured by parents highest' education and social class (dominance method) on their children's performance in national exams at the end of primary school through compulsory secondary school and on their enrolment in higher education. The analysis uses the Longitudinal Study of Young People in England (LSYPE), which samples children born in 1989-90 and links their survey data to their achievements in the education system's national standardised tests. It measures their test results at ages 11 (end of primary schooling), 14 and 16 (end of compulsory schooling), and records whether or not they are enrolled in higher education at the age of 20.

Figure 2 shows the proportion scoring in the top quartile of the Key Stage tests for each of four parental education groups at ages 11, 14 and 16 (GCSE results), and also the proportion enrolled in university at age 20 for these four groups. It suggests a widening of the differentials by parents' education between the ages of 11 and 14 and at least maintenance of the differentials at subsequent ages. The widening during secondary school in England is backed up by formal statistical analysis in Del Bono and Ermisch (2012), and Magnusson et al. (2012). In Figure 2 for example, the difference between the parental degree group and the low parent education group in being the top quartile is 40 percentage points at age 11 and 47 percentage points at age 14, the same as the difference in the percentage enrolled in university at age 20.

We now focus on the probability of being in university at age 20. In line with Bukodi, Erikson and Goldthorpe (2014) it allows for independent effects of parents' education and social class on their offspring's enrolment in higher education as well as a cognitive ability measure, but not, as they also suggest, parental status. Any random variable y can be decomposed into the conditional expectation function and a random term that is orthogonal to it: $y = E[y|SC,PE,A] + e$, where y is the dichotomous variable of being enrolled in higher education or not at age 20; SC is parents' social class; PE is parents' education and A is an achievement measure earlier in their life. We assume that $E[y|SC, PE,A]$ is linear in the independent variables. The justification is that it provides the minimum mean squared error linear approximation to the conditional expectation function.[12] In the first analysis, we only include the parental education and social class variables (i.e. exclude A), and in the second we also control for the child's KS4 (GCSE) results at age 16.

The first column of Table 8 indicates a steep gradient in the probability of being in university with respect to parents' education, but this virtually disappears when we control for GCSE results (second column). In addition, the probability of attending university is strongly associated with the parents' social class when there is no control for GCSE results (first column). Controlling for GCSE results in the second column produces a set of marginal effects of social class that are neither individually, nor jointly significantly different from zero at the 0.01 level and quantitatively very small. Thus, the large differentials in university enrolment by social background is mostly accounted for by the large impacts of social class and parents' education on getting good GCSE results, which in turn have a large impact on university entry. In other words, the association of parental background with university enrolment appears to work almost solely through the child's performance in school up to age 16.

The virtual disappearance of parent education and social class effects is not consistent with Bukodi, Erikson and Goldthorpe (2014), which finds little change in the education and social class effects on the highest level of educational attainment when a cognitive ability measure at age 10-11 is introduced. To make the comparison sharper, the analysis is repeated with end of primary school (KS2) test percentile scores replacing the GCSE scores, and is shown in col. 3 of Table 8. While still present, the social background effects are much smaller when we control for test score results at the end of primary school than in col. 1. Of course, the outcome measure is different (enrolment in university rather than highest educational attainment), and this could account for the difference. It is also possible that the KS2 test results are a better indicator of abilities related to educational attainment than the cognitive tests administered in surveys.

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[12] In practical terms the average marginal effects from a non-linear model like logit are usually very close to those from the linear model. Of course, with the linear approximation there is no assurance that $E[y|SC, PE, A]$ is bounded between 0 and 1 for all A, but that does not matter for the purposes of the paper, which only needs marginal effects. Also, strictly speaking, the parameters of a non-linear model are not identified in the absence of a distributional assumption (e.g. logistic), which is usually not justified on grounds other than convenience.

Table 8: Impacts of Parents' Education and Social Class on the Probability of Being Enrolled in University at Age 20 and on GCSE test scores Percentile at Age 16

	University enrolment			GCSE results	
	(1) Without GCSE Results	(2) With GCSE Results	(3) With KS2 (age 11) Results	(4) Without KS2 Results	(5) With KS2 Results
Parents' Education: Low (omitted)					
Medium	-0.016 (0.016)	-0.089 (0.012)	-0.073 (0.015)	6.84 (1.13)	0.51 (0.83)
Some Tertiary	0.124 (0.023)	-0.024 (0.018)	0.032 (0.021)	13.83 (1.37)	3.78 (0.98)
High	0.329 (0.023)	0.046 (0.018)	0.159 (0.021)	26.42 (1.41)	8.80 (1.00)
Parents' Social Class: Upper Salariat (omitted)					
Lower salariat	-0.061 (0.020)	-0.008 (0.016)	-0.032 (0.019)	-4.89 (1.04)	-1.67 (0.71)
Intermediate non-manual	-0.151 (0.020)	-0.027 (0.016)	-0.068 (0.019)	-11.50 (1.09	-3.32 (0.077)
Semi-routine	-0.211 (0.023)	-0.021 (0.020)	-0.093 (0.023)	-17.62 (1.51)	-6.03 (1.00)
Routine manual	-0.264 (0.025)	-0.029 (0.020)	-0.130 (0.023)	-21.82 (1.51	-8.73 (1.06)
Never worked/ unemployed	-0.217 (0.030)	0.027 (0.023)	-0.056 (0.028)	-22.60 (1.97)	-6.71 (1.54)
Female (mean=0.51)	0.079 (0.012)	0.018 (0.009)	0.080 (0.011)	5.61 (0.75)	5.43 (0.49)
Age in mos., Sept. 2005 (mean=186.4)	0.00073 (0.0015)	-0.003 (0.001)	-0.007 (0.001)	0.38 (0.09)	-0.32 (0.07)
KS4 (GCSE) Percentile Score (mean=52.3)		0.0107 (0.00017)			
KS2 (age 11) Percentile Score (mean=51.9)			0.0070 (0.0002)		0.69 (0.01)
Constant	0.274	0.512	1.266	27.07	67.53

Comparisons between the two sets of estimates in cols. 1 and 2 of Table 8 are related to the concepts of 'primary' and 'secondary' effects in educational sociology. Primary effects in our context relate to the impact of family background on ability or eligibility to pursue higher education. Secondary effects capture the impact of family background on the decision to enrol in higher education among the eligible/able.

