Educational Inheritance and the Distribution of Occupations: Evidence from South Africa

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Abstract

We investigate the implications of the Markovian assumption for predicting the long run distribution of occupations. We postulate that the dynamical structure of the underlying transition process governing educational attainment and occupational choice, in the case of South Africa, is the result of direct and indirect factors, where direct factors are factors that exacerbate the accident of birth, and indirect factors are factors that operate through variables that manipulate one's chances for climbing the occupational ladder relative to one's parents. Conditional on parental occupation and the educational investments of the offspring generation, we show that the opportunity to make such educational investments has a strong conditioning role in shaping occupational transition probabilities between generations. We test the implications of this finding for long-run occupational structure.

JEL Keywords: Intergenerational Mobility, Occupation, Dynastic Inequality

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1 Introduction

Much is known about inequality in South Africa.[1] By contrast, strikingly little is known about the *dynamics* of inequality. [2] Recent theoretical work on the emergence of poverty traps highlights the interplay of educational investments and occupational structure in exacerbating initial inequalities. Specifically, if the initial distribution of wealth is such that there are rich dynasties in which all generations invest in education, engage in skilled labour and leave large bequests, and poor dynasties in which agents inherit less, engage in unskilled labour and leave small bequests, multiple steady states obtain, where households falling below some threshold initial wealth level become stuck in poverty, while households that lie above this threshold become wealthier over time. A key feature of studies which present formal models of this process is that past investments in human capital constrain the extent to which future investments can be made (Banerjee and Newman 1993, Galor and Zeira 1993, Giannini 2003, Atkinson and Bourguignon 2000). This sort of path dependency in educational investments can therefore dramatically shape the aggregate distribution of occupations and therefore long-run inequality.

Snapshots of the distribution of incomes from cross-sectional surveys are undoubtedly useful in telling us what the level of inequality is at any one point in time, and careful synthetic comparisons across time, taking into account the underlying samples from which a cross-section might be drawn, can serve as a useful description of the aggregate pattern of unfolding inequality. But these sorts of comparisons tell us little about long-run trajectories. To shed light on the extent to which the educational opportunities of the previous generation shape the occupational opportunities of the future generation, one requires a complete description of the dynamic structure of the underlying process governing transitions between the relative positions of individuals.[3] One way in which this issue can be interrogated is by looking at intergenerational patterns of persistence in educational attainment and occupational choice.

We take up these issues in this paper. We begin in section 2 by describing broad patterns in the data concerning intergenerational mobility and persistence of schooling outcomes before considering three broad aspects of the transmission process: non-linearity, racial and gender heterogeneity and temporal effects. Section 3 looks at the question of how these movements in the marginal distribution of schooling impacts on

[1] See the review of this extensive literature in Leibbrandt, Woolard, Finn and Argent (2010)

[2] In this paper we make use of Wave 1 of South Africas National Income Dynamics Study (NIDS) data. As additional waves are added to this panel data set, analysts will have a better basis of exploring these dynamics.

[3] Maybe a short illustration of why this matters together with some references?

the steady-state distribution of occupations. We start by postulating a Markov process for the underlying dynamical system as our theoretical framework. We then discuss our construction of occupational classes, before moving on to a discussion of our core test of the Markovian postulates. Finally, we conclude in section 6 with some remarks about the broader implications of our findings for what is known about inequality in South Africa, and suggest several promising new avenues for building on this research.

2 Trends in Educational Attainment and Persistence

2.1 Description of Trends

The data used in this paper come from Wave 1 of NIDS. Mobility analysis is technically the domain of panel data. However, intergenerational mobility is one of the chief themes in NIDS and special attention was given to this theme in the Wave 1 questionnaire. Even in the cross-section of NIDS Wave 1, it is possible to compare parents and their children in terms of their education and occupation status. Indeed, NIDS provides rich data for these topics.[4]

Table 1 below provides a broad breakdown of mean years of education by race. By restricting the sample to those respondents aged between 20 and 35 and respondents aged 50 and older, we are able to look more closely at within-generation temporal patterns in schooling attainment. The parents of the younger cohort would be in their late forties, fifties and early sixties, whereas the parents from the older cohort would be from the generation born prior to 1945. Thus, in effect this table displays a picture of three generations educational achievement.

The table shows clearly that mean education is increasing across generations: educational attainment appears to have doubled between the parental generation and the offspring generation (5.2 to 10.2 years). Interestingly, this pattern is closely mirrored for the older cohort as well (which shows an increase in average parental education from 2.95 years to 5.7 years). Not surprisingly, most of this effect is driven by changes in attainment for Africans and Coloureds. This patterns confirms similar findings using the 10% sample of the 1991 census (see for example Thomas (1996)).

White parents are, on average, more educated than their African and Coloured counterparts in both generations, but the education gap is shrinking: in this generation, White parents have approximately 2.6 and 1.48 times more years of education than

[4]The NIDS Wave 1 data set is described in Woolard, Leibbrandt and de Villiers (2010) and the Wave 1 variables for use in the analysis of intergenerational mobility are described in detail in Girdwood and Leibbrandt (2009)

African and Coloured parents respectively; whereas a generation ago, White parents had approximately 13.6 times more and 4.17 times more years of education than African and Coloured parents respectively.

Further evidence of these patterns is reflected in table 2, which shows the intergenerational transition probabilities for the 6 educational categories by race over the average of parental years of schooling.[5] Several features of these transition matrices bare particular resemblance to the story told by the descriptive statistics. Firstly, there is greater mass below the diagonal than above it. Secondly Africans and Coloureds are more mobile than Whites. Thirdly, the rate of intergenerational mobility is clearly non-linear, since the very bottom and top quantiles show greater persistence than in any of the other quantiles, and this pattern is especially pronounced for Whites and to a lesser extent coloureds.

Figure 1 shows a 3-dimensional view of the educational transition matrix. To gain further purchase on these patterns, we look instead at the years of schooling transition. The height of the surface in cell (i, j) is the unconditional probability that an individual, whose parents have i years of education, will have j years of education. The plot indicates that an individual with parents with the highest level of education is 915 times more likely to achieve that level over an individual whose parents have zero education. Figure 2 reflects where the highest concentration of mass lies along the conditional distribution 1. The relatively even spread in mass at around 12 years of education for the child demonstrates the advances made in education as well as the predominance of the Matric as an exit out of the education trajectory. This plot also exhibits the non-linear attainment of education where larger gains in education years are made at the higher end of the parental education distribution than at the lower. A 45 degree line is also apparent, separating the relatively inactive side (dark areas) from the higher probabilities (ligher shaded areas). Figure 3, shows that a major source of this pattern is the increasing numbers of Africans completing high school (or equivalent).

Some of these patterns might be explained by the fact that Africans and Coloureds

[5]The columns of table 2 refers to the six educational categories indexed by each row, lowest to highest, into which the average of parental schooling falls. The entries in each cell refer to the proportions of individuals occupying the relevant state, where columns sum to 1. These proportions are population weighted using the post-stratification weights. Tables A.22-A.24 of the web appendix (downloadable from xxx) gives a further breakdown of these transition matrices by race, gender of the child, gender of the parent and location. Interestingly, rural and Tribal Authority areas have exactly the same profiles in terms of education mobility. Unsurprisingly, urban dwellers are more mobile than their rural or tribal counterparts and experience greater upward mobility and downward mobility. In particular, an urban respondent has a 28% probability of attaining the same education level as his or her parent, a 62% probability of achieving an education level higher than that of his or her parent, and 10% probability of obtaining an education level less than his or her parent.

experienced a much higher growth rate in educational attainment in the post-WWII period than did Whites. For example, Louw, der berg and Yu (2007) report that 40% of African individuals aged between 21-25 in the 1970 census had never enrolled in school and only 1% had passed matric, whereas these attainment percentages had improved to 9% and 36% respectively for the same age group in the 2001 census. Similar patterns are reported by Thomas (1996) for Africans born in the 1950s and 1960s relative to those born before.

Given these temporal shifts in educational attainment, how does one interpret the apparent non-linearity in the transmission process reflected in table 2? The expansion of publicly funded schooling to non-White populations gained momentum during the last decade of Apartheid. Yet it would be implausible to interpret these non-linearities purely in terms of temporal shifts in public policy. Indeed, from the work of Bowles and Gintis (2000) and others, we know that family background and neighbourhood characteristics that might be highly correlated with race is the predominant force in perpetuating inequality across generations. It therefore becomes important to distinguish these temporal effects from that of race (and its correlates). We take up this issue in the next sub-section.

2.2 Transmission Mechanisms

Our purpose here is to get a handle on the relative magnitudes of the different forces underlying the non-linearity in the transmission process governing the dynamics of educational attainment. Our empirical approach is based on regressing the educational status of the offspring generation against a range of controls, including dummies for the educational category of each parent (with the lowest level of education serving as our base category). Given the ordinal nature of the educational status variable, we employ the ordinal logit esitmator. Tables 3, 10, 11, 12, and 13 show the results of the different specifications we tried.[6]

2.2.1 Nonlinear Persistence

The first observation we make is that there is clear evidence of a non-linear transmission process, as is demonstrated by the increasing size of the coefficients on mothers and

[6] Since our purpose here is mainly to get additional purchase on the patterns we conjectured in the previous subsection, we only include the marginal effects for a subset of the reported specifications; namely those corresponding to the six columns of table 3, which are labelled chronologically as tables 4–9. Interested readers may wish to consult tables B.25 – B.44 of the web appendix B (available for download at xxx) for the marginal effects of the remaining specifications reported; namely tables 10 - 13.

fathers education levels. Children whose mothers have tertiary education are associated with a 1.7 ordered log-odds in having a higher level of education than children whose mothers have no or limited schooling, holding all other variables constant.[7]

Secondly, we can be quite precise about at least one type of non-linearity operating on the transmission process. The marginal effects corresponding to the specifications given in columns 1 and 2 of table 3 are shown in tables 4 and 5 respectively. These tables show that the pattern of *persistence* is clearly non-linear. Reading diagonally across both tables, one can eye-ball the conditional transition probabilities between states (benchmarking against either parents educational level).[8] For example, the probability of a child attaining level 5 education (completing high school) is 24% higher if the child's father also attained level 5, compared to a child who's parent attained only level 1. For level 6 (tertiary education), the probability rises to 37%. The corresponding figures for the mother-to-child transition, again for levels 5 and 6, are shown to be 17% and 16% respectively. The table also shows that the transition probabilities are declining between states 2-5. Since these probabilities are benchmarked against level 1, the conditional transition matrix implied by these marginal effects tells essentially the same story as the unconditional transition probabilities reported earlier (see table 2).

2.2.2 Race and Gender Differentiated Persistence

Focusing now on the effects of race and gender shown in table 4, male respondents appear to have a small negative coefficient suggesting that males are situated slightly lower down the educational distribution than females, all other things held equal. Being male improves the probability of attaining education at the lower levels; however, it proves to be a disadvantage at higher levels of education.

Tables 10-13 reports the results by gender and race. We focus first on the question of race. From the descriptive statistics discussed above, and the prior work of Thomas (1996), it would not be surprising to find that race turns out to be a salient driver of educational mobility patterns. This is indeed what we find. As table 10 indicates, there is a clear ranking of the ordinal logit index coefficients between whites and Africans on the father education dummies. Interestingly however, the pattern reverses when we look at the corresponding relationship with maternal education level. The index coefficients

[7] An alternative interpretation is that the odds of attaining a higher level of education are increased by 5.5 times when a child has a mother with tertiary education to one who has limited to no schooling, holding all other variables constant.

