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

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

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Abstract

We analyse the role of educational opportunity in shaping inequality in the distribution of occupations in the long-run. We start by modelling the probability that a child occupies the same or a different rung on the occupational ladder as her parents controlling for both the educational attainment of the child, as well as the level of educational opportunity of the child. These conditional probabilities are then used to construct separate transition matrices by level of educational opportunity, race and gender, which in turn are used to the compute the steady-state distribution of occupations. Finally, we use the timing of political events in the history of the struggle to end Apartheid to devise an identification strategy that permits a causal interpretation of the role of educational opportunity. We find evidence that educational opportunity has a strong conditioning effect on the distribution of occupations in steady state. In particular, African female children who inherit the same level of educational opportunity as their parents are 9% more likely to be in the bottom of the occupation distribution in steady-state, than the observed rate for the population at large, whereas they would face a 4% lower probability if they were exposed to better educational opportunities.

JEL Keywords: Intergenerational Mobility, Occupation, Dynastic Inequality

1 Introduction

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 educational opportunities of the previous generation (Banerjee and Newman 1993, Galor and Zeira 1993, Atkinson and Bourguignon 2000). In this paper we explore this relationship empirically for the case of South Africa. If the predictions of these models are correct, we would expect to see a gradient in the relationship between climbing the occupational ladder, and increasing educational opportunities.

Our paper is part of the broader literature on social mobility. In this literature a great deal of emphasis is often placed on the intergenerational linkage in occupations. For example, standard Markov models, as well as the less standard "mover-stayer" variety of such models, focus attention on the relationship in occupational status between parents and their children. In such studies, the occupational outcomes of the children are regressed against the occupational outcomes of their parents. However, viewed from the poverty traps literature cited above, these types of regressions are misspecified. The occupational outcomes of parents determine the educational opportunities of their children, since parents who have jobs that are higher up on the occupational ladder can afford better schooling for their children. To give a causal interpretation to the intergenerational association in occupations, one has to control for the child's opportunity set to acquire more schooling.

This is the problem we seek to address in this paper. In particular, we seek to understand the extent to which educational opportunity might be an important determinant of long-run occupational structure. More precisely, we ask: *does having more or less educational opportunity affect the distribution of occupations in steady-state in a way that is consistent with the hypothesis that human capital matters for occupational structure*? The empirical identification of this effect however, is far from clear cut, as omitted ability of the parent might also be correlated with the opportunity set (for acquiring education) of the child, through the occupational attainment of the parent.

To resolve this identification issue, we make use of exogenous variation in schooling attainment derived from the "legacy effect" of Apartheid. The basic components of our empirical strategy is to control for essential features of educational opportunity, alongside the realised schooling attainment of children and occupational outcomes of their parents, and then to examine the effects of varying the level opportunity for older and younger cohorts of children. The reasoning is that children schooled in the post Apartheid era would have faced better opportunities for educational advancement than their older counterparts. In particular, we restrict attention to that subset of the population who are 50 years or older.

The youngest members of this cohort of children will have completed schooling before the 1976 Soweto riots. Restricting the sample in this way would be important as there is a concern that post 1976, the variation in schooling by cohort would be less defensible as exogenous, since a major part of the 1976 uprisings was precisely in response to several fundamental policy shifts in education.

The paper is structured as follows. We begin in section 2 by describing the data used in this study. There are two objectives of this discussion. The first objective is to demonstrate that there is variation in educational attainment by cohort, as this is crucial to identifying the effects we are interested in. The second objectives is to describe our method of measuring occupational attainment.

Section 3 then outlines the core analytical framework of the paper. Our main objective here is to sketch a framework that is capable of backing out a causal effect of educational opportunity on the steady-state distribution of occupations. The precise way in which we do this proceeds in three steps. The first step is to estimate the extent to which a child's occupational status is conditioned by her parent's occupational status, controlling for educational opportunity. These estimates are then used to construct transition matrices of occupational mobility. In the second step, we use these transition matrices to compute steady-state distributions of occupations for each level of educational opportunity, and for each age cohort. This step in the analysis is key and we describe in detail the underlying model that gives rise to the steady-state distribution that we later go on to estimate. In the third and final step, we then compare these steady-state distributions between the young and older cohorts, holding the level of opportunity constant. The idea here is that if we are able to hold educational opportunity constant, then a comparison of the effect of any given level of opportunity between the old cohort and the young cohort captures the exogenous part of opportunity, and thus identifies the effect of interest.