In the sociological literature, primary and secondary effects are defined for comparisons between social groups. Their computation has been complicated by non-linear models for the probability of the event of interest. They have usually been carried out in terms of 'counterfactual experiments'[13] (Erikson et al. 2005; Jackson et. al 2007) or a non-

[13] Another parametric assumption is required for the counterfactuals: the distribution of the 'achievement' or 'ability' measure within each social group.

linear decomposition[14] (Fairlie 2005) for a few rather broadly defined social groups, such as two or three classes (Erikson et al. 2005; Jackson et. al 2007; Schindler and Lörz 2012). They are less feasible for more narrowly defined groups (because of sample sizes), and here we would like to distinguish groups by both parents' education and social class.

Taking the linear expectation function approach used here we can easily obtain an exact decomposition without arbitrary functional form assumptions. The predicted probability for any social group (defined here by parents' social class and education) is given by the linear expectation function for the model with the GCSE variable (2nd col. Table 8). It depends on the coefficients of parents' education and social class in the regression (from which we derive the secondary effects), and the product of the impact of the KS4 percentile score on university enrolment and the expectation of the KS4 score conditional on being in a particular family background group (from which we derive the primary effects).[15] By taking the difference between any two social groups, we can obtain the primary and secondary effects on the difference.

For illustration, we focus on two large groups in the population for whom the estimates will be more precise: children of parents with medium education and children of parents from intermediate non-manual occupations. In Figure 3, we compare the intermediate class with all other social classes among children of parents with a medium level of education. There are small secondary effects for the two salariat groups, but primary effects of social class dominate. In Figure 4 we compare different parents' education groups among children whose parents are from the intermediate class. Here there are large secondary effects of having parents with some tertiary education and particularly having parents with a degree. But primary effects are even larger. For parents with low education, primary effects reduce university enrolment while secondary effects increase it.

The division into primary and secondary effects requires a consistent estimate of the parameter showing the impact of GCSE achievement on entry to university, which we denote as α. Suppose there is a persistent family or person-specific factor, call it 'motivation to study at university'.[16] But motivation also encourages the student to study harder in school, making the estimate of α biased upward. In effect, heterogeneity in personal or family traits affecting both study in university and achievement in school is likely to be confused with the impact of achievement on entry to university. Such bias overstates the primary effect, making the estimate of the secondary effect a lower bound.

[14] The non-linear decomposition allows for a number of possible differences between the composition of groups while here we only consider differences in GCSE results.

[15] The probability of university enrolment of being from social class k and parental education level m is given by $E[y|SC_j=k, PE_j=m, A]= \beta_k + \gamma_m + \alpha E[A|SC_j=k, PE_j=m]$. The 'secondary effect' is derived from $\beta_k + \gamma_m$ and the 'primary effect' is derived from $\alpha E[A| SC_j=k, PE_j=m]$ for the two social groups being compared.

[16] E.g. let $y= \sum \gamma_j PE_j + \alpha A + \mu + e$, where μ is motivation to sudy. But motivation also encourages the student to study harder in school, and so $A=\sum \lambda_j PE_j + \rho\mu + \varepsilon$, with $E[e\ \varepsilon]= E[e\ \mu]=0$. Then the covariance between A and the error term in the main equation for y, $\mu + e$, is given by $\rho \mathrm{var}(\mu)$, and so the estimate of α tends to be biased upward whenever $\rho>0$ and μ varies among students.

Analogous analysis of GCSE (KS4) percentile scores is given in columns 4 and 5 of Table 8. The regression that is conditional on end of primary school (KS2) test percentile scores (col. 5 of Table 8) indicates the existence of both primary and secondary effects of parents' education and social class on GCSE achievement, as Figures 5 and 6 illustrate. But the primary effects are larger (again noting their likely overstatement). Thus, family background has an important influence at least as early as primary school. Indeed the influence of parental background on cognitive performance is apparent before the child goes to school. Analysis of Foundation Stage test scores, which are taken around age 5 before entering school (using the UK Millennium Cohort Study, born 2000-01), indicates similar differentials in the proportion in the top quartile by parents' highest education to those in Figure 4 (Del Bono and Ermisch 2012).

7. *Multigenerational demography*

A recent strand of research on social mobility aims to wed social stratification research with social demography. The social mobility analysis surveyed above is concerned with the role of the family of origin in affecting destinations in terms of education, social class and income. But variation in family background produces differential growth of segments of the population, and as a consequence the distribution of outcomes <u>in the population</u> must also incorporate biological reproduction into the picture.

The 'population dynamics' perspective aims to integrate intergenerational transmission of status with demographic processes, such as fertility, marriage and migration to provide a population level perspective on social mobility. It addresses what Mare (2011) calls 'the tandem nature of demographic and socioeconomic reproduction' in his 2011 Population Association of America presidential address on 'multigenerational demography'. A research focus which conditions on the distribution of the key aspects of the family environment 'is inadequate for analysing the population question of how a socioeconomic distribution in one generation gets transformed into a distribution in later generations.' (Mare 2011, p.15).