[8] Another way of putting it is that these implied transition matrices are summaries of the degree of *relative* educational mobility, since the imaginary diagonal we wish to draw attention to gives a conditional probability for state $(i, i)\ \forall\ i = 2, \ldots, 6$, relative to the conditional probability of being in state $(1, 1)$.

here tend to be negative except for level 6. One interpretation we give to this is that any disadvantage faced by White mother's tends to be reversed in the next generation when it comes to the White population, but reinforced when it comes to the African population. On the hand, the advantageous positions (i.e., high levels of attainment of the previous generation) of both parents, seem to be preserved across all races. Interestingly, these patterns in the probability of educational advancement also appear to be conditioned on the gender of the child. For Coloureds and Whites the coefficient on *Male* was positive and for Africans it was negative, further supporting our earlier descriptive findings of higher rates of attainment for African females.

To check the sensitivity of this result to the assumption of separate error distributions by race, we reversed the type of conditioning employed, by running separate regressions for sons and daughters, controlling for race. For sons, the educational transmission was stronger for the father than the mother at the high end of the fathers education distribution. Equally for daughters, the educational transmission was stronger for the mothers at the upper ends of the distribution. This father-son and mother-daughter link is most prominent for Colourds.

2.2.3 Temporal Effects

As pointed out earlier, the effect of time greatly affects the interpretation we might give to any comparisons we might wish to make according to the types of ascriptive traits that would seem important from the discussion so far; namely race and gender. Key to our story is that disadvantages faced by the children of individuals with meagre education, could persist and come to have a bearing on the steady-state distribution of occupations. A first step in this analysis therefore is to show that these unequal opportunities for educational advancement might have been key. Our discussion thus far focuses on the differences (in some instances, quite sharp differences) in the probability of undoing previous disadvantage between Whites and Africans. This evidence would seem to accord with the idea that these differences might serve to amplify inequalities in the distribution of occupations. However, if Africans and Whites exhibit very different preferences with regard to educational attainment to begin with, which may or may not be compounded by changes in the policy environment that might have differentially affected each group, then our inferences concerning the race-based origins of non-linear persistence could be false.

To fully explore the independent effects of intergenerational patterns of transmission, from these unobserved types of effects, we condition on the age of the parents, under the assumption that the policy environment, demographics, and preferences for schooling, are all inherently endogenous variables that might best be captured by controlling for the time period over which we might wish to estimate a matrix of transition probabilities. We proxy for time by directly controlling for the age of both parents in the regressions.

The addition of parents age does indeed alter the picture somewhat. The coefficient on *Africans* decreased in magnitude by 1.8 times its value from -1.56 to -0.87. Yet at the same time, we know that African attainment grew faster (by construction) thus closing the White-African gap substantially over time, as highlighted earlier by the descriptive statistics. Importantly however, is the (well known) finding that Africans still remain at a substantial disadvantage relative to whites. Interestingly also, controlling for the "black box" of age, does not account for non-linearity in the transmission process. If anything, a comparison of the probability of persisting at level 6 between tables 4-5 shows a rise from 37% to 41% for fathers' education, and a sharp rise from 16% to 37% for mothers' education.

Finally, to see if greater explanatory power could be extracted out of the age data, we repeated our analysis over two synthetic cohorts: 20 to 35 year olds and individuals greater than 50 years of age. The results of these specifications are reported in the last 4 columns of table 3, and the marginal effects are shown in tables 6-9. Strikingly, looking at the results for the over-50 year old cohort of children, we see that controlling for parental age results in persistence at the very top of the conditional education distribution by 69% for fathers and 52% for mothers. Even more strikingly, these probabilities drop to 24% and 33% for the younger (20-35 year old cohort) for fathers and mothers respectively.

By judging mobility purely on the values of the pseudo-R2s, the older generation would appear the least mobile: 28% of the variation in the individuals education is explained by the variation in the model versus a mere 8% for the younger generation. The magnitudes of the age coefficients are similar for both generations suggesting that one can compare the role played by parents education and racial group in explaining education attainment between the two age groups. The significantly larger coefficients across parents education for the older generation suggest much greater persistence in that generation and less mobility. Furthermore, the reduction in the magnitudes of the race coefficients implies that the racial gap between Africans and Coloureds, versus Whites has decreased. This supports the descriptive statistics from earlier. Finally, it is interesting to note the change in sign on the male coefficient hinting at the recent educational advancement of women over and above that of men.

3 Theoretical Framework

In this section, we outline the theoretical framework that guides the empirical approach we have taken. As suggested by the discussion of section 2, our main preoccupation in the paper is to tease out the consequences of the social, political and economic rigidities and distortions resulting from Apartheid era educational and occupational structure for the long run distribution of occupations. Taking as a package the types of rigidities and distortions imposed by Apartheid era policies operating directly and indirectly on occupational structure, if we can show that the "natural experiment" of Apartheid implies a significant constraint on equalizing tendencies in the distribution of occupations, this will suggest that a purely stochastic account of mobility rates is misleading, lending support to the recent theoretical emphasis on the instrumental role of education in generating and perpetuating poverty traps. Of course this agenda requires us to be explicit about what precisely we mean by "equalizing tendencies". We postpone this discussion to section 4, and for the moment clarify how we will attempt to measure the importance of prior rigidities and distortions, for these equalizing tendencies, however they may be measured.[9]

Our working hypothesis is as follows. Measured differences in the occupational structure between generations can be the result of direct and indirect factors. Direct factors are factors that exacerbate the accident of birth. For example, when black children are confined to the same occupational levels as their parents by virtue of being black, while at the same time facing a direct limit on their own advancement imposed by policies like job reservation. Indirect factors operate through variables that manipulate one's chances for climbing the occupational ladder. Conditional on parental occupation, we postulate that educational investments of the present generation, as well as some measure of the (lack of) educational opportunities will matter. The precise content of these direct and indirect factors is taken up in section 5. However, for the moment, we wish to specify a theoretical framework that is capable of describing the long run distribution of occupations while at the same time giving specific attention these types of key features which have characterized post-WWII South African labour markets. This model is described in section 3.2. We begin however, by establishing the case where neither direct or indirect factors operate as constraints on occupational mobility and structure. We call this case the "counterfactual case", for obvious reasons.

[9]Indeed, as we will clarify in section 4 the regularity assumptions that we will (plausibly) impose on the model will imply that our theoretical framework should be invariant to how we measure occupational mobility, rightly understood, in the standard sense as a mathematical criterion by which to judge transition matrices satisfying standard some standard axioms in this literature.

3.1 Equal Opportunities: Basic Markov Process

We start by indexing generations as a discrete variable. An individual must occupy exactly one of a finite number of discrete states from the set of states $\mathcal{N} = \{1, \ldots, N\}$. Thus we define p_{ij} as the probability of an individual ending up in occupation level i after a single generation, given that that person's parents started out in occupation level j in the previous time period.[10] These p_{ij} define the following matrix of transition probabilities (which by defining have to be positive).

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix} \tag{1}$$

This matrix describes a so called one-step transition process: i.e., it fully describes what it would take to reconcile differences in the distribution of occupations that can be expected to emerge within a generation. Since each individual starting in any given state must also end up in one of the N states, it must be the case that the columns of this matrix sum to one:

$$\sum_{j=1}^{N} p_{ij} = 1 \;\; \forall \;\; p_{ij} \geq 0$$

In our formulation, these probabilities are subscripted p_{ij} implying that the first subscript indexes the offspring generation, whereas the second subscript indexes the parental generation.[11] If we assume that the p_{ij} are fixed and independent of generations, then the dynamics of this system follows a Markov process. To describe the underlying dynamics of such a system, we denote x_j^{n-1} as the fraction of a population of size N_1 that is in state j in generation $n-1$, so that the total number of members of this population found in state j in generation n is given by $x_j^n N_1$. If the p_{ij} are stationary, as we've assumed, then

$$x_i^{(n)} N_1 = \sum_{j=1}^{N} p_{ij} x_j^{(n-1)} N_1 \tag{2}$$

In words, the total number of members of this population that we can expect to find in state i in generation n is given by the sum over all of the members occupying state

[10]In order to avoid empty cell problems in later sections when we condition on race, gender and age, we restrict attention in the parental generation to just fathers.

[11]We could also set up the model such that the rows have to sum to one, in which case we would have to reverse our subscripting convention because then the parental generation would be denoted along the rows of the matrix and the offspring generation would be denote across the columns.

j in generation $n-1$ that have moved into state i. Under the standard (first-order) Markov process, this movement can only happen in the following way: in order to be observed in state i in generation n, an individual must have been observed in one of the N states in generation $n-1$, and then must move from state j to i within a generation (or more precisely, in the immediately preceding step of the Markov chain). Given that we can construct equations of this sort for all $N \times N$ possible transitions, we can put the resulting system of equations into matrix form (after dividing through by N_1), giving

$$\begin{pmatrix} x_1^{(n)} \\ x_2^{(n)} \\ \vdots \\ x_N^{(n)} \end{pmatrix} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1N} \\ p_{21} & p_{22} & \cdots & p_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N1} & p_{N2} & \cdots & p_{NN} \end{pmatrix} \begin{pmatrix} x_1^{(n-1)} \\ x_2^{(n-1)} \\ \vdots \\ x_N^{(n-1)} \end{pmatrix} \tag{3}$$

or more compactly, $\mathbf{x}^{(n)} = (x_1^{(n)}, x_2^{(n)}, \ldots, x_N^{(n)})' = P\mathbf{x}^{(n-1)}$ where we have denoted $\mathbf{x}^{(n-1)} = (x_1^{(n-1)}, x_2^{(n-1)}, \ldots, x_N^{(n-1)})'$. The right hand side is a Markov chain over states $1, 2, \ldots, N$. The important thing to note about system 3 is that it is recursive, which implies that

$$\mathbf{x}^{(n)} = P^{(n)}\mathbf{x}^{(0)} \tag{4}$$

$$\mathbf{x}^{(n)} = P^{n}\mathbf{x}^{(0)} \tag{5}$$

This is because the nth power of the one-step transition matrix P is equal to the n-step transition matrix; $P^n = P^{(n)}$. If we restrict attention of P to Markov matrices, some power of which only ever has positive entries, then P is said to be a regular Markov matrix, and by a standard limit theorem of regular Markov chains (see Karlin and Taylor (1975) and Feller (1950) for example), we have the following result: (a) 1 is an eigenvalue of P of multiplicity 1; the absolute value of every other eigenvalue of P is always less than 1; eigenvalue 1 has eigenvector $\mathbf{w}_1$ with strictly positive components; if we normalize $\mathbf{w}_1$ by the sum of its components (which we can do by dint of the structure of the general solution of system 3), and call this new vector $\mathbf{v}_1$, then this new vector will represent a fixed-point *probability* vector.[12] This is the most basic type of stochastic process one can benchmark against. Our discussion of predicted occupational mobility in section 5 starts by computing these fixed point probability vectors $\mathbf{w}_1$ implied by equation 5.

[12]More precisely, as $n \to \infty$, we must have $P^n \to W$, where the matrix W has identical rows all equal to $\mathbf{w}_1$, such that $\mathbf{w}_1 = \mathbf{w}_1 P$. The fact that $\mathbf{w}_1$ is left unchanged after post-multiplying by P means that $\mathbf{w}_1$ must be a fixed point vector of P.