Section 4 presents a test of the main hypothesis of the paper, which derives from the literature on poverty traps. The main empirical content of this body of theory is that we should expect to see a gradient between better educational opportunities and movement up the occupational ladder. We find that there is clear evidence supporting our hypothesis. Better educational opportunity decreases the mass at the bottom of the long-run distribution of occupations, whereas the reverse is true when children merely inherit the same level of educational attainment as their parents. In particular, we find that educational opportunity has a strong conditioning effect on the distribution of occupations in steady state. In particular, African female children who inherit the same level of educational opportunity as their parents are 9% more likely to be in the bottom of the occupation distribution in steady-state, than the observed rate for the population at large, whereas they would face a 4% lower probability if they were exposed to better educational opportunities.

2 Data Description

Much is known about the levels and correlates of inequality in South Africa.[1] By contrast, strikingly little is known about the *dynamics* of inequality. This paper seeks to address this gap in our knowledge, by using data from the first wave of the South African National Income Dynamics Study (NIDS). Only the first wave of this panel data set is publicly available, so we exploit only the cross-sectional variation available in this wave. This poses a challenge for the type of analysis we wish to conduct as it means that we have to synthetically extract the temporal dimensions of the data. It is possible to do this because parental and offspring education as well as occupational status is measured in this first wave.[2] We now turn our attention to describing the key variables in our analysis.

2.1 Educational Attainment

In order for our strategy to work, we have to be able to show that there is variation in educational attainment, between young and old cohorts as well as between generations, within and across cohorts. Table 1 below contains the key elements necessary for making this case. 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 of 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 gap is shrinking because non-whites have experienced increases in average attainment whereas Whites have little scope for upward mobility. In the present generation, White parents have approximately 2.6 and 1.48 times more years of education than African and Coloured parents respectively; whereas a generation ago, White

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

[2] 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). Intergenerational mobility is one of the main themes in NIDS and special attention was given to this theme in the first wave of data collection. As additional waves are added to this panel data set, other topics related to the themes addressed in this paper will become feasible. Examples are the dynamics of income and unemployment.

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 6 educational categories by race over the average of parental years of schooling.[3]

Several features of these transition matrices accord with 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.

To gain further purchase on these patterns, we look instead at the years of schooling transition. Figure 1 shows a 3-dimensional view of the educational transition matrix. 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 shows where the highest concentrations of mass lies in figure 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 weight of secondary school completion in this bivariate distribution. 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 African females completing high school (or equivalent).

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

[3]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 NIDS post-stratification weights. Further breakdowns of these results (not shown here but available from the authors upon request), by race, gender of the child, gender of the parent and location reveal several other interesting patterns. For example, rural and Tribal Authority areas have exactly the same profiles in terms of education mobility, whereas 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.

2.2 Occupational Status

Our coding of occupations is based on the adaptation of the South African Standard Classification of Occupations (SASCO) suggested by Ziervogel and Crankshaw (2009). This coding convention, developed by Statistics South Africa, is based on the International Standard Classification of Occupation 1988 (ISCO-88) of the International Labour Office (ILO). Table 3 describes how the SASCO coding convention maps into skill levels. These skill levels are an ISCO88 convention that aims 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 serve to transform the SASCO occupational categories into a quasi-hierarchical variable, with ordered occupational levels.

We used the SASCO codes to construct three variables: child's occupation; mothers occupation and fathers occupation. The occupational status of the child 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.[4]

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 4 shows the effects of our recoding exercise in this regard.