For instance, in Mare and Maralani's (2006) model of intergenerational transmission, only women's educational attainment is taken to be exogenous. The woman's fertility and her child's educational achievement depend on the education of both parents, while the education of the man she matches with depends on her education. The joint distribution of marital status, husband's education, fertility, and offspring's education is endogenously determined by women's education. They are able to estimate the total effect of women's education on the education of the next generation operating both through direct 'effects' of parents' education on offspring education and indirect effects through differential fertility and assortative mating by parents' education.

In our data, information about how partnering and fertility vary with the mother's education is available for the cohort women aged 46-65 in 2009-10, who have completed childbearing. Table 9 shows the proportion of women who have a partner in 2009-10, the education level of the partner for women who have one and the woman's completed fertility. Women with no qualifications are less likely to have a partner, and there is fairly strong assortative mating by education with 49% of couples having the same education level. Women's fertility declines as her education increases. Table 9 suggests that at the population level the tendency for highly educated mothers to produce better educated children is offset somewhat by their lower fertility—their children are better educated but they have fewer of them.

Table 9: Distribution of Spouse's Education and Fertility for Women aged 46-65 in 2009-10, *Understanding Society*

Woman's education:	Has partner, 2009-10	Partner's Education				Ave. Family size	Woman's Educ. Dist.
		none	school	post school	degree		
none	0.662	0.599	0.316	0.053	0.033	2.16	0.187
school	0.718	0.269	0.494	0.112	0.125	1.77	0.488
post school	0.714	0.157	0.382	0.151	0.310	1.63	0.143
degree	0.726	0.059	0.227	0.095	0.619	1.22	0.183

There are considerable challenges in identifying the parameters of such multi-process models and estimating them. It is, however, important to do so in order to assess the population-level consequences of policy interventions, such as child care or schooling policies, for the distribution of the population in terms of educational attainments and other social groups.

8. *Conclusions*

The social transition matrix introduced by Sig Prais 60 years ago remains the foundation of the measurement of social mobility today. It has been extended by distinguishing relative mobility from structural change (although Sig recognised the important of adjusting for the latter), and new summary measures have been introduced in an effort to describe complex social processes in terms of a few parameters or a single one. But some social mobility measures introduced by Sig Prais, such as the actual relative to the equilibrium distribution and the average number of generations spent in a social class, are now rarely reported. There is also no effort made to compare observed social mobility with a perfectly mobile benchmark. If for no other reason than the importance of measuring social mobility from different perspectives, the neglect of these concepts and measures is regrettable.

One important area for future research concerns the path between origins and destinations. In other words, how does inequality in relation to family background evolve over childhood and into adulthood to produce inequality in destinations. There have been a large number of recent contributions in this area (e.g. Ermisch et al. 2012).

Another important and rarely researched area is the population level question of how a social class or educational distribution in one generation gets transformed into a corresponding distribution in later generations, incorporating differential biological reproduction and migration. This is a challenging, but rewarding research area because the impacts of policy interventions need to be assessed at the population level.

Finally, the present paper makes a substantive contribution with respect to intergenerational education mobility in the UK. In particular, using parents' highest education as the origin indicator, neither relative mobility nor overall educational mobility has changed much across cohorts born between the mid-1940s to the mid-1980s. Figure 7 illustrates this by plotting the average number of generations with a degree (for children having parents with a degree) and Shorrocks' mobility index for 3-year birth cohorts (sample N ranging from 1,600-2,100) indexed by their age in 2009-10, along with linear trend lines. There is little evidence of a meaningful trend in either measure over these 30 years. The analysis also indicated that parents' social class and education are already influencing outcomes relevant to ultimate educational attainment in primary school and probably earlier.

References

Agresti, A. (2013) *Categorical Data Analysis*. 3rd Edition. Hoboken, NJ: John Wiley and Sons.

Bartholomew, D.J. (1982) *Stochastic Models for Social Processes*, 3rd Edition. Chichester: Wiley.

Beller, E. (2009) Bringing Intergenerational Social Mobility Research into the Twenty-first Century: Why Mothers Matter, *American Sociological Review* 74:507-528.

Björklund, A., and Jäntti, M. (2000) Intergenerational income Mobility and the role of family background. Pp. 491-521 in W. Salverda, B. Nolan and T. M. Smeeding, *The Oxford Handbook of Economic Inequality*. New York, NY: Oxford University Press

Bukodi, E., Goldthorpe, J.H., Walker, L. and Kuham J. (2014) The mobility problem in Britain: new findings from the analysis of birth cohort data, *British Journal of Sociology*, forthcoming.

Bukodi, E., Erikson, R. and Goldthorpe, J.H The effects of social origins and cognitive ability on educational attainment, *Acta Sociologica* 57:293-310.

Chetty, R., N. Hedren, P. Kline and E. Saez (2014a) 'Where is the land of opportunity? The geography of intergenerational mobility in the United States' *Quarterly Journal of Economics*, 129, pp. 1553-1623.

Chetty, R. Hendren, N., Kline, P. Saez, E. and Turner, N. (2014b) Is the United States still a land of opportunity? Recent trends in intergenerational mobility, *American Economic Review, Papers & Proceedings 2014*, 104(5): 141–147.

Cox, D.R., Jackson, M. and Lu. S. (2009) On square ordinal contingency tables: a comparison of social class and income mobility for the same individuals, *Journal of the Royal Statistical Society*. Series A. 172:483–493.

Cunha, Flavio, and James J. Heckman. (2007) The technology of skill formation. *American Economic Review*, 97 (Papers and Proceeding): 31-47.

Del Bono, E. and Ermisch, J. (2012) Inequality in achievements during adolescence. In: *From Parents to Children: The Intergenerational Transmission of Advantage*. John Ermisch, Markus Jäntti and Tim Smeeding, editors. New York: Russell Sage.

Erikson R. (1984) Social Class of Men, Women and Families, *Sociology* 18: 500–14.

Erikson R. et. al (2005) On class differentials in educational attainment. *Proceedings of the National Academy of Sciences* 102: 9730–9733.