3.2 Unequal Opportunities: Mover-Stayer Markov Process

We now present an adapted version of the above Markov process. The key difference is that we now relax the homogeneity assumption imposed on the data by the standard Markov chain model. We now allow different groups to have different transition probabilities. This type of model is dubbed the "mover-stayer" Markov model. The application of this model to occupational mobility was first carried out by Blumen, Kogan and McCarthy (1955). Our formulation follows that of Goodman (1961). In particular, we denote as *movers* people who have some non-zero probability of changing occupational classes between generations and *stayers* as people who will persist in the same occupations as their parents with certainty. For the moment, we assume that the matrix of transition probabilities for the movers is constant across all movers and is given by the matrix M, whose elements m_{ij} are the probabilities of transition from the jth occupational class in the parental generation to the ith occupational class in the offspring generation. By contrast the matrix of transition probabilities of the stayers is given by the identity matrix. This process implies that someone observed in the present generation as occupying the ith state, whose parents also occupied the ith state, could persist in this category in two ways: something about the social structure determines that he is sure to remain stuck in the same occupational rung as his father, or *by chance* he ends up in the same occupational rung with probability m_{ii}. As we will see momentarily, the distinguishing feature of this adapted Markov model is that the classic limit theorem for a standard Markov process will carry through for the movers in this set-up, but unlike the standard model, the limiting matrix of transition probabilities will not have a fixed-point (i..e, it will in general depend on the distribution of occupations in the parental generation).

Let the matrix S denote a $N \times N$ diagonal matrix with s_i representing the fraction of people in the ith state who will stay there with certainty. Then, by the above description, we can write

$$p_{ij} = \begin{cases} (s_i(1) + (1 - s_i)m_{ii} & \text{if} \quad j = i \\ (1 - s_i)m_{ij} & \text{if} \quad j \neq i \end{cases} \tag{6}$$

or, more compactly

$$P = S + (I - S)M \tag{7}$$

and, for the nth power of the matrix P, we have

$$P^{(n)} = S + (I - S)M^n \tag{8}$$

Since M^n is regular, its limiting matrix, which we denote as V, has a fixed point vector (i.e., all the rows are the same). The same argument in representing the components of this fixed point vector as probabilities made above applies, so we can denote $\mathbf{v}_1$ as the fixed point probability vector of the movers. However, note that V is the limiting matrix of only the movers. The limiting matrix of the combined population of movers *and* stayers is given by the left hand side of 8, which, as the right hand side of this equation makes clear, will not have identical rows. Applying equation 4, we will have

$$\mathbf{x}^{(n)} = P^{(n)}\mathbf{x}^{(0)} \rightarrow [S + (I - S)M^n]\mathbf{x}^{(0)} \tag{9}$$

This formulation of the problem is appealing because it allows the effects of past rigidity to affect the long-run distribution of occupations. By comparing the predictions given by equation 4 with those of equation 9, we are able to gauge the extent to which previous restrictions on occupational mobility operate as a constraint on any equalizing tendencies that might be playing out in the labour market across generations. It is one yardstick by which we might measure the "long shadow of Apartheid", if such a "shadow" does indeed exist.

4 Measuring Occupational Status in South Africa

In this section, we discuss the different methods that are available for coding occupational status. We begin by discussing the International Standard Classification of Occupation 1988 (ISCO88) of the International Labour Office (ILO) and its South African adaptation: the South African Standard Classification of Occupations (SASCO). Next we consider an alternative to the skills classification under ISCO88 proposed by Ziervogel and Crankshaw (2009). We then outline two other internationally comparable measures of occupation status: Treimans Standard International Occupational Prestige Scale (SIOPS) and Ganzeboom and Treiman (2003) International Socio-economic Index of Occupational Status (ISEI). Although our goal is not to try to provide a comprehensive evaluation of the occupational status literature, we feel that some discussion of the alternative approaches that have been proposed is warranted to explain the approach we come to reply on.

Table 14 describes the occupation codes and associated skill levels of the South African Standard Classification of Occupations (SASCO) taken from Statistics SA and based on the United Nations International Standard Classification of Occupations (ISCO-1988). The ISCO88 attempts to classify work, in the first instance, according tasks and duties related to an occupation and, in the second instance, according to the relevant skills that are necessary for fulfilling the formal and practical requirements of a particular occupation (Bergman and Joye 2001). The skill levels associated with each major group are based on education qualifications and thus serves to transform the SASCO occupational catagorisations into a quasi-hierarchical variable that could be used in order to conduct an ordinal analysis of between generation movement in occupations.

Using the SASCO codes three variables were constructed: individuals occupation; mothers occupation and fathers occupation. Individuals occupation was created by taking the 1-digit occupation codes from Section E of the NIDS adult questionnaire for regular work 1, regular work 2, casual work, self-employed work and the occupation code for when the individual once ever worked.[13]

A major problem with the skill levels embedded in the SASCO approach is that two of the four categories relate to tertiary education. Due to the sparse nature of tertiary education qualifications in South Africa, this approach is likely to lead to artifactual biases in the estimates of transition probabilities between the four states. To deal with this problem, we follow Ziervogel and Crankshaw (2009) by reassigning the ISCO-88 major groups to four skills groups that more accurately reflect the distribution of skills in South Africa. Table 15 shows the effects of our recoding exercise in this regard.

We also constructed Treiman's Standard International Occupations Prestige (SIOPS) scale (Treiman 1976, Ganzeboom and Treiman 1996, Ganzeboom and Treiman 2003). This scale not only gives a ranking to occupations in terms of their subjectively perceived prestige, but is useful for international comparisons. The basic idea behind Treimans SIOPS scale is to construct a single ordered prestige scale based on the subjective prestige ratings of occupations, which would reflect a hierarchy of occupations according to their "power and privilege" across all social and cultural groups, as well as across all societies sufficiently complex as to called "modern" (Bergman and Joye 2001). Treiman (1976) originally constructed SIOPS by averaging results of prestige evaluations carried out in approximately sixty countries. Occupational titles from national and local prestige studies were matched to the three-digit version of ISCO-68. Ganzeboom and Treiman (2003) then updated the scale for ISCO-88 codes. The scale ranges from 6 to 78 where 78 denote Medical Doctors and Higher Education Teaching Professionals (including University Professor) and 6 denote Hunters and Trappers (including whalers). These

[13]Precedence was given to the occupation from regular work 1 in the case of multiple jobs. Parental occupation variables include information from two sources: for non-resident or deceased parents, the respondents recollection of parental occupations captured in section D of the NIDS adult questionnaire; for resident parents, the respondent's self-reported occupational status reported in section E of the NIDS adult questionnaire was used).

eight deciles were then simplified to single-digit categories in an effort make our subsequent analysis more tractable. Thus, the ordinal prestige score (SIOPS) was recoded into 8 categories. In all cases, higher numbered categories represent higher skill levels or prestige scores. The number in each cell represents the percentage of individuals in that skill or prestige category that share the same origin and destination category.

Figures 4 and 5 shows a 3-dimensional transition matrix of Treimans SIOPS scale, for father's and mothers, respectively, recorded according to the approach described above. The height of the surface in cell (i, j) is the probability that an individual, whose father has an occupation prestige score of i, will have an occupation prestige score of j. An individual whose father has a prestige score of 3 has a 40% probability of also having a prestige score of 3. By contrast 50% of individuals whose mothers have a prestige score of 7, have a prestige score of 4.

In what follows, we do not use the SIOPS measure of occupational status, in spite of the obvious benefits. This is mainly because use of the SIOPS measure shows that it can be tremendously sensitive to the the use of (post-stratification) sampling weights.

5 Empirical Implementation and Results

We now are in a position to explore how the qualitative outcome of the (heterogeneous) educational transitions come to bear on the steady-state distribution of occupations. We begin first by commenting on the raw transition matrices.

5.1 Basic Characteristics of the Transmission Process

Tables 16-17 show occupational transition matrices for the whole sample, and by race respectively. The cells here indicate the population weighted proportions of individuals falling into a given state. It is clear that there is substantial persistence (55%) for the very highest level of occupations (Managers and Professionals category). Overall the transitions bear a mobility pattern that appears quite localised: for any given state i, more mass appears to be concentrated closer to state i than states that are further away. Undoubtedly, some of this is artifactual: individuals at the very bottom cannot drop further down the conditional distributions; *vice-versa* for individuals at the very top.

The second panel of table 16 looks at the mother to child transition, because unlike the case for education, the correlation in occupational status between parents is quite low (less than 50%) suggesting little evidence of assortative matching in the domain of occupation. For this reason, it is not altogether surprising to see lower persistence at the top end of the conditional distribution than is evident for the father to child transition: given the low correlation across parental occupation status, a high degree of persistence in the status of one parent would suggest a relatively lower degree of persistence in the status of the other parent. Yet some of the difference might also be driven by the types of temporal shifts that seem to be at work in explaining the educational transmission process. If the educational system favours one gender over another, and at some point a switch takes place (driven either by overt policy choices or through small changes in sex-ratios) then these gender differentiated persistence levels might have little to do with assortative matching, properly understood (i.e., it could be the case that there is little differentiation within gender to begin with). Table 17, which shows a racial breakdown of occupation transitions lends some credence to this view – Africans and Whites have greater persistence at the top of the father-child conditional distribution whereas for Coloureds, the mother-child transition dominates persistence at the very top.[14] Given the low correlation between parents occupations, from here on in we restrict attention only to that of the father's occupation when predicting offspring occupational levels.

5.2 Long-Run Occupational Structure: Basic Markov Model

Table 20 is a summary table of the steady state distribution of occupations computed under varying assumptions, for the younger cohort of 20-35 year olds (Panel A) and an older cohort of workers aged 50 and older (Panel B). The second row of each panel, labelled "Homogeneous Markov Process" corresponds to the fixed point probability vector where the columns of the table each represent one of the four components of this probability vector. We interpret each of these percentages as that proportion of total occupations we can expect to be taken up by positions in each rung in steady-state. The key assumption here is that no member of the population faces the prospect that their parents will have occupied the same rung as they are expected to with certainty. In a sense then, this line of the table (for both panels) tell us what we would expect to be the situation if intergenerational occupational mobility were modeled as a pure first-order Markov process.

Some interesting things are apparent. First, consistent with what we would expect from this sort of model, the distribution of occupations for the younger cohort appears relatively flat. There is a bit more dispersion in the distribution of the older cohort. This too is not that surprising, given that this model would predict far more accurately for the younger generation which would have been exposed to a more meritocratic market

[14] Web appendix C.1 downloadable from xxx provides further breakdowns by the gender of the child (Tables C.45-C.47), and by location and age cohort (Tables C.48-C.49).

structure where chance would play a stronger role.

5.3 Long-Run Occupational Structure: Mover-Stayer Model

The problem with the above result however is that it potentially hides a great deal by imposing on the data the assumption of a homogeneous transmission process. The remaining rows of the table, with labels ending with "B, C," or "D", presents the steady state distributions allowing for the possibility of unequal opportunity by race and gender. The key thing to keep in mind here is that the reported distributions are not independent of the base distribution.

5.3.1 Estimating M_k

A distinguishing feature of our approach is that, the matrices S and M are not taken as fixed constants but rather estimated directly from the data. In this respect, our approach is much more in line with Goodman (1961). Estimation of these two unknowns is required in order to compute these steady-state distributions. Thus our empirical analysis begins by computing the probabilities of transitioning between occupation levels from one generation to the next; i,e., the elements of the matrix M (equation 7).

This is the first type of heterogeneity we allow. Under the standard Markov model, these transition probabilities are given by the raw numbers of people in each cell of table 16, and we compute the steady-state distribution by computing the normalized eigenvector corresponding to eigenvalue 1. However, unequal opportunity operates to change the matrix of transition probabilities, such that chance is allowed to affect the probabilities of transition of the movers but not the stayers.