3 Modeling the Distribution of Occupations

Synthetic temporal comparisons of the distribution of occupations in repeated cross-sectional surveys can serve as a useful diagnostic about unfolding inequality. But they are only descriptive and not predictive at the end of the day. To shed light on a *causal* question of the sort we have in mind requires a theory that: (a) adequately specifies the assumptions that underpin the dynamics of the processes governing transitions between relative positions within the bivariate occupational distribution; and (b) links these assumptions to the existence of a steady-state distribution. In order to analyse whether educational opportunity predicts occupational structure in steady-state, we have to know that some type of steady-

[4]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, we used the respondents recollection of their parent's current or last occupation captured in section D of the NIDS adult questionnaire; for resident parents, we used the respondent's self-reported occupational status reported in section E of the NIDS adult questionnaire.

state is actually possible. In this section, we outline two such frameworks. One permits opportunity to play a role, and the other does not. Under the first framework, we make the strong assumption that the population is homogeneous with respect to the rate of transition between occupational states; in this framework long-run outcomes are determined purely stochastically, so educational opportunities are not allowed to play any role. Therefore the first framework corresponds to a standard first-order Markov process. In the second framework, we explicitly relax these assumptions. In both cases, our objective is to derive the relevant steady-state distribution as these equations are the focal point of the empirical estimates presented in section 4.

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 this individual's parents started out in occupation level j in the previous time period. These p_{ij} define the following matrix of transition probabilities (which by definition 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. 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:

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

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. If we assume that p_{ij} are fixed and independent of generations (i.e., P is stationary), then the dynamics of this system follow a Markov process. To describe these underlying dynamics, 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 $x_j^n N_1$. By stationarity, we have

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

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 j in generation $n-1$ that have moved into state i. Under the standard (first-order) Markov process, 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.[5]

[5] 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.

The empirical discussion presented in section 4 starts by computing the matrix P, and then, by the standard result just stated, we know that the eigenvector corresponding to the eigenvalue 1 (which itself is always an eigenvalue of a matrix like P), will always be a fixed point vector. This is the starting point to characterizing the steady-state distribution. We will now use this fact about regular Markov matrices to develop the key equation we have to estimate to answer the main question posed in this paper.

3.2 Unequal Opportunities: Mover-Stayer Markov Process

In this section, we modify the standard Markov process to account for the possibility that better educational opportunities will affect the steady-state distribution in occupations. This can only happen if the conditional probability of a child's occupational choice, given parental occupation is affected by whether the child was exposed to better educational opportunities than their parents. For expositional purposes, let us denote two types of individuals: those who acquire more education than the highest level attained by either of their parents are denoted as "high opportunity children", and those who acquire less education than the highest level attained by either of their parents are denoted as "low opportunity children". The key departure under this adapted Markov process is that we no longer assume that all types of children (high and low opportunity alike) are homogenous with respect to the transition matrix. In other words, the matrix P (which was key to the derivation of the steady-state under the standard model that we outlined above) no longer applies. We require separate matrices that will be unique to the specific type of individual, while at the same time, possessing the same properties as the original matrix P that guarantees that a steady-state of the distribution of occupations will exist for each type. Our objective below is to explain how these type-specific matrices are defined.

The main tweak to the model is that we now allow different groups (defined along opportunity type, race and gender) to have different transition probabilities. This type of model is sometimes 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: the dynamics of the social structure determines that he is sure to remain stuck in the same occupational rung as his parents, 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

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

and for the kth sub-population for the nth generation, we have

$$P_k^{(n)} = S_k + (I - S_k)M_k^n \tag{9}$$

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 9, which, as the right hand side of this equation makes clear, will not have identical rows. Applying equation 4, we will have

$$\mathbf{x}^{(n)} \quad = \quad P^{(n)}\mathbf{x}^{(0)} \rightarrow [S + (I - S)V]\mathbf{x}^{(0)} \tag{10}$$

We estimate this equation for several sub-populations (chiefly delineated by race and gender). Thus we can write the steady-state distribution for the kth sub-population as

$$\mathbf{x}_k^{(n)} \quad = \quad P_k^{(n)}\mathbf{x}_k^{(0)} \rightarrow [S_k + (I - S_k)V_k]\mathbf{x}_k^{(0)} \tag{11}$$