Erikson, R. and Goldthorpe, J. H**.** 1992 *The Constant Flux: A Study of Class Mobility inIndustrial Societies*, Oxford: Clarendon Press.

Ermisch, J and Pronzato, C. (2011) Causal effects of parents' education on children's education. In: *Persistence, Privilege and Parenting: The Comparative Study of Intergenerational Mobility* (T. Smeeding, R. Erikson, M. Jäntti, , editors). New York: Russell Sage Foundation.

Ermisch, J. Markus Jäntti and Tim Smeeding, editors. *From Parents to Children: The Intergenerational Transmission of Advantage*. New York: Russell Sage, May 2012.

Fairlie, R.W. (2005) An extension of the Blinder-Oaxaca decomposition technique to logit and probit models, *Journal of Economic and Social Measurement* 30:305–316.

Glass, D. V. Editor (1954) Social mobility in Britain. London: Routledge and Kegan Paul.

Goldthorpe, J. H. and Jackson, M. **(**2007) Intergenerational Class Mobility in Contemporary Britain: Political Concerns and Empirical Findings', *British Journal of Sociology* 58: 526–46.

Goodman, Leo. 1979. Multiplicative Models of the Analysis of Mobility Tables and Other Kinds of Mixed-Classification Tables." *American Journal of Sociology* 84:804–819.

Hertz, T. et al. (20070 The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends, *The B.E. Journal of Economic Analysis & Policy*, *Advances* 7, article 10.

Jackson, M. et al. (2007) Primary and Secondary Effects in Class Differentials in Educational Attainment: TheTransition to A-Level Courses in England and Wales, *Acta Sociologica* 50:211-229.

Jäntti, M. and Jenkins, S.P. Income Mobility, *Handbook of Income Distribution* Vol 2A. North Holland, forthcoming

Kemeny, J.G. and Snell, J.L. (1960) *Finite Markov Chains*. London: D. Van Nostrand Company.

Lee, C-I and Solon, G. (2009) Trends in intergenerational income mobility." *Review of Economics and Statistics*, 91 (4): 766–72.

Magnusson, K. Waldfogel, J. and Washbrook, E. (2012) SES gradients in skills during the school years. In: *From Parents to Children: The Intergenerational Transmission of Advantage*. John Ermisch, Markus Jäntti and Tim Smeeding, editors. New York: Russell Sage.

Mare, R.D. (2011) A Multigenerational View of Inequality, *Demography*. 48: 1–23.

Mare, R.D. and Maralani, V. (2006) The Intergenerational Effects of Changes in Women's Educational Attainments, *American Sociological Review*, 71: 542-564.

Prais, S.J. (1955a) Measuring social mobility, *Journal of the Royal Statistical Society*. Series A (General), 118:56-66.

Prais¸ S.J. (1955b) The formal theory of social mobility, *Population Studies*, 9:72-81.

Schindler, S. and Lörz, M. (2012) Mechanisms of Social Inequality Development: Primary and Secondary Effects in the Transition to Tertiary Education Between 1976 and 2005, *European Sociological Review*, 28:647–660.

Shorrocks A. (1978) The measurement of mobility, *Econometrica*, 46: 1013-1024

Sobel, M.E., De Graaf, N.D., Heath, A. and Zou, Y. 2004. Men matter more: the social class identity of married British women, 1985–1991. *Journal of the Royal Statistical Society A.* 167:37-52

Solon G. (1992) Intergenerational income mobility in the United States, *American Economic Review* 82:393-408.

Solon G. (2004) A Model of Intergenerational Mobility Variation over Time and Place, in Miles Corak (ed.), *Generational Income Mobility in North America and Europe*, pp. 38-47, Cambridge: Cambridge University Press, 2004.

Tyree, A. (1973). Mobility ratios and association in mobility tables, *Population Studies* 27:577-588.

Figure 1: Parental influences over the life course

Figure 1. Model of Intergenerational Transmission of Advantage by Life Stage*.

*It is implicit in the model that outcomes at any life stage can be associated with outcomes at any subsequent life stage.