In addition to the occupational level of the parent (the only variable held constant between the standard Makov model and the mover-stayer model), we postulate three additional key dimensions in which these occupation transition probabilities might be conditioned: race, gender and the educational opportunities one has relative to one's parents, where the latter is to be interpreted as a summary measure of the constraints placed on the level of attained schooling. Race and gender are shown as headings of the broad sub-sections within each panel of the table, whereas "educational background" is shown as separate rows within each sub-section. Specifically, the "B", "C" and "D" labels refer to "higher than", "lower than", or "the same as" educational attainment as one's parents. So, for example, the transition matrix that was used to construct row 6 of the table is based on an ordinal logit regression of the occupational level of the offspring against dummies for race, gender, B and a range of other controls, including years of schooling and age. These ordinal logit regressions that underpin the computed transition matrices of the kth group M_k are shown in tables 18 and 19. Using the estimated coefficients from these regression, we then compute predicted probabilities for each possible contrast of the child-parent occupational transition matrix, conditioning on the ascriptive indicators shown in table 20. Since each contrast is for a given level of the child occupational variable against all possible levels of the parent occupation level, these probabilities must sum to one. Putting these probabilities into a matrix results in a matrix of *predicted* transition probabilities, where the columns sum to one, as required by our set-up in section 3.2.

5.3.2 Measuring the Mobility Exhibited by M_k

In order to shed light on the extent of overall persistence, an appropriate scalar measure needs to be used that summarizes all the information in the transition matrix. The most common scalar measures derived from transition matrices are the trace and determinant. The trace measure (Shorrocks, 1978), captures the inverse of the harmonic mean length of stay in a particular state (scaled by $n/(n-1)$) and is expressed as $M_{TR}(\mathbf{P}) = (trace(\mathbf{P})-1)/(n-1)$, where $\mathbf{P}$ refers to an $n \times n$ transition matrix. But this measure is know to violate important several axiomatic conditions. Geweke *et al*(1986) for example, shows a counterexmple for which the this measure violated the assumption of monotonicity, which requires that $M_{TR}(\mathbf{P}) > M_{TR}(\mathbf{P}^*)$ if $p_{jk} \geq p^*_{jk}$ for all $j \neq k$, and $p_{jk} > p^*_{jk}$ for some $j \neq k$. A further problem is that this measure does not account for variations in the magnitude of movements away from the diagonal. A more appropriate measure would be the determinant of $\mathbf{P}$, if it can be expressed as a strictly monotonically decreasing function of the moduli of the eigenvalues of $\mathbf{P}$ (Geweke *et al*, 1986; Dardoni, 1993; and Conlisk, 1990). To account for these types of monotonicity violations, it makes sense to summarize the behavior of each matrix in a variety of ways. In table 21, we present estimates of five commonly used scalar measures to describe the mobility exhibited in the kth transition matrix estimated from the ordinal logit results.

5.3.3 Using the Estimated M_k to Estimate the Long Run Distribution of Occupations $\mathbf{x}_k^{(n)}$

The second unknown in estimating this model is the proportion of the population who are stayers. We follow Goodman (1961) and let the diagonal elements of this new matrix of predicted transition probabilities represent the elements $s_1, \ldots, s_N$ of the diagonal matrix S shown in equation 7.

Rows 3-5 of table 20 reports results where M was computed without any race or gender conditioning, but where educational background/opportunity was controlled for. "Mover-Stayer Markov Process B" is for individuals with better educational opportunities than their parents, whereas "Mover-Stayer Markov Process C" is for individuals with worse educational opportunities than their parents.

The final column of table 20 labelled "Difference" is a measure of the direct effects of labour market structure. In particular, we note three things of interest. First, if we look at any within letter (B, C or D) comparison across any cut of table 20, we are effectively holding educational opportunity (a major indirect factor) constant. So the difference between the prediction for the younger cohort and the observed outcome for that cohort is then a measure of labour market structure (direct factors). For example, combining the first two occupation levels, 66 of black females that have had better education opportunities than their parents (Process B) occupy the bottom half of the occupation distribution, whereas line 2 "Unconditional Distribution" tells us that it should be 55%. So the direct effect of labour market structure on the steady-state distribution of occupations is 11%

Second, since we know the younger cohort have been exposed to more meritocratic labour markets, the difference between any comparison of the distributions (i.e., a one-to-one comparison of the columns 1-4) between a young and older cohort should capture the distance travelled towards equalizing tendencies in the structure of labour market (i.e., the muting of direct distortions on the labour market), over and above the improvements in educational opportunity (because this held constant). This is evident when comparing the proportion of people in the lowest occupational rung, conditional on having attained more education that one's parents. For example, as a comparison between rows 3 of panels A and B show, 18% of people with better educational opportunities than their parents end up in the lowest level occupations for the younger cohort, whereas this difference is larger (25%) for the older 50 plus generation.

Thirdly, again since we know the younger cohort have been exposed to more meritocratic labour markets, the difference between any comparison between a young and older cohort of the final column in the table should capture the distance *not* travelled towards equalizing tendencies in the structure of labour market (i.e., the persistence of direct distortions on the labour market). For example the difference between the prediction of the 11% difference discussed above for the case of African Females, and the counterpart figure for the older cohort of African females, which is 15%, tells us that only about 36% of the negative effects of labour market structure that affected the older cohort has been eradicated. This is one measure by which we might track the so-called "footprint" of Apartheid labour market policies.

6 Conclusion

Formal models of the emergence of poverty traps highlight the interplay of educational investments and occupational structure. A key feature of this literature is the idea that non-convexities in the production of human capital are induced by indivisibilities in its investment as well as imperfections in credit markets. In this class of models, the shape of the aggregate distribution of occupations (and therefore long-run inequality) is strongly dependent on the education opportunities of the previous generation. Viewed from the perspective of this class of poverty trap models, a purely stochastic account of occupational structure is misleading.

In this paper, we have shown that the long run distribution of occupations is quite sensitive to the assumptions we make about the underlying stochastic process that governs the matrix of occupational transition probabilities across generations. Conditional on parental occupation and the educational investments of the offspring generation, we show that educational *opportunities*, as measured by whether children acquire less, more, or the same level of education as their parents, has a strong conditioning role on occupational structure.

Table 1: Descriptive Statistics: Schooling of Children Aged $20-35$

	Age2035				Age50			
	African	Coloured	White	Total	African	Coloured	White	Total
Child's years of education	10.201	11.026	12.564	10.449	3.675	5.614	12.679	5.702
	(3.040)	(3.310)	(2.485)	(3.087)	(4.010)	(4.172)	(2.846)	(5.275)
Mother's years of education	4.417	7.541	11.360	5.186	0.702	2.432	10.508	2.888
	(4.443)	(4.081)	(3.238)	(4.774)	(2.116)	(3.331)	(3.271)	(4.696)
Father's years of education	4.348	8.032	11.616	5.178	0.845	2.621	10.543	3.011
	(4.599)	(4.668)	(3.871)	(5.020)	(2.329)	(3.594)	(3.756)	(4.818)

Table shows mean years of schooling for the sample of children aged 20-35 and the corresponding schooling of the matched parental sample. Standard deviation in parentheses. Post-stratification weights are used.

Table 2: Education Transition Probabilities

	Parental Education Level Full Sample						
Educational Categories	1 %	2 %	3 %	4 %	5 %	6 %	Total %
No Education	32.0	5.6	1.5	1.4	0.5	0.2	15.9
Some Primary	24.5	17.8	9.6	3.8	1.3	0.1	15.9
Lower Secondary	12.7	16.8	14.7	7.7	6.4	1.6	12.0
Upper Secondary	15.9	30.3	33.1	31.9	15.3	10.1	21.7
Completed Secondary	12.3	22.9	32.9	36.2	48.3	27.1	23.4
Tertiary	2.7	6.6	8.2	18.9	28.2	60.9	11.1
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Africans						
Educational Categories	1 %	2 %	3 %	4 %	5 %	6 %	Total %
No Education	32.6	5.8	1.5	2.5	0.8	0.4	19.0
Some Primary	24.1	17.3	9.9	5.5	3.2	0.4	18.1
Lower Secondary	12.6	16.0	13.9	10.1	6.4	2.0	12.7
Upper Secondary	15.7	30.6	34.2	33.7	16.5	17.5	22.3
Completed Secondary	12.5	23.6	33.3	35.8	52.8	44.1	21.7
Tertiary	2.5	6.7	7.3	12.4	20.3	35.7	6.2
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Whites						
Educational Categories	1 %	2 %	3 %	4 %	5 %	6 %	Total %
No Education	5.1	0.0	0.0	0.0	0.3	0.0	0.3
Some Primary	0.0	4.3	2.9	0.0	0.0	0.0	0.4
Lower Secondary	28.3	44.5	14.4	2.6	6.4	1.2	7.3
Upper Secondary	16.6	27.8	37.5	33.7	12.0	5.4	18.0
Completed Secondary	31.2	22.5	34.4	36.8	47.0	18.4	35.5
Tertiary	18.7	1.0	10.8	26.9	34.4	75.0	38.5
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	Coloureds						
Educational Categories	1 %	2 %	3 %	4 %	5 %	6 %	Total %
No Education	30.2	5.2	2.7	0.0	0.0	0.0	10.2
Some Primary	35.3	26.9	15.1	5.6	0.7	0.0	19.0
Lower Secondary	15.7	18.2	23.8	9.7	8.3	3.6	15.1
Upper Secondary	10.8	28.0	28.1	26.1	24.8	8.0	21.4
Completed Secondary	6.5	15.6	21.3	44.7	42.0	18.2	22.5
Tertiary	1.5	6.0	9.0	13.9	24.2	70.2	11.9
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 3: Educational Mobility: Ordinal Logit (Age Cohorts)

	Base b/se	Basep b/se	Age2035 b/se	Age2035p b/se	Age50 b/se	Age50p b/se
Age	-0.029***	0.017***	0.107***	0.186***	-0.249***	-0.831***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.000***	-0.001***	-0.002***	-0.002***	0.002***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	-0.004***	-0.032***	-0.080***	-0.166***	0.445***	0.637***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black	-1.559***	-0.875***	-1.691***	-1.060***	-2.324***	-1.783***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Coloured	-1.546***	-1.132***	-1.712***	-1.342***	-2.053***	-1.821***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==2	0.766***	0.533***	0.652***	0.439***	1.420***	1.308***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
a_father_edu==3	0.808***	0.558***	0.722***	0.501***	1.224***	0.799***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==4	1.221***	1.035***	0.957***	0.779***	1.842***	1.324***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==5	1.585***	1.504***	1.294***	1.230***	2.448***	1.618***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==6	2.786***	2.120***	1.819***	1.364***	4.415***	3.402***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==2	0.701***	0.372***	0.702***	0.406***	1.073***	0.371***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
a_mother_edu==3	0.975***	0.770***	0.979***	0.775***	1.022***	0.774***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==4	1.047***	0.947***	1.016***	0.840***	0.591***	0.504***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==5	1.050***	1.162***	1.073***	1.212***	1.235***	1.506***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==6	1.707***	1.928***	1.295***	1.467***	1.906***	2.418***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)
Age of mother		0.018***		0.017***		0.004***
		(0.00)		(0.00)		(0.00)
Age of father		-0.009***		-0.010***		0.006***
		(0.00)		(0.00)		(0.00)
cut1	-4.354***	-3.168***	-1.720***	-0.569***	-11.102***	-30.130***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.04)	(0.12)
cut2	-3.107***	-1.548***	-0.443***	1.279***	-9.627***	-28.103***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.04)	(0.12)
cut3	-2.341***	-0.709***	0.491***	2.431***	-8.535***	-27.127***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.04)	(0.12)
cut4	-1.069***	0.612***	1.811***	3.849***	-7.168***	-25.896***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.04)	(0.12)
cut5	0.924***	2.618***	3.680***	5.777***	-5.618***	-24.376***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.04)	(0.12)
Observations	14206731	6511532	17308572	8638130	3976417	1181748
R2_McFadden	0.186	0.125	0.154	0.116	0.282	0.254
BIC	40766952.6	18355301.4	51506615.1	24903897.4	9052979.9	2974627.3
lrx2	9320774.2	2633082.6	9402118.3	3261436.0	3559034.6	1010057.7