Our main goal in this paper is to estimate equation 11. Before we turn to exactly how we went about doing this, note that the k subscripting operationalises the notion that steady-states can be group-specific. In the empirical implementation below, groups are defined along three dimensions: opportunity type, race and gender. Notice also that V_k is the limiting matrix of M_k^n, where the latter is nothing but the nth power of the occupational transition matrix for the kth group. So to compute the steady-state vector $\mathbf{x}_k^{(n)}$, we first must estimate M_k^n, then compute the eigenvector that corresponds to the first eigenvalue of this matrix, and finally scale it by the sum of it's components. We now turn to these details.

4 Empirical Implementation and Results

Under the standard Markov model, the matrix of transition probabilities P (equation 1) that is used to calculate the steady-state distribution of occupations (equation 5) is comprised of raw percentages of children in each occupation, conditional on the occupation of their parents. However, unequal opportunity operates to change this matrix, such that chance is allowed to affect the transition probabilities of the movers but not the stayers. In section 3.2, we showed how this sort of heterogeneity in the transition process (as defined by the matrices S and M) leads to a different steady-state distribution (equation 11). Our goal in this paper is to estimate this key equation, in a way that permits us to ask a causal question about this heterogeneity: i..e, how does heterogeneity in one important dimension (educational opportunity) cause the steady-state distribution to change. In order to be able to answer this question, we need to compute equation 11. This in turn requires computation of the matrices M and S, as well as a specification of the measure of educational opportunity that we apply to this task. The empirical content behind these issues is taken up in this section.

4.1 Estimating the Steady-State Distribution of Occupations

4.1.1 Estimating M_k and S_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 in equation 7.

Keeping in mind that M is nothing more than a matrix of *predicted* probabilities rather than the raw percentages of people which constitutes the elements of P, the first question of empirical significance that we need to address is what to condition these probabilities on. Here we are guided by what can be learnt from a careful examination of the raw transition matrices.

Tables 5-6 are examples of matrices such as P, computed separately for each parent. The cells in these tables indicates the population weighted proportions of individuals falling into a given state, conditional on the state occupied by the previous generation. It is clear that there is substantial persistence in the very highest level of occupations (Managers and Professionals) in the case of fathers (55%), compared to mothers (44%). Part of this can be explained by the fact that the correlation in occupational status between parents is quite low (less than 50%): 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. These differential patterns of persistence by the gender of the parent suggest that it will be important to control for the occupational statuses of both parents, as well as the gender of the child when modeling the conditional probabilities of the child occupational status.

Table 6 gives a breakdown by race as well as the genders of the parents. It is clear from these initial diagnostics that 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. Therefore, in modeling the conditional probabilities of the child's occupational status, we should also control for race.

The final variable we have to control for is our variable of interest: the educational opportunities of the child. We measure educational opportunity in terms of the educational levels of children relative to their parents, by constructing three dummy variables: children that acquire more schooling than their parents (*high opportunity children*), children that acquire less schooling than their parents (*low opportunity children*), and children that acquire the same amount of schooling than their parents (*same opportunity children*).

To compute the matrix of M_k^n, we estimate ordered logit regressions of the occupational level of the child using as explanatory variables age, age squared, completed schooling, dummies for race, gender, occupational level of the father, occupational level of the mother, age of the father, age of the mother, and dummies for the level of educational opportunity. These ordinal logit regressions underpin the computed transition matrices of the kth group M_k and are shown in table 7.[6]

Using the estimated coefficients from the regressions shown in table 7, we then compute predicted probabilities for each possible contrast of the child-parent occupational transition matrix. In computing these predicted probabilities, we hold age and schooling at their sample means while conditioning on race, gender, educational opportunity and parental occupational status. Since there are 4 occupation levels, this defines 16 possible contrasts. Since each contrast is for a given level of the child occupational variable against all possible levels of the parent occupation level, the conditional probability of the child being in a given occupation level is defined over 4 possible values, where the sum of these values must be equal to one. Collecting these probabilities into separate matrices (by each of the conditioning variables) results in M_k.[7] This matrix is a positive matrix, since we only