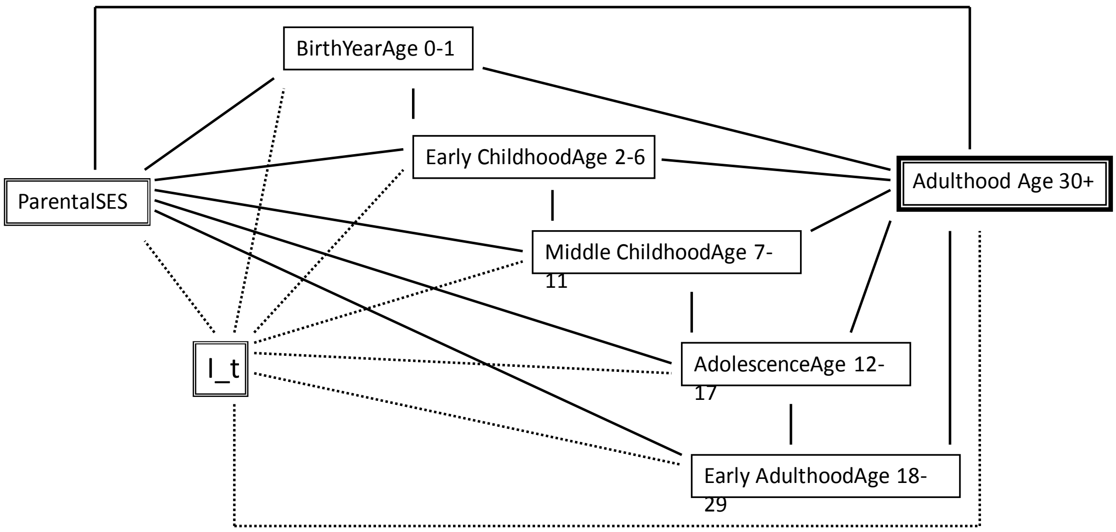
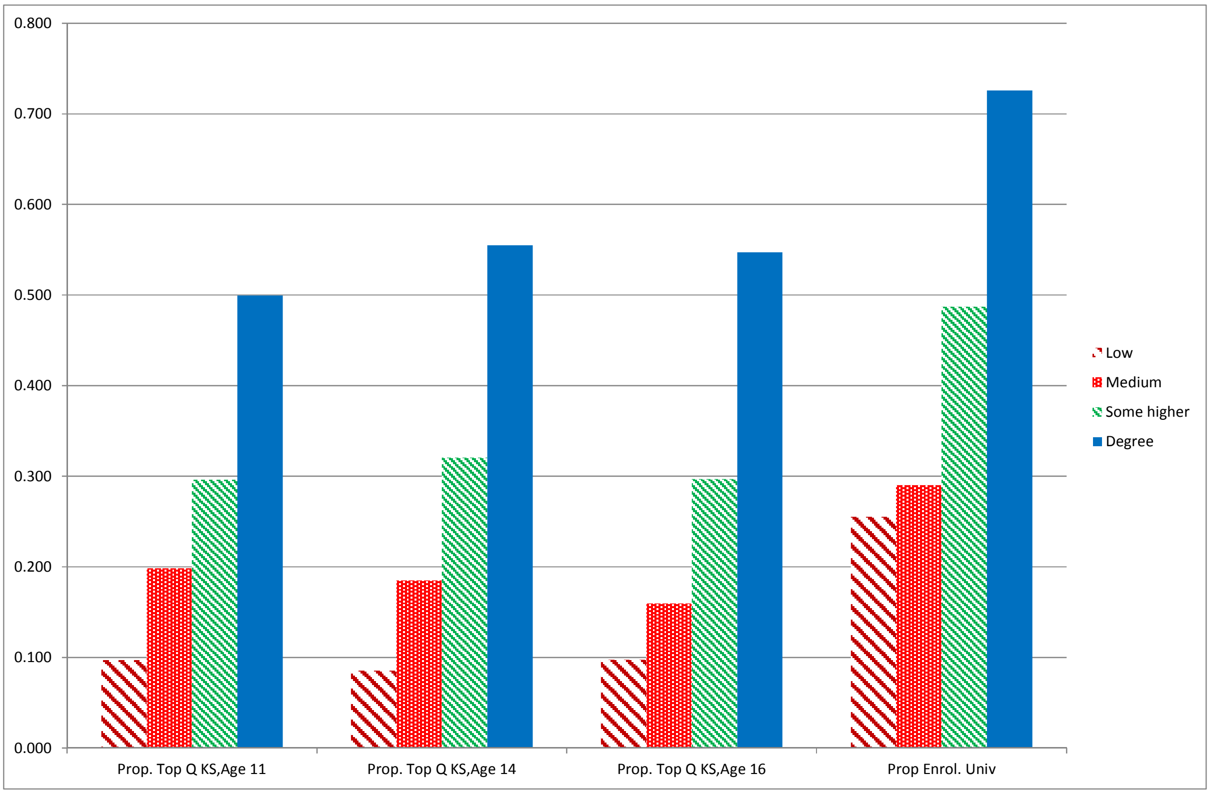


Table A. Variable Definitions and Examples of Proposed Measures at Different Points in the Life Course

Parental Variables (P_{SES})	Childhood/Early Adulthood Life Stages	I_t Data Points	Adulthood (Age 30+)
Education, Income, Earnings, SES, Occupation, Wealth, Employment	BirthYear (C_0), Early Childhood (C_1) Middle Childhood (C_2), Adolescence (C_3) Early Adulthood (C_4) Educational attainment, cognitive measures, socio-emotional behavior, employment/labor market, health/physical	I_t is assumed to be different public and private investments in children's development that vary by country.	SES, Income, Education, Employment/Labor Market Attachment

Source: Ermisch, Jäntti and Smeeding 2012.