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: Educational Mobility: Marginal Effects of Ordinal Logit (Base Specification)

	Index b/se	Level1 b/se	Level2 b/se	Level3 b/se	Level4 b/se	Level5 b/se	Level6 b/se
Age	-0.029***	0.002***	0.003***	0.001***	-0.002***	-0.004***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.000***	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (d)	-0.004***	0.000***	0.000***	0.000***	-0.000***	-0.001***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black (d)	-1.559***	0.097***	0.142***	0.095***	0.011***	-0.236***	-0.109***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coloured (d)	-1.546***	0.224***	0.136***	-0.008***	-0.150***	-0.164***	-0.039***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2 (d)	0.766***	-0.053***	-0.077***	-0.047***	0.013***	0.121***	0.044***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==3 (d)	0.808***	-0.054***	-0.080***	-0.051***	0.009***	0.128***	0.048***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==4 (d)	1.221***	-0.071***	-0.111***	-0.080***	-0.017***	0.191***	0.087***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==5 (d)	1.585***	-0.085***	-0.134***	-0.102***	-0.044***	0.236***	0.129***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==6 (d)	2.786***	-0.100***	-0.169***	-0.151***	-0.177***	0.229***	0.368***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==2 (d)	0.701***	-0.050***	-0.072***	-0.043***	0.015***	0.111***	0.039***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==3 (d)	0.975***	-0.063***	-0.094***	-0.062***	0.003***	0.155***	0.061***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==4 (d)	1.047***	-0.064***	-0.098***	-0.068***	-0.005***	0.166***	0.070***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==5 (d)	1.050***	-0.065***	-0.099***	-0.068***	-0.004***	0.166***	0.069***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==6 (d)	1.707***	-0.081***	-0.134***	-0.110***	-0.073***	0.241***	0.157***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	14206731	14206731	14206731	14206731	14206731	14206731	14206731
R2_McFadden	0.186	0.186	0.186	0.186	0.186	0.186	0.186
BIC	40766952.6	40766952.6	40766952.6	40766952.6	40766952.6	40766952.6	40766952.6
LRX2(15)	9320774.2	9320774.2	9320774.2	9320774.2	9320774.2	9320774.2	9320774.2

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: Educational Mobility: Marginal Effects of Ordinal Logit (controlling for parental age)

	Index b/se	Level1 b/se	Level2 b/se	Level3 b/se	Level4 b/se	Level5 b/se	Level6 b/se
Age	0.017***	-0.000***	-0.001***	-0.001***	-0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.001***	0.000***	0.000***	0.000***	0.000***	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (d)	-0.032***	0.001***	0.002***	0.002***	0.003***	-0.004***	-0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black (d)	-0.875***	0.014***	0.047***	0.055***	0.092***	-0.089***	-0.120***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coloured (d)	-1.132***	0.035***	0.102***	0.084***	0.048***	-0.175***	-0.094***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2 (d)	0.533***	-0.009***	-0.029***	-0.034***	-0.057***	0.058***	0.071***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==3 (d)	0.558***	-0.009***	-0.030***	-0.035***	-0.061***	0.058***	0.076***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==4 (d)	1.035***	-0.014***	-0.048***	-0.059***	-0.115***	0.075***	0.160***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==5 (d)	1.504***	-0.018***	-0.063***	-0.078***	-0.163***	0.066***	0.255***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==6 (d)	2.120***	-0.019***	-0.069***	-0.089***	-0.213***	-0.022***	0.412***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==2 (d)	0.372***	-0.006***	-0.021***	-0.024***	-0.039***	0.043***	0.048***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==3 (d)	0.770***	-0.011***	-0.039***	-0.047***	-0.084***	0.072***	0.110***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==4 (d)	0.947***	-0.013***	-0.045***	-0.054***	-0.105***	0.073***	0.144***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==5 (d)	1.162***	-0.015***	-0.053***	-0.064***	-0.128***	0.077***	0.184***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==6 (d)	1.928***	-0.018***	-0.064***	-0.083***	-0.199***	-0.007***	0.371***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of mother	0.018***	-0.000***	-0.001***	-0.001***	-0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of father	-0.009***	0.000***	0.001***	0.001***	0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6511532	6511532	6511532	6511532	6511532	6511532	6511532
R2_McFadden	0.125	0.125	0.125	0.125	0.125	0.125	0.125
BIC	18355301.4	18355301.4	18355301.4	18355301.4	18355301.4	18355301.4	18355301.4
LRX2(17)	2633082.6	2633082.6	2633082.6	2633082.6	2633082.6	2633082.6	2633082.6

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: Educational Mobility: Marginal Effects of Ordinal Logit (Base Specification, age cohort: 20-35)

	Index b/se	Level1 b/se	Level2 b/se	Level3 b/se	Level4 b/se	Level5 b/se	Level6 b/se
Age	-0.204***	0.006***	0.014***	0.015***	0.016***	-0.037***	-0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	0.004***	-0.000***	-0.000***	-0.000***	-0.000***	0.001***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (d)	-0.198***	0.006***	0.013***	0.015***	0.015***	-0.036***	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black (d)	-0.099***	0.003***	0.006***	0.007***	0.008***	-0.018***	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coloured (d)	-0.162***	0.005***	0.012***	0.012***	0.011***	-0.030***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2 (d)	0.463***	-0.011***	-0.028***	-0.033***	-0.043***	0.080***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==3 (d)	0.469***	-0.011***	-0.028***	-0.033***	-0.045***	0.080***	0.037***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==4 (d)	0.705***	-0.015***	-0.038***	-0.047***	-0.073***	0.113***	0.061***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==5 (d)	1.457***	-0.026***	-0.065***	-0.083***	-0.162***	0.175***	0.160***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==6 (d)	2.242***	-0.029***	-0.076***	-0.101***	-0.240***	0.117***	0.329***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==2 (d)	0.459***	-0.011***	-0.028***	-0.032***	-0.042***	0.080***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==3 (d)	0.823***	-0.018***	-0.045***	-0.054***	-0.085***	0.130***	0.072***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==4 (d)	0.950***	-0.019***	-0.048***	-0.060***	-0.103***	0.141***	0.089***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==5 (d)	1.363***	-0.024***	-0.062***	-0.079***	-0.152***	0.171***	0.146***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==6 (d)	1.708***	-0.025***	-0.066***	-0.087***	-0.193***	0.154***	0.218***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	5680639	5680639	5680639	5680639	5680639	5680639	5680639
R2_McFadden	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845	0.0845
BIC	16379730.7	16379730.7	16379730.7	16379730.7	16379730.7	16379730.7	16379730.7
LRX2(15)	1511501.7	1511501.7	1511501.7	1511501.7	1511501.7	1511501.7	1511501.7

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: Educational Mobility: Marginal Effects of Ordinal Logit (controlling for parental age, age cohort: 20-35)

	Index b/se	Level1 b/se	Level2 b/se	Level3 b/se	Level4 b/se	Level5 b/se	Level6 b/se
Age	-0.175***	0.002***	0.007***	0.011***	0.023***	-0.027***	-0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	0.004***	-0.000***	-0.000***	-0.000***	-0.001***	0.001***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (d)	-0.191***	0.002***	0.008***	0.012***	0.025***	-0.030***	-0.017***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black (d)	0.158***	-0.002***	-0.007***	-0.010***	-0.020***	0.025***	0.014***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coloured (d)	0.001	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2 (d)	0.261***	-0.002***	-0.010***	-0.016***	-0.035***	0.038***	0.025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==3 (d)	0.327***	-0.003***	-0.012***	-0.020***	-0.044***	0.045***	0.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==4 (d)	0.517***	-0.004***	-0.018***	-0.029***	-0.070***	0.066***	0.055***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==5 (d)	1.619***	-0.009***	-0.041***	-0.070***	-0.201***	0.088***	0.234***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==6 (d)	1.571***	-0.008***	-0.038***	-0.065***	-0.194***	0.071***	0.235***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==2 (d)	0.107***	-0.001	-0.004***	-0.007***	-0.014***	0.016***	0.010***
	(0.00)	(.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==3 (d)	0.692***	-0.005***	-0.023***	-0.038***	-0.093***	0.083***	0.076***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==4 (d)	0.757***	-0.006***	-0.024***	-0.040***	-0.102***	0.085***	0.087***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==5 (d)	1.341***	-0.008***	-0.037***	-0.062***	-0.173***	0.101***	0.180***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==6 (d)	1.992***	-0.009***	-0.041***	-0.072***	-0.228***	0.018***	0.333***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of mother	0.010***	-0.000***	-0.000***	-0.001***	-0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of father	-0.014***	0.000***	0.001***	0.001***	0.002***	-0.002***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	3390428	3390428	3390428	3390428	3390428	3390428	3390428
R2_McFadden	0.0936	0.0936	0.0936	0.0936	0.0936	0.0936	0.0936
BIC	8939663.8	8939663.8	8939663.8	8939663.8	8939663.8	8939663.8	8939663.8
LRX2(17)	922988.3	922988.3	922988.3	922988.3	922988.3	922988.3	922988.3

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Educational Mobility: Marginal Effects of Ordinal Logit (Base Specification, age cohort: > 50)

	Index b/se	Level1 b/se	Level2 b/se	Level3 b/se	Level4 b/se	Level5 b/se	Level6 b/se
Age	-0.249***	0.046***	0.014***	-0.022***	-0.025***	-0.010***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	0.002***	-0.000***	-0.000***	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (d)	0.445***	-0.081***	-0.028***	0.038***	0.046***	0.019***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black (d)	-2.324***	0.322***	0.198***	-0.069***	-0.235***	-0.158***	-0.058***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coloured (d)	-2.053***	0.468***	-0.120***	-0.173***	-0.122***	-0.042***	-0.012***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2 (d)	1.420***	-0.186***	-0.151***	0.044***	0.161***	0.097***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==3 (d)	1.224***	-0.167***	-0.128***	0.048***	0.140***	0.079***	0.027***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==4 (d)	1.842***	-0.211***	-0.201***	0.015***	0.194***	0.147***	0.056***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==5 (d)	2.448***	-0.247***	-0.254***	-0.029***	0.210***	0.221***	0.099***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==6 (d)	4.415***	-0.274***	-0.334***	-0.168***	0.018***	0.299***	0.459***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==2 (d)	1.073***	-0.153***	-0.108***	0.051***	0.123***	0.065***	0.022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==3 (d)	1.022***	-0.146***	-0.103***	0.050***	0.118***	0.062***	0.020***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==4 (d)	0.591***	-0.095***	-0.052***	0.040***	0.066***	0.030***	0.010***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==5 (d)	1.235***	-0.170***	-0.127***	0.051***	0.141***	0.079***	0.027***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==6 (d)	1.906***	-0.207***	-0.211***	-0.001	0.195***	0.160***	0.063***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	3976417	3976417	3976417	3976417	3976417	3976417	3976417
R2_McFadden	0.282	0.282	0.282	0.282	0.282	0.282	0.282
BIC	9052979.9	9052979.9	9052979.9	9052979.9	9052979.9	9052979.9	9052979.9
LRX2(15)	3559034.6	3559034.6	3559034.6	3559034.6	3559034.6	3559034.6	3559034.6

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9: Educational Mobility: Marginal Effects of Ordinal Logit (controlling for parental age, age cohort: > 50)