[6] We do not report the corresponding marginal effects as they are not of direct interest to us, but they can be made available upon requet

[7] The number of transition matrices obviously varies by the number of possible contrasts chosen for parental occupation status. Since we include both mothers' and fathers' occupation dummies as controls (see table 7), for any given value of the gender, race, and educational opportunity dummies, there exist 16

make the computation for the kth matrix if every possible contrast exists, with non-zero probability. Given this criterion, it also means that the columns of m_k must sum to one, so that M_k satisfies the properties as required by our set-up in section 3.2.

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.

4.1.2 Estimates of the Long Run Distribution $\mathbf{x}_k^{(n)}$

Table 8 reports the main results of the paper. Panel A shows the estimated distribution of occupations in steady state for the younger cohort of 20-35 year olds, and panel B reports the same for the older cohort of workers aged 50 and older. The first row of each panel gives the observed distribution of occupations for the child's generation. The remaining rows of the table gives the steady-state distribution depending on whether or not educational opportunity is factored into the transition process.

In the second row of each panel, labelled "Basic Markov Model", educational opportunity plays no role. This steady state is the empirical counterpart to equation 5. 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 in these results. 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 labour market structure where chance would play a stronger role.

Rows 3-8 of both panels in table 8 report the steady-state distributions when educational background is varied. The final column of table 8 labelled "Difference" is a measure of the difference between the predicted probability of being in the bottom half of the occupational distribution in steady state, and what is actually observed to be the case for the child distribution. Setting aside the question of causation for the moment, the first important point to note is that our hypothesis of a gradient between educational opportunity and occupational advancement is borne out by the data. Focusing on the first part of panel A (all races), we see that, relative to the unconditional distribution, children with higher educational opportunities have an 8% higher chance of being in the bottom half of the distribution, whereas this difference increases to 11% and 22% for children with the same or

possible combinations of parental occupation. To keep these computations manageable, we therefore only condition on the probability that *both* parents occupy the same occupational rung.

lower educational opportunities respectively. For African females (the second part of panel A), the same pattern holds, with higher opportunity children having a 12% higher probability of being in the bottom half of the distribution compared to 23% for lower opportunity children. Since we are effectively holding educational opportunity constant when looking at any one row among rows 3-8 of either panel, the comparison reflected in the final column can also be interpreted as the direct effect of labour market structure on the steady-state distribution of occupations. In the case of African females who have higher opportunities, we see that the mover-stayer model predicts these children to have a 12% higher probability than the larger population of 20-35 year old children. Given the approach adopted, this difference cannot be due to differences in educational background since this result only holds for high opportunity children.

We also see a similar pattern for the older cohort of children (panel B). Again, focusing on the case of African females (the second part of panel B), we see that higher opportunity children have a 16% higher probability of being in the bottom half of the distribution compared to 26% for lower opportunity children. Again, theses results cannot be due to differences in educational background since, in either case educational opportunity is held constant. The interesting question that now arises of course, is whether we can interpret these differences in a causal way: i.e., does increasing educational opportunity cause these predicted shifts in the distribution, or do they merely reflect the types of unobservable influences mentioned earlier. We now turn to making the case for a causal interpretation.

4.2 Do Better Educational Opportunities Cause Changes in the Distribution?

At first glance, it is not unreasonable to assume that that the racial variation in educational attainment under Apartheid was exogenously driven. After all, for most of the period in question, it was one of the explicit intentions of Apartheid policy to socially engineer a racially organised class structure in South Africa, and educational policy was a major component of this strategy (Wilson and Ramphele 1989, Fiske and Ladd 2004, Louw et al. 2007). However, the struggle to end Apartheid intensified in the 1980's and the catalyst for the conflict surrounding this period has its roots in the 1976 Soweto riots. Prior to 1976, political mobilisation and opposition to end Apartheid was not primarily centered on educational policy, whereas after the Soweto riots of 1976, opposition to the educational policy of the day took centre stage. So exposure to Apartheid era educational policy cannot *in general* be treated as a natural experiment.