Figure 2: Differential Child Achievements by Parents' Highest Education Level



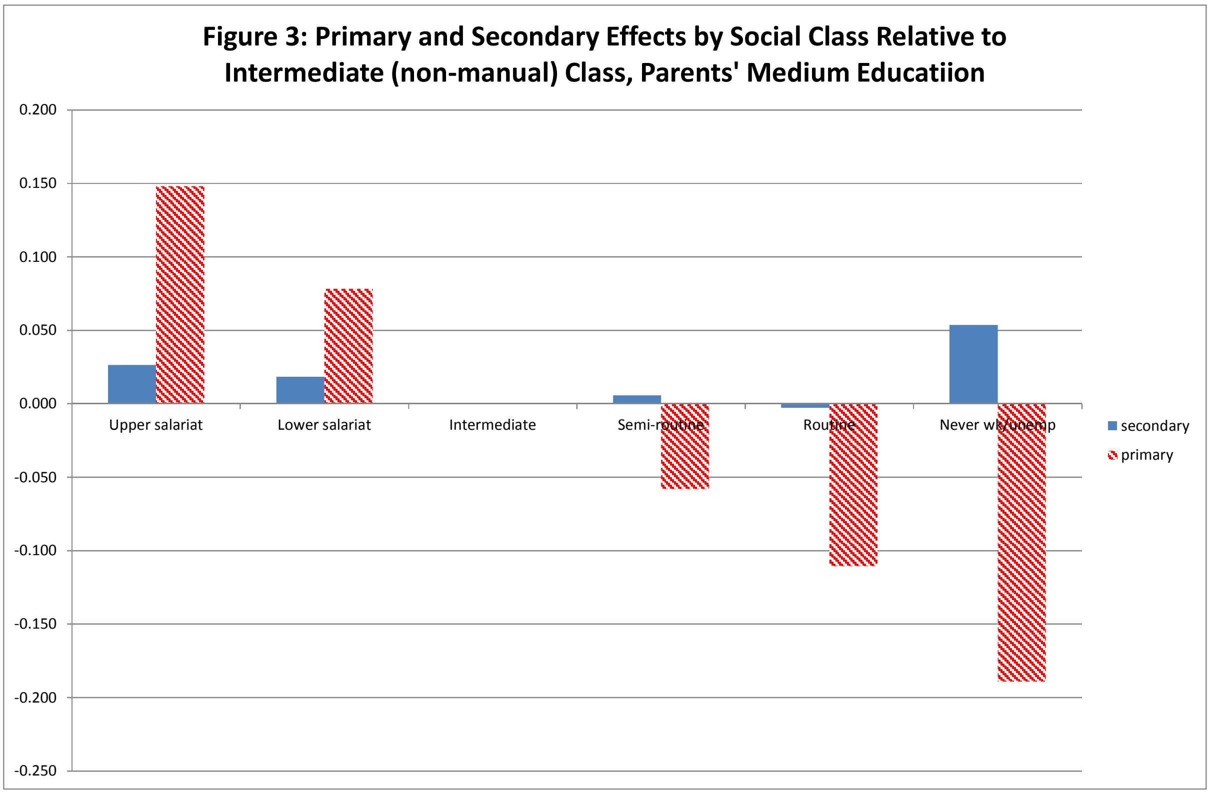


Figure 3: Primary and Secondary Effects by Social Class Relative to Intermediate (non-manual) Class, Parents' Medium Educatiion
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
-0.150
-0.200
-0.250
Upper salariat
Lower salariat
Intermediate
Semi-routine
Routine
Never wk/unemp
secondary
primary

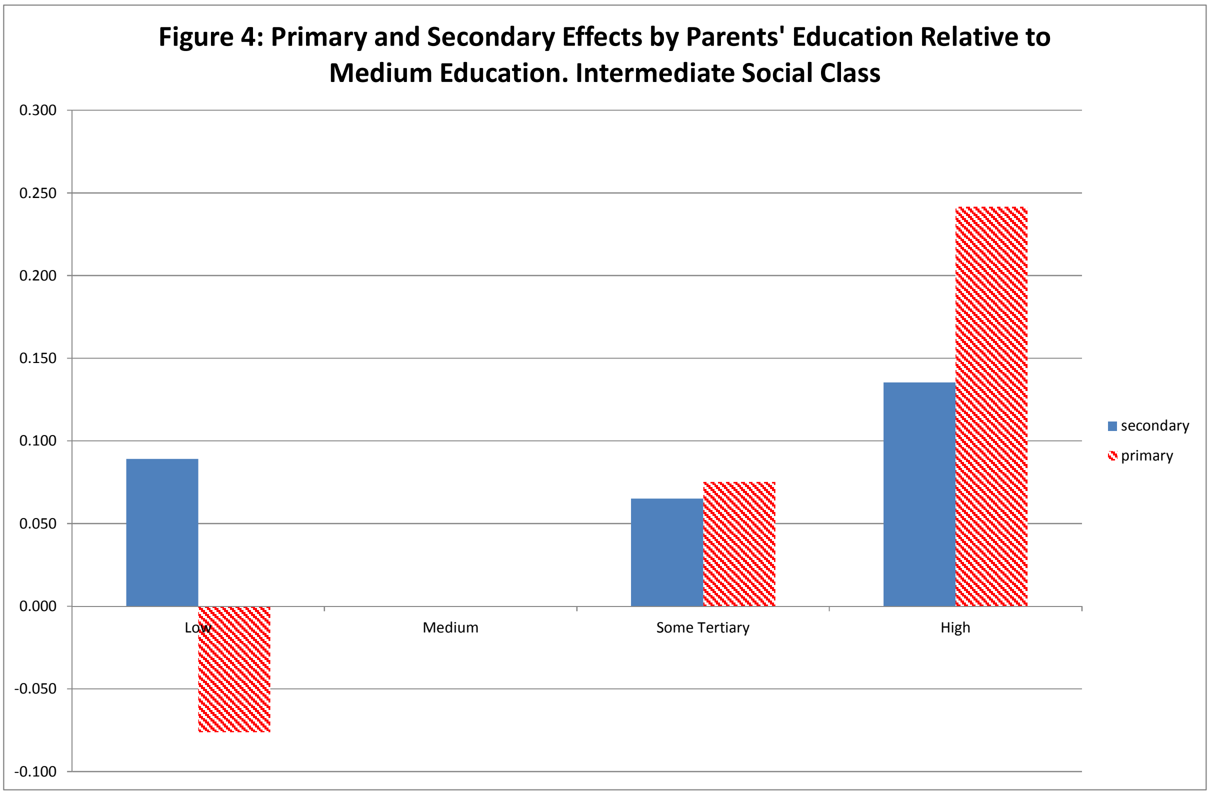


Figure 4: Primary and Secondary Effects by Parents' Education Relative to Medium Education. Intermediate Social Class
0.300
0.250
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
Low
Medium
Some Tertiary
High
secondary
primary