	Index b/se	Level1 b/se	Level2 b/se	Level3 b/se	Level4 b/se	Level5 b/se	Level6 b/se
Age	-0.831***	0.011***	0.060***	0.070***	0.067***	-0.080***	-0.127***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	0.006***	-0.000***	-0.000***	-0.001***	-0.000***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (d)	0.637***	-0.008***	-0.045***	-0.053***	-0.051***	0.058***	0.099***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black (d)	-1.783***	0.031***	0.150***	0.142***	0.094***	-0.167***	-0.250***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Coloured (d)	-1.821***	0.059***	0.224***	0.125***	-0.029***	-0.216***	-0.163***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2 (d)	1.308***	-0.012***	-0.065***	-0.087***	-0.131***	0.038***	0.257***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==3 (d)	0.799***	-0.008***	-0.046***	-0.060***	-0.077***	0.048***	0.143***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==4 (d)	1.324***	-0.011***	-0.065***	-0.087***	-0.133***	0.035***	0.262***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==5 (d)	1.618***	-0.014***	-0.081***	-0.106***	-0.156***	0.041***	0.318***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==6 (d)	3.402***	-0.020***	-0.111***	-0.150***	-0.262***	-0.146***	0.689***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==2 (d)	0.371***	-0.004***	-0.024***	-0.030***	-0.034***	0.030***	0.062***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==3 (d)	0.774***	-0.008***	-0.045***	-0.057***	-0.076***	0.046***	0.140***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==4 (d)	0.504***	-0.006***	-0.031***	-0.039***	-0.047***	0.038***	0.086***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==5 (d)	1.506***	-0.014***	-0.081***	-0.104***	-0.143***	0.056***	0.286***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_mother_edu==6 (d)	2.418***	-0.015***	-0.085***	-0.120***	-0.220***	-0.082***	0.522***
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of mother	0.004***	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of father	0.006***	-0.000***	-0.000***	-0.000***	-0.000***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1181748	1181748	1181748	1181748	1181748	1181748	1181748
R2_McFadden	0.254	0.254	0.254	0.254	0.254	0.254	0.254
BIC	2974627.3	2974627.3	2974627.3	2974627.3	2974627.3	2974627.3	2974627.3
LRX2(17)	1010057.7	1010057.7	1010057.7	1010057.7	1010057.7	1010057.7	1010057.7

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10: Educational Mobility: Ordinal Logit by Gender or Race (Base Specification)

	Males b/se	Females b/se	African b/se	Coloured b/se	White b/se
Age	-0.013***	-0.045***	-0.005***	-0.043***	0.111***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.000***	-0.000***	-0.001***	0.000***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black	-1.646***	-1.434***			
	(0.00)	(0.00)			
Coloured	-1.669***	-1.452***			
	(0.00)	(0.00)			
a_father_edu==2	0.764***	0.773***	0.721***	1.048***	1.663***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==3	0.813***	0.777***	0.814***	0.779***	1.535***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==4	1.075***	1.397***	1.003***	1.925***	2.433***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==5	1.682***	1.506***	1.498***	2.312***	2.871***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_father_edu==6	3.169***	2.170***	2.365***	4.008***	4.213***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
a_mother_edu==2	0.593***	0.818***	0.641***	1.391***	-1.800***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==3	1.224***	0.843***	0.955***	1.254***	-1.043***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==4	0.952***	1.107***	1.014***	1.873***	-1.041***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==5	0.792***	1.396***	1.251***	1.929***	-0.840***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
a_mother_edu==6	0.889***	2.546***	1.142***	6.033***	0.660***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)
Male			-0.050***	0.045***	0.339***
			(0.00)	(0.00)	(0.00)
cut1	-3.843***	-4.793***	-2.672***	-2.601***	-1.774***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
cut2	-2.599***	-3.533***	-1.371***	-0.851***	-0.801***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
cut3	-1.892***	-2.714***	-0.613***	0.075***	1.583***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
cut4	-0.667***	-1.390***	0.641***	1.615***	3.245***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
cut5	1.348***	0.624***	2.622***	3.737***	5.260***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	6036924	8169807	11371488	855995	1979248
R2_McFadden	0.174	0.200	0.153	0.224	0.147
BIC	17552874.4	23014415.3	33310517.1	2332384.9	4177684.8
lrx2	3710195.3	5769407.3	6032838.2	671990.5	719118.7

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11: Educational Mobility: Ordinal Logit by Gender or Race (Controlling for Parental Age)

	Male	Female	African	Coloured	White
	b/se	b/se	b/se	b/se	b/se
Age	0.006***	0.045***	0.086***	0.079***	0.202***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.000***	-0.001***	-0.002***	-0.002***	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black	-1.215***	-0.501***			
	(0.00)	(0.00)			
Coloured	-1.075***	-1.122***			
	(0.01)	(0.00)			
a_father_edu==2	0.662***	0.442***	0.513***	1.365***	-0.968***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)
a_father_edu==3	0.758***	0.364***	0.563***	1.165***	-1.290***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)
a_father_edu==4	1.295***	0.841***	0.772***	2.286***	-0.179***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)
a_father_edu==5	1.862***	1.251***	1.523***	3.776***	0.035
	(0.01)	(0.00)	(0.00)	(0.02)	(0.04)
a_father_edu==6	2.572***	1.588***	2.139***	3.370***	0.806***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
a_mother_edu==2	0.385***	0.383***	0.317***	1.096***	-0.231***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)
a_mother_edu==3	1.100***	0.577***	0.699***	0.758***	0.749***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)
a_mother_edu==4	0.591***	1.361***	1.071***	1.300***	0.635***
	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)
a_mother_edu==5	0.748***	1.720***	1.400***	2.513***	1.038***
	(0.01)	(0.01)	(0.00)	(0.02)	(0.03)
a_mother_edu==6	0.854***	3.078***	0.936***	6.028***	3.321***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.03)
Age of mother	0.013***	0.019***	0.009***	0.131***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of father	0.002***	-0.018***	-0.003***	-0.065***	-0.041***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male			-0.201***	0.815***	0.750***
			(0.00)	(0.01)	(0.00)
cut1	-2.828***	-3.171***	-1.611***	1.550***	-1.251***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.03)
cut2	-1.315***	-1.404***	0.044***	4.519***	-0.018
	(0.01)	(0.01)	(0.01)	(0.05)	(0.03)
cut3	-0.625***	-0.425***	0.879***	5.598***	2.120***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.02)
cut4	0.711***	0.915***	2.220***	6.951***	3.790***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.02)
cut5	2.727***	3.003***	4.259***	9.716***	5.774***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.02)
Observations	2846601	3664931	4706280	389611	1415641
R2_McFadden	0.134	0.135	0.0788	0.239	0.149
BIC	8021752.4	10115369.1	14108929.3	951080.2	2772781.5
lrx2	1239361.1	1575849.1	1207464.7	298898.4	485898.3

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12: Educational Mobility: Ordinal Logit by Gender and Race (Base Specification)

	AFemale	AMale	CFemale	CMale	WFemale	WMale
	b/se	b/se	b/se	b/se	b/se	b/se
Age	-0.011***	0.004***	-0.100***	0.048***	0.118***	0.103***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age squared	-0.001***	-0.001***	0.001***	-0.001***	-0.001***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2	0.746***	0.703***	0.941***	1.218***	0.954***	0.317***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
a_father_edu==3	0.877***	0.700***	0.449***	0.984***	1.186***	0.584***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
a_father_edu==4	0.980***	1.046***	1.516***	2.351***	2.647***	0.749***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)
a_father_edu==5	1.665***	1.353***	1.922***	3.343***	2.311***	2.028***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)
a_father_edu==6	2.260***	2.364***	1.617***	5.975***	3.368***	3.519***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)
a_mother_edu==2	0.735***	0.539***	1.401***	1.603***	-0.254***	-4.585***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)
a_mother_edu==3	0.872***	1.099***	2.078***	0.751***	-1.289***	0.368***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
a_mother_edu==4	0.997***	1.036***	2.510***	1.308***	-0.956***	-0.641***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)	(0.01)
a_mother_edu==5	1.751***	1.105***	2.802***	0.080**	-0.193***	-0.850***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
a_mother_edu==6	1.449***	0.931***	7.209***	0.672***	1.460***	0.027
	(0.01)	(0.01)	(0.04)	(0.09)	(0.02)	(0.02)
cut1	-3.025***	-2.166***	-4.372***	0.103**	-1.492***	-4.917***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)
cut2	-1.705***	-0.879***	-2.444***	1.684***	-0.628***	-0.376***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
cut3	-0.902***	-0.172***	-1.288***	2.357***	1.438***	1.784***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.03)
cut4	0.411***	1.019***	0.270***	4.017***	3.075***	3.964***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	(0.03)
cut5	2.389***	3.029***	2.818***	5.826***	5.123***	
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)	
Observations	6596835	4774653	511795	344200	1061177	918071
R2_McFadden	0.173	0.131	0.261	0.219	0.172	0.179
BIC	18824298.5	14380930.6	1315580.8	944847.3	2271526.2	1749494.0
lrx2	3949300.0	2162763.0	463420.7	265587.3	471741.7	381840.4

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: Educational Mobility: Ordinal Logit by Gender and Race (Controlling for Parental Age)

	AFemale b/se	AMale b/se	CFemale b/se	CMale b/se	WFemale b/se	WMale b/se
Age	0.152***	0.041***	-0.070***	0.322***	0.314***	0.141***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Age squared	-0.002***	-0.001***	-0.000***	-0.005***	-0.003***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
a_father_edu==2	0.443***	0.634***	1.244***	2.396***	0.769***	-4.088***
	(0.00)	(0.00)	(0.02)	(0.03)	(0.01)	(0.05)
a_father_edu==3	0.410***	0.711***	0.097***	3.174***	0.186***	-4.224***
	(0.00)	(0.00)	(0.02)	(0.03)	(0.01)	(0.05)
a_father_edu==4	0.616***	1.066***	1.036***	3.804***	1.077***	-2.954***
	(0.00)	(0.01)	(0.02)	(0.03)	(0.01)	(0.04)
a_father_edu==5	1.262***	1.834***	2.981***	5.624***	1.072***	-2.397***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.05)
a_father_edu==6	1.964***	2.334***	3.099***	5.420***	1.802***	-1.697***
	(0.01)	(0.01)	(0.03)	(0.05)	(0.01)	(0.05)
a_mother_edu==2	0.373***	0.278***	1.236***	0.167***	-2.479***	1.627***
	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)	(0.04)
a_mother_edu==3	0.482***	1.080***	2.334***	-1.224***	-1.442***	2.079***
	(0.00)	(0.00)	(0.02)	(0.03)	(0.01)	(0.03)
a_mother_edu==4	1.428***	0.647***	3.553***	-0.673***	-0.962***	1.161***
	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)	(0.03)
a_mother_edu==5	1.942***	1.098***	4.352***	2.425***	-0.069***	1.157***
	(0.01)	(0.01)	(0.02)	(0.07)	(0.01)	(0.04)
a_mother_edu==6	1.344***	0.685***	8.519***	18.267***	2.613***	2.836***
	(0.01)	(0.01)	(0.05)	(0.06)	(0.01)	(0.04)
Age of mother	0.012***	0.002***	0.139***	0.161***	0.015***	0.146***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of father	-0.013***	0.011***	-0.067***	-0.053***	-0.032***	-0.151***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
cut1	-1.245***	-1.337***	-1.494***	8.039***	0.238***	-2.899***
	(0.01)	(0.01)	(0.05)	(0.11)	(0.03)	(0.04)
cut2	0.583***	0.196***	1.660***	10.705***	1.497***	-0.599***
	(0.01)	(0.01)	(0.06)	(0.11)	(0.02)	(0.04)
cut3	1.556***	0.889***	3.087***	11.460***	3.566***	1.419***
	(0.01)	(0.01)	(0.06)	(0.11)	(0.02)	(0.04)
cut4	2.927***	2.221***	4.749***	12.891***	5.174***	
	(0.01)	(0.01)	(0.06)	(0.11)	(0.02)	
cut5	4.981***	4.314***	8.268***	15.381***	7.346***	
	(0.01)	(0.01)	(0.06)	(0.11)	(0.02)	
Observations	2620454	2085826	251262	138349	793215	622426
R2_McFadden	0.0844	0.0824	0.339	0.188	0.208	0.131
BIC	7704092.5	6302984.0	536970.0	352648.3	1535030.3	1124432.1
lrx2	710094.4	565606.7	275220.9	81602.5	402971.0	169626.0