The period of Apartheid up until 1976 however can be thought of as a natural experiment. The variation in educational attainment of adult children who are likely to have completed their schooling before the Soweto riots (i.e., children age 50 years or older at the date of survey) can be treated as exogenous because differences in preferences for schooling or unobserved ability are unlikely to have been binding for this cohort since the very purpose of policies like “Bantu Schooling” was to artificially limit opportunities. So one source of exogenous variation in educational opportunity comes from restricting attention to this group of adult children. Thus, the gradients in educational opportunity reported in panel B of the table can be given a causal interpretation. In particular, we notice a strictly monotonic relationship between increasing the level of opportunity and the shape of the occupational distribution in steady state.

However, this story only conveys part of the full effect of educational opportunity, since the gradient in educational opportunity for the older cohort is unlikely to be very informative about the causal role it might be expected to play under a more meritocratic labour market structure. To capture the full effect, one needs to look also at the role of opportunity in more recent times. The dismantling of Apartheid is another potential source of exogenous variation. As the descriptive statistics indicated (table 1), there are sharp differences in average attainment between the younger and older cohorts in our sample. Younger African children have almost triple the amount of schooling than older African children, and younger African parents having more than quadruple the amount of schooling than their older counterparts. While it is probably true that the increases in attainment for Africans were sharp enough so that restricting attention only to the population of young people schooled after Apartheid (1994-2008) is a plausible way of extracting exogenous variation in attainment, this would not be true for the population at large. Indeed, if one were to look at the total population, one would see more gradual increases in attainment in the decade prior to the end of Apartheid because of the extension of partial suffrage to Indians and Coloureds in the the early 1980’s, and the concomitant changes in education spending witnessed in this period (Fiske and Ladd 2004). Our solution to this problem is to include children that would have benefited from the shifts in educational spending that would have taken place in the 1980’s, by restricting the younger cohort of children to people aged 20-35. This restriction makes it possible for a member of this cohort to obtain at least half their schooling (6 years) after 1983.

One drawback of this approach however, is that the changes in educational attainment are not sharp enough to warrant interpretation as exogenous. Our approach to dealing with this problem is to take the difference (between the older and young cohorts) in the differences reported in the final column. Subtracting the reported difference for any particular row of the young cohort, from the corresponding row for the older cohort should identify a causal effect of the relevant level of opportunity, because, as we’ve argued above, the results for the older cohort can be given a causal interpretation. For example, comparing rows 6-8 of panels A and B shows that having higher educational opportunities cause a 4% reduction in the probability of being in the bottom half of the steady-state distribution (12%-16%), whereas inheriting the same opportunities as one’s parents causes a 9% *increase* in this probability (29%-20%).

5 Conclusion

The main goal of the paper was to estimate the long-run distribution of occupations in South Africa. The standard approach in this type of research programme is to model the distribution in steady-state, by assuming that the matrix of transition probabilities is homogenous across members of the population. However, since the probabilities that make up the elements of such a matrix also reflect other things about the transition process, one cannot usually ask causal questions about the mechanisms through which a correlation in the occupational outcomes of parents and their children might come to exist. One such causal connection, common in models of poverty traps where occupational structure is the main driver of inequality, is that of educational opportunity. The key contribution of this paper is on this issue.

Empirical evidence of the connection between educational opportunity and occupational structure is quite rare, because the educational outcomes of an individual are likely to be *determined* by the parents choice of occupation. We make several contributions in this regard. First, we explicitly model the probability that a child occupies the same or a different rung on the occupational ladder as her parents. Second, in modeling this probability, we control for both the educational attainment of the child, as well as the level of educational opportunity of the child, measured by whether the child attained more, less or the same amount of schooling than her parents. Third, these conditional probabilities then constitute separate transition matrices by level of educational opportunity, race and gender. These matrices are then used to the compute the steady-state distribution under the more plausible assumption that different race-gender pairings facing different levels of educational opportunity result in different long-run occupation distributions. Our final contribution is to argue that political events in the history of the struggle to end Apartheid provides the raw material for an identification strategy that would permit a causal interpretation of the role of educational opportunity.