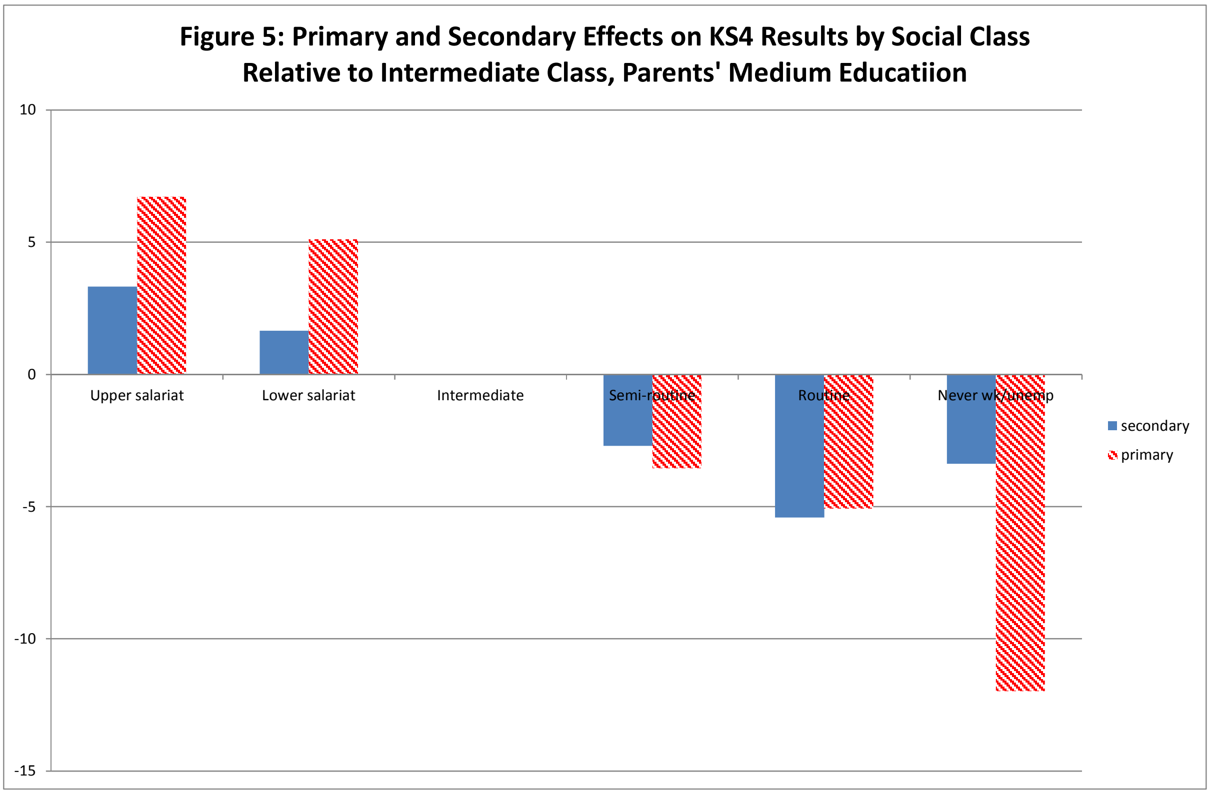


Figure 5: Primary and Secondary Effects on KS4 Results by Social Class Relative to Intermediate Class, Parents' Medium Educatiion
10
5
0
-5
-10
-15
Upper salariat
Lower salariat
Intermediate
Semi-routine
Routine
Never wk/unemp
secondary
primary

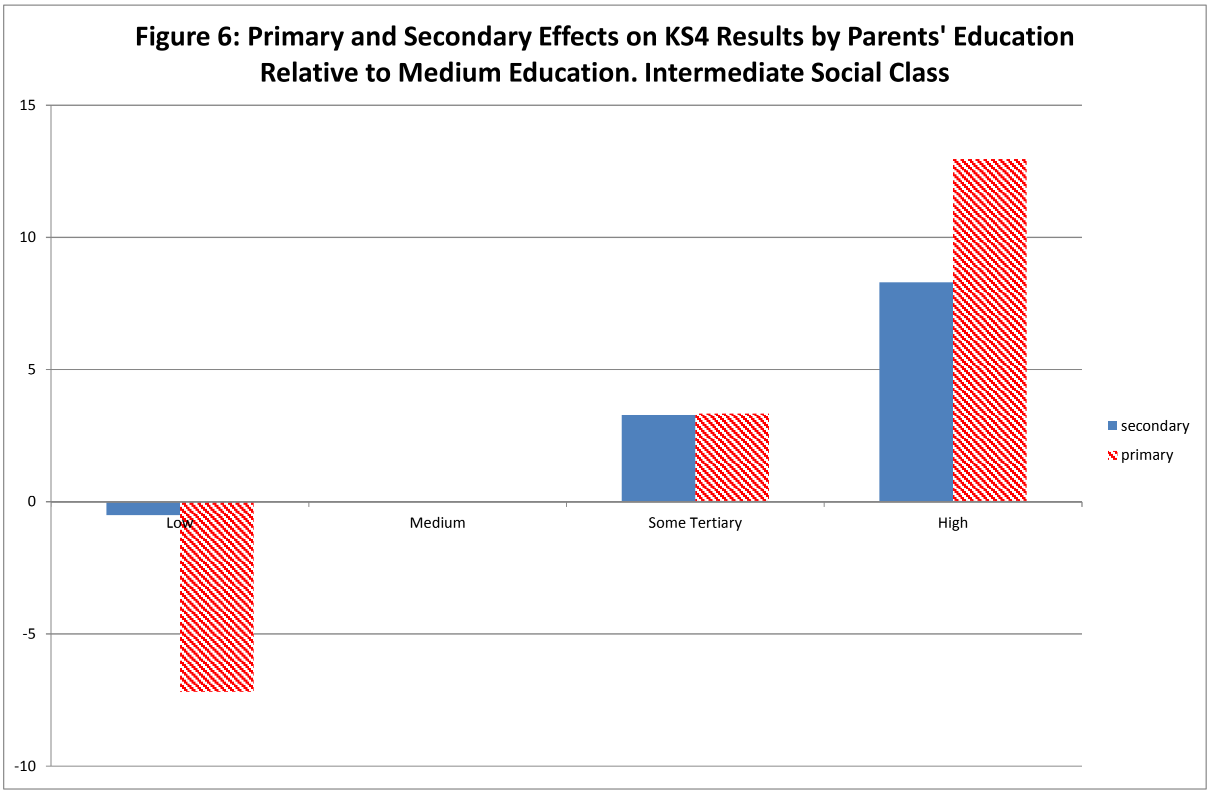


Figure 6: Primary and Secondary Effects on KS4 Results by Parents' Education Relative to Medium Education. Intermediate Social Class
15
10
5
0
-5
-10
Low
Medium
Some Tertiary
High
secondary
primary