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 14: Occupation Codes and Skill Level (SASCO)

Code	Major Group	Skill Level
1.	Legislators, senior officials and managers	n/a (4)
2.	Professionals	4
3.	Technicians and associate professionals	3
4.	Clerks	2
5.	Service Workers and shop and market sales workers	2
6.	Skilled agricultural and fishery workers	2
7.	Craft and related trades workers	2
8.	Plant and machinery operators and assemblers	2
9.	Elementary occupations	1
0.	Armed forces and unspecified occupations	n/a (1)

Table 15: ISCO88 Occupation Skill Groups

Skill Level	Education qualification
First Skill Level	Primary Education (approx. 5 years)
Second Skill Level	Secondary Education (between 5 and 7 years)
Third Skill Level	Tertiary Education (between 3 and 4 years): not leading to a university degree
Fourth Skill Level	Tertiary education (between 3 and 6 years): Leading to a university degree or equivalent

Table 16: Occupation Transition Probabilities

	Father's Occupation Level Full Sample				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	38.2	27.0	19.7	7.9	24.7
2	22.7	34.9	26.1	14.9	28.7
3	24.2	21.5	31.3	22.0	23.4
4	14.8	16.6	22.8	55.3	23.2
Total	100.0	100.0	100.0	100.0	100.0

Table 17: Occupation Transition Probabilities by Race

	Father's Occupation Level Africans				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	40.5	31.4	27.4	13.7	30.7
2	22.2	36.7	25.4	24.0	31.3
3	25.9	20.7	30.4	26.2	23.6
4	11.4	11.1	16.8	36.1	14.4
Total	100.0	100.0	100.0	100.0	100.0
	Mother's Occupation Level Africans				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	38.1	29.2	12.1	18.3	32.5
2	26.6	32.1	15.8	15.9	25.2
3	23.0	25.1	44.0	37.2	26.7
4	12.2	13.5	28.1	28.7	15.6
Total	100.0	100.0	100.0	100.0	100.0
	Father's Occupation Level Coloureds				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	33.6	26.5	6.3	27.6	25.8
2	28.6	34.0	45.2	15.8	32.6
3	19.3	22.0	19.9	19.3	21.1
4	18.5	17.5	28.5	37.3	20.5
Total	100.0	100.0	100.0	100.0	100.0
	Mother's Occupation Level Coloureds				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	35.5	20.4	16.4	14.8	26.4
2	34.9	35.4	28.3	18.4	31.6
3	18.6	17.0	45.1	24.2	21.7
4	11.0	27.2	10.2	42.6	20.3
Total	100.0	100.0	100.0	100.0	100.0
	Father's Occupation Level Whites				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	41.7	3.6	4.4	0.5	3.7
2	13.6	24.3	27.7	6.8	18.0
3	4.9	25.9	35.2	16.5	23.4
4	39.9	46.2	32.7	76.2	54.8
Total	100.0	100.0	100.0	100.0	100.0
	Mother's Occupation Level Whites				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	8.4	6.1	5.3	2.2	3.5
2	30.3	11.1	15.8	16.8	16.8
3	52.3	6.9	29.0	25.9	26.8
4	9.0	75.9	49.8	55.1	52.9
Total	100.0	100.0	100.0	100.0	100.0

Table 18: Occupational Mobility: Ordinal Logit

	Base	Basep
	b/se	b/se
Age	0.104***	0.089***
	(0.00)	(0.00)
Age squared	-0.001***	-0.001***
	(0.00)	(0.00)
Male	0.169***	-0.099***
	(0.00)	(0.00)
Black	-1.305***	-0.834***
	(0.00)	(0.00)
Coloured	-1.348***	-0.801***
	(0.00)	(0.01)
ans_father_occ==2	0.099***	0.073***
	(0.00)	(0.01)
ans_father_occ==3	0.225***	0.258***
	(0.00)	(0.01)
ans_father_occ==4	1.031***	1.355***
	(0.00)	(0.01)
ans_mother_occ==2	0.519***	0.489***
	(0.00)	(0.01)
ans_mother_occ==3	1.165***	0.993***
	(0.00)	(0.00)
ans_mother_occ==4	1.196***	1.026***
	(0.00)	(0.01)
Age of mother		0.024***
		(0.00)
Age of father		-0.019***
		(0.00)
cut1	0.310***	0.554***
	(0.02)	(0.03)
cut2	1.662***	1.656***
	(0.02)	(0.03)
cut3	3.007***	3.198***
	(0.02)	(0.03)
Observations	2710829	1504525
R2_McFadden	0.104	0.106
BIC	6731682.5	3658173.6
lrx2	781601.3	435194.4

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 19: Occupational Mobility: Ordinal Logit by Gender and Race (Base Specification)

	AFemale	AMale	CFemale	CMale	WFemale	WMale
	b/se	b/se	b/se	b/se	b/se	b/se
Age	0.067***	0.080***	0.396***	0.198***	-0.268***	-0.651***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Age squared	-0.001***	-0.001***	-0.005***	-0.002***	0.003***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ans_father_occ==2	0.039***	-0.442***	-0.085***	2.280***	42.491***	-1.131***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
ans_father_occ==3	0.915***	-0.358***	0.128***	3.522***	41.550***	-2.686***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
ans_father_occ==4	1.054***	0.095***	0.884***	4.530***	44.048	
	(0.01)	(0.01)	(0.02)	(0.04)	(.)	
ans_mother_occ==2	0.817***	-0.442***	1.915***	-0.381***	5.527***	4.550***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)
ans_mother_occ==3	1.236***	1.271***	1.020***	0.246***	3.503***	2.649***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.05)	(0.04)
ans_mother_occ==4	1.270***	0.735***	1.243***	0.413***	5.024***	1.289***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.05)	(0.04)
o.ans_father_occ==4						0.000
						(.)
cut1	1.458***	-0.871***	8.041***	3.637***	36.893***	-18.355***
	(0.03)	(0.04)	(0.10)	(0.10)	(0.15)	(0.14)
cut2	1.956***	1.359***	8.817***	6.908***	38.032***	-14.563***
	(0.03)	(0.04)	(0.10)	(0.10)	(0.15)	(0.13)
cut3	3.279***	2.932***	10.292***	7.654***	40.037***	-13.191***
	(0.03)	(0.04)	(0.10)	(0.10)	(0.15)	(0.13)
Observations	853532	941549	186707	176458	263756	168692
R2_McFadden	0.0596	0.0457	0.0975	0.137	0.192	0.168
BIC	2024509.1	2297894.7	445101.6	367099.7	306227.8	313686.3
lrx2	128351.7	110024.2	48073.3	58108.0	72949.2	63519.6

Marginal effects. Standard errors in parentheses. (d) for discrete change of dummy variable from 0 to 1. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 20: Distribution of Occupations

Panel A: 20-35 Year Olds	Level 1	Level 2	Level 3	Level 4	Difference
All Race Groups					
1 Unconditional Distribution	0.26	0.29	0.29	0.17	0.00
2 Basic Markov Process A	0.23	0.25	0.31	0.21	-0.07
3 Mover-stayer Markov Process B	0.18	0.44	0.27	0.11	0.07
4 Mover-stayer Markov Process C	0.28	0.45	0.20	0.06	0.19
5 Mover-stayer Markov Process D	0.23	0.40	0.23	0.14	0.08
African Females					
6 Mover-stayer Markov Process B	0.19	0.47	0.26	0.08	0.11
7 Mover-stayer Markov Process C	0.28	0.49	0.19	0.05	0.22
8 Mover-stayer Markov Process D	0.48	0.35	0.14	0.04	0.28
African Males					
9 Mover-stayer Markov Process B	0.23	0.48	0.22	0.06	0.16
10 Mover-stayer Markov Process C	0.44	0.42	0.12	0.03	0.31
11 Mover-stayer Markov Process D	0.37	0.39	0.18	0.06	0.21
Coloured Females					
12 Mover-stayer Markov Process B	0.22	0.47	0.24	0.07	0.14
13 Mover-stayer Markov Process C	0.34	0.44	0.18	0.04	0.23
14 Mover-stayer Markov Process D	0.15	0.46	0.29	0.10	0.06
Coloured Males					
15 Mover-stayer Markov Process B	0.17	0.47	0.28	0.09	0.09
16 Mover-stayer Markov Process C	0.24	0.46	0.24	0.07	0.15
17 Mover-stayer Markov Process D	0.28	0.43	0.22	0.07	0.17
Panel B: 50 Year Olds and Older	**Level 1**	**Level 2**	**Level 3**	**Level 4**	**Difference**
All Race Groups					
1 Unconditional Distribution	0.35	0.29	0.12	0.24	0.00
2 Basic Markov Process A	0.29	0.25	0.13	0.33	-0.10
3 Mover-stayer Markov Process B	0.25	0.43	0.15	0.16	0.04
4 Mover-stayer Markov Process C	0.41	0.42	0.10	0.07	0.19
5 Mover-stayer Markov Process D	0.18	0.36	0.15	0.31	-0.10
African Females					
6 Mover-stayer Markov Process B	0.36	0.43	0.08	0.13	0.15
7 Mover-stayer Markov Process C	0.58	0.32	0.05	0.05	0.26
8 Mover-stayer Markov Process D	0.36	0.47	0.10	0.08	0.19
African Males					
9 Mover-stayer Markov Process B	0.25	0.50	0.14	0.10	0.12
10 Mover-stayer Markov Process C	0.52	0.37	0.08	0.04	0.24
11 Mover-stayer Markov Process D	0.48	0.44	0.06	0.03	0.28
Coloured Females					
12 Mover-stayer Markov Process B	0.24	0.47	0.13	0.15	0.07
13 Mover-stayer Markov Process C	0.33	0.46	0.10	0.10	0.15
14 Mover-stayer Markov Process D	0.23	0.47	0.14	0.16	0.07
Coloured Males					
15 Mover-stayer Markov Process B	0.21	0.37	0.15	0.27	-0.06
16 Mover-stayer Markov Process C	0.25	0.46	0.13	0.16	0.07
17 Mover-stayer Markov Process D	0.31	0.46	0.11	0.11	0.13

Notes:

Table 21: Scalar Measures of Occupational Mobility

Panel A: 20-35 Year Olds	MET	IR	DET	AJ	NAJ
All Race Groups					
2 Basic Markov Process A	0.82	0.26	0.85	0.92	0.46
3 Mover-stayer Markov Process B	0.88	0.20	0.96	0.90	0.45
4 Mover-stayer Markov Process C	0.88	0.21	0.95	0.91	0.45
5 Mover-stayer Markov Process D	0.75	0.12	0.84	0.70	0.35
African Females					
6 Mover-stayer Markov Process B	0.94	0.25	0.99	1.00	0.50
7 Mover-stayer Markov Process C	0.96	0.28	0.99	1.05	0.53
8 Mover-stayer Markov Process D	0.73	0.16	0.94	0.74	0.37
African Males					
9 Mover-stayer Markov Process B	0.93	0.24	0.99	0.98	0.49
10 Mover-stayer Markov Process C	0.87	0.24	0.96	0.94	0.47
11 Mover-stayer Markov Process D	0.88	0.16	0.89	0.85	0.42
Coloured Females					
12 Mover-stayer Markov Process B	0.90	0.22	0.96	0.93	0.47
13 Mover-stayer Markov Process C	0.88	0.21	0.98	0.92	0.46
14 Mover-stayer Markov Process D	0.99	0.33	0.95	1.16	0.58
Coloured Males					
15 Mover-stayer Markov Process B	0.93	0.24	0.97	0.99	0.49
16 Mover-stayer Markov Process C	0.91	0.21	0.95	0.93	0.47
17 Mover-stayer Markov Process D	0.84	0.17	0.97	0.84	0.42
Panel B: 50 Year Olds and Older	MET	IR	DET	AJ	NAJ
All Race Groups					
2 Basic Markov Process A	0.80	0.25	0.84	0.91	0.46
3 Mover-stayer Markov Process B	0.85	0.24	0.91	0.91	0.46
4 Mover-stayer Markov Process C	0.89	0.27	0.97	1.00	0.50
5 Mover-stayer Markov Process D	0.68	0.10	0.79	0.63	0.32
African Females					
6 Mover-stayer Markov Process B	0.76	0.24	0.96	0.82	0.41
7 Mover-stayer Markov Process C	0.87	0.26	0.96	0.95	0.48
8 Mover-stayer Markov Process D	0.91	0.26	0.98	0.98	0.49
African Males					
9 Mover-stayer Markov Process B	0.92	0.27	0.98	1.01	0.51
10 Mover-stayer Markov Process C	0.99	0.34	0.98	1.30	0.65
11 Mover-stayer Markov Process D	0.97	0.45	0.99	1.39	0.70
Coloured Females					
12 Mover-stayer Markov Process B	0.83	0.21	0.95	0.86	0.43
13 Mover-stayer Markov Process C	0.90	0.26	0.99	0.97	0.49
14 Mover-stayer Markov Process D	0.87	0.26	0.94	0.94	0.47
Coloured Males					
15 Mover-stayer Markov Process B	0.89	0.31	0.88	1.01	0.51
16 Mover-stayer Markov Process C	0.82	0.22	0.97	0.86	0.43
17 Mover-stayer Markov Process D	0.77	0.17	0.89	0.77	0.38

Notes: The table shows scalar measures of intergenerational mobility patterns between occupation categories. Each row of the table is based on an underlying matrix of (conditional) transition probabilities between 4 orderd occupational categories. These transition probabilities are computed by estimating ordinal logit regressions of occupational status, conditional on parental occupational status, the qualitative outcome of educational transitions between the two generations (i.e., upwardly mobile, downwardly mobile, or persistent), a quadratic in age, years of schooling of the offspring generation, as well as race and gender dummies. The rows of the table give the conditioning on the dummy variables (with age and schooling held at their respective means). The predicted probabilities from these regressions are then used to form the underlying matrices. Since these predicted probabilities always sum to one for any given base state, every matrix can be described as a Markov matrix. The table reports the results for regular markov matrices (i.e., we exclude Markov matrices where some transitions have zero probability). "MET" = Shorrocks' Trace measure. "IR" = Atkinson's Immobility Ratio. "DET" = Determinant measure. "AJ" = Average Jump. "NAJ" = Normalised average jump.

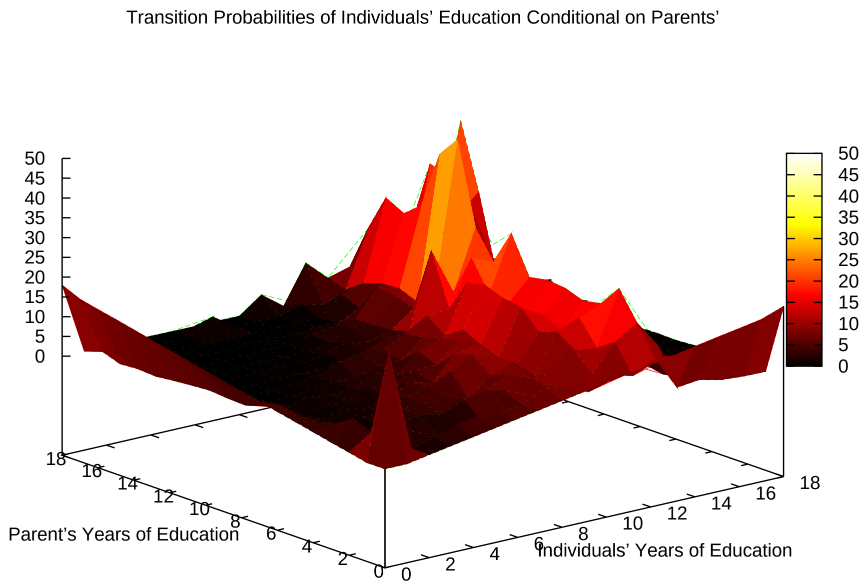

Figure 1: Unconditional Transition Probabilities: 3-D Surface Plots

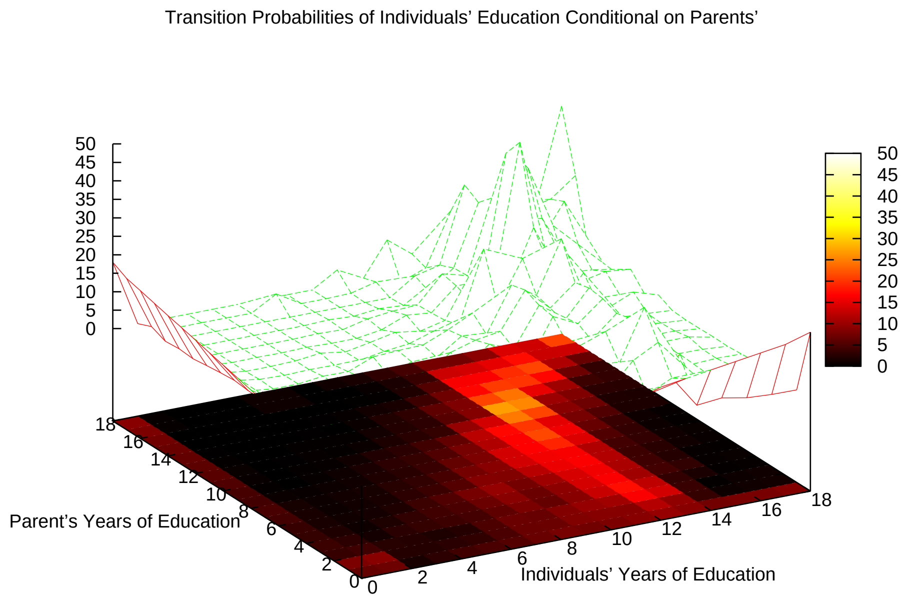

Figure 2: Unconditional Transition Probabilities: Heat plot

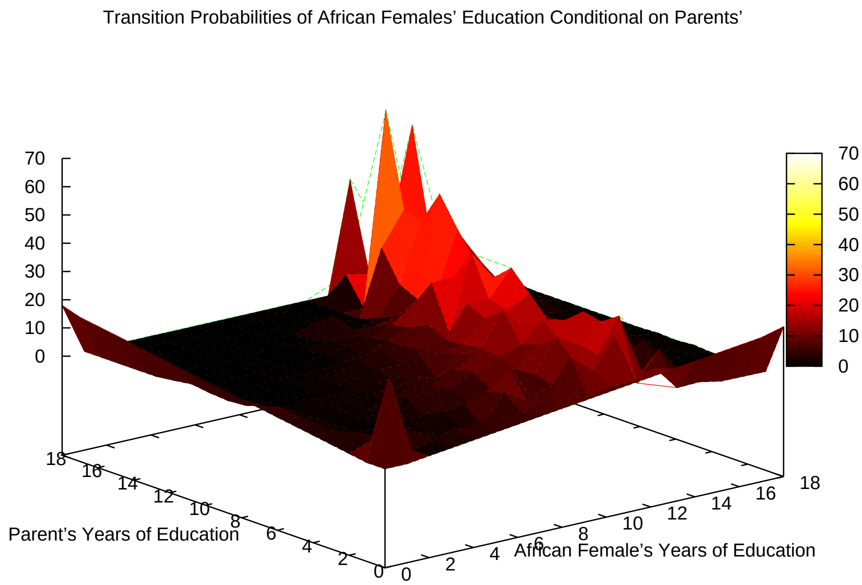

Figure 3: Unconditional Transition Probabilities: 3-D Surface Plots (African Females)

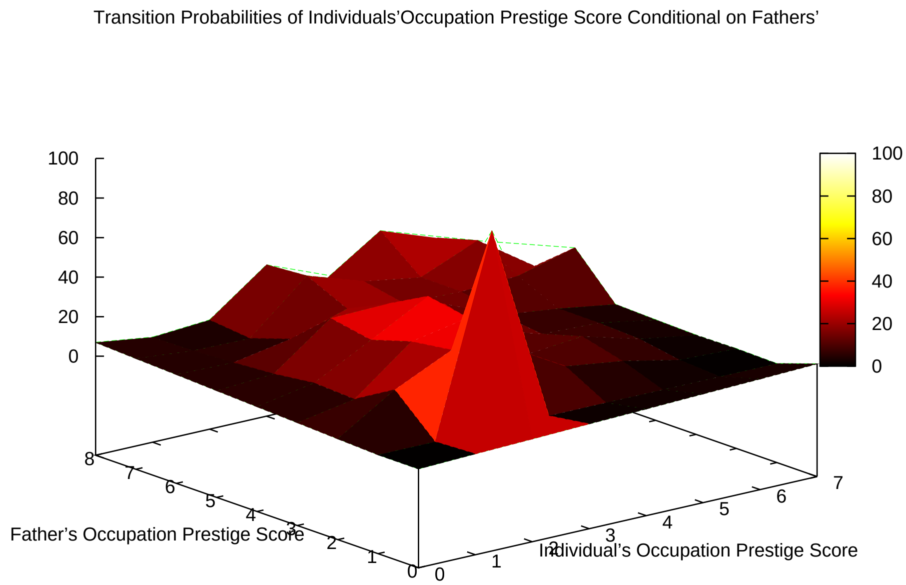

Figure 4: Unconditional Transition Probabilities: 3-D Surface Plots (SIOPS)

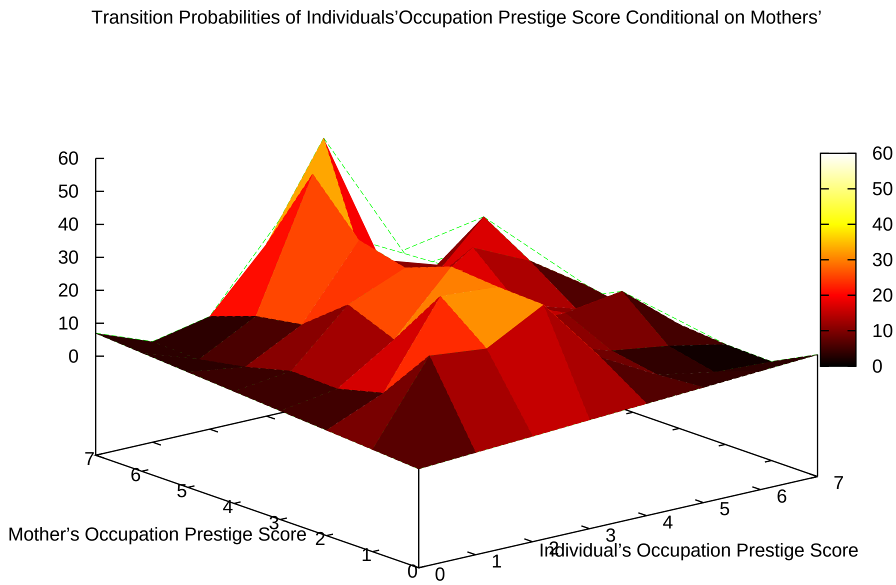

Figure 5: Unconditional Transition Probabilities: 3-D Surface Plots (SIOPS)

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