We find evidence that educational opportunity has a strong conditioning effect on the distribution of occupations in steady state. In particular, African female children who inherit the same level of educational opportunity as their parents are 9% more likely to be in the bottom of the occupation distribution than the observed rate for the population at large, whereas they would face a 4% lower probability if they were exposed to better educational opportunities.

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: 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 4: ISCO88 Occupation Skill Groups

Skill Level	Education qualification
Level 1	Primary Education (approx. 5 years)
Level 2	Secondary Education (between 5 and 7 years)
Level 3	Tertiary Education (between 3 and 4 years): not leading to a university degree
Level 4	Tertiary education (between 3 and 6 years): Leading to a university degree or equivalent

Table 5: 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
	Mother's Occupation Level Full Sample				
ans_child_occ	1 %	2 %	3 %	4 %	Total %
1	37.6	25.5	10.0	10.3	27.5
2	27.4	32.7	16.8	15.8	24.7
3	22.9	22.5	37.8	30.0	26.0
4	12.1	19.2	35.4	43.9	21.9
Total	100.0	100.0	100.0	100.0	100.0

Table 6: 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 7: Occupational Mobility: Ordinal Logit

	B_Young	B_Older	C_Young	C_Older	D_Young	D_Older
	b/se	b/se	b/se	b/se	b/se	b/se
Age	0.263***	0.139***	0.302***	0.289***	0.315***	0.292***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age squared	-0.003***	-0.001***	-0.004***	-0.002***	-0.004***	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male	0.064***	0.733***	0.062***	0.490***	0.075***	0.655***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Black	-0.490***	-0.262***	-0.487***	-0.143***	-0.433***	0.244***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Coloured	-0.353***	0.514***	-0.329***	0.849***	-0.292***	1.249***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
ans_father_occ==2	0.245***	0.498***	0.225***	0.387***	0.231***	0.431***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ans_father_occ==3	0.019**	-0.317***	-0.005	0.220***	-0.024***	0.082***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
ans_father_occ==4	0.542***	-0.133***	0.524***	0.366***	0.426***	-0.210***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
ans_mother_occ==2	0.220***	1.351***	0.240***	1.343***	0.241***	1.541***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ans_mother_occ==3	1.089***	-0.268***	1.129***	-0.244***	1.089***	-0.188***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ans_mother_occ==4	0.902***	0.775***	0.955***	1.488***	0.885***	0.990***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Child's years of education	0.327***	0.433***	0.315***	0.310***	0.332***	0.464***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
uped	-0.053***	-1.392***				
	(0.00)	(0.01)				
downed			-0.213***	-0.776***		
			(0.00)	(0.01)		
stayers					0.316***	1.880***
					(0.00)	(0.01)
cut1	6.913***	6.092***	7.270***	10.821***	7.850***	12.792***
	(0.09)	(0.39)	(0.09)	(0.40)	(0.09)	(0.40)
cut2	8.569***	7.849***	8.927***	12.524***	9.512***	14.604***
	(0.09)	(0.39)	(0.09)	(0.40)	(0.09)	(0.40)
cut3	10.517***	8.928***	10.880***	13.544***	11.462***	15.740***
	(0.09)	(0.39)	(0.09)	(0.40)	(0.09)	(0.40)
R-squared	0.147	0.303	0.147	0.285	0.148	0.325
BIC	3414599.4	695056.1	3411809.2	712415.3	3408964.4	672853.3
lrx2	586650.8	301670.5	589441.1	284311.4	592285.9	323873.4

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 8: Distribution of Occupations

Panel A: 20-35 Year Olds	Level 1	Level 2	Level 3	Level 4	Difference
All Races					
Unconditional Distribution	0.26	0.29	0.29	0.17	0.00
Basic Markov Model	0.23	0.25	0.31	0.21	-0.07
Mover-Stayer