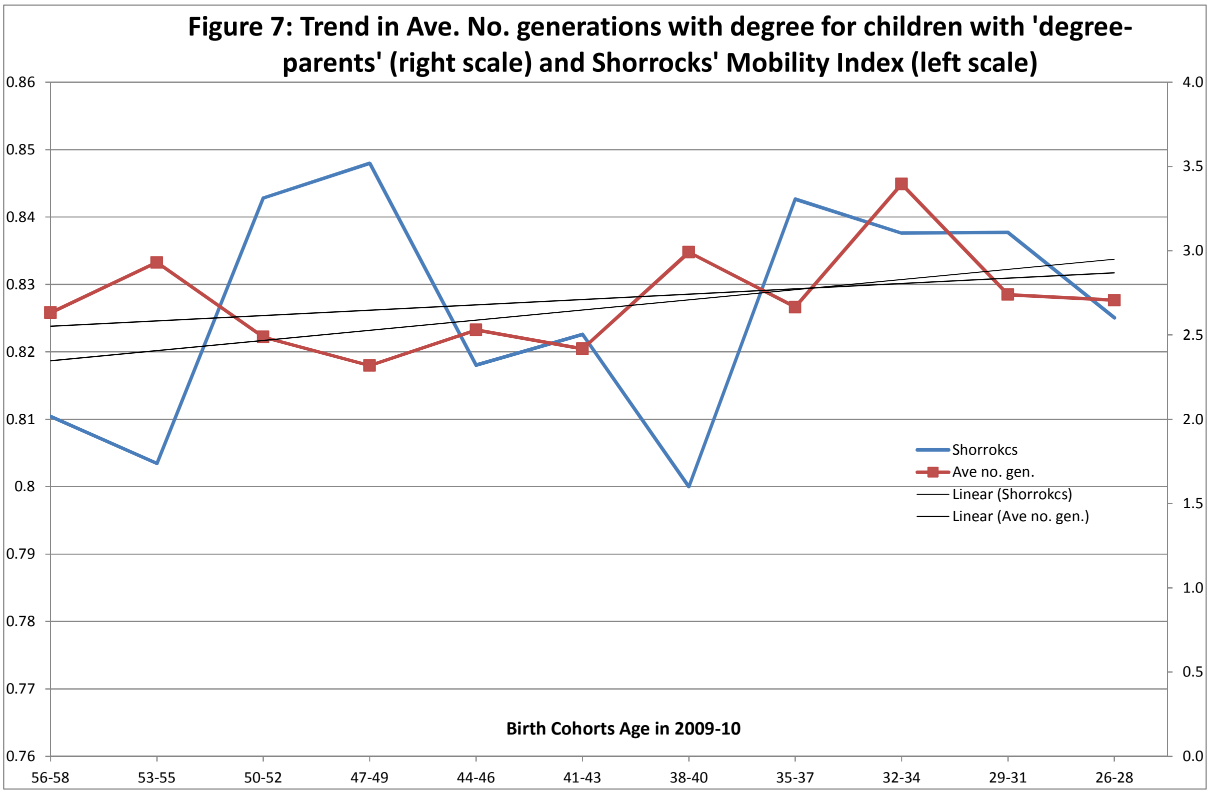


Figure 7: Trend in Ave. No. generations with degree for children with 'degree-parents' (right scale) and Shorrocks' Mobility Index (left scale)
0.86
0.85
0.84
0.83
0.82
0.81
0.8
0.79
0.78
0.77
0.76
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Shorrokcs
Ave no. gen.
Linear (Shorrokcs)
Linear (Ave no. gen.)
Birth Cohorts Age in 2009-10
56-58
53-55
50-52
47-49
44-46
41-43
38-40
35-37
32-34
29-31
26-28

Appendix Table 1: Equilibrium educational distributions, Aged 26-65 in 2009-10*

Education	Men	Women
none	0.043	0.051
school	0.425	0.392
post school	0.113	0.156
degree	0.419	0.401

*Equilibrium vector $\mathbf{x_e}$ solves the equation $\mathbf{x_e}=\mathbf{P}\mathbf{x_e}$, where **P** is the appropriate transition matrix.

Appendix Table 2:
Average number of generations spent in educational class, Aged 26-65 in 2009-10*

A. Men

	1.Actual	2.Perfectly Mobile	3.Actual/PM	4.Std. Dev. actual
none	1.27	1.04	1.21	0.58
school	2.21	1.74	1.27	1.63
post school	1.19	1.13	1.06	0.48
degree	2.59	1.72	1.51	2.03

B. Women

	1.Actual	2.Perfectly Mobile	3.Actual/PM	4.Std. Dev. actual
none	1.33	1.05	1.26	0.66
school	2.15	1.64	1.31	1.57
post school	1.21	1.19	1.02	0.51
degree	2.66	1.67	1.60	2.11

* The average is given by $1/(1-p_{jj})$, where p_{jj} is the diagonal element of the transition matrix for that educational class. Its standard deviation is given by $\sqrt{p_{jj}}/(1- p_{jj})$.

Appendix Table 3: Shorrocks Mobility Index (SE), Aged 26-65 in 2009-10*

Men	Women
0.8225 (0.0064)	0.8060 (0.0056)

*Standard error of the difference=0.0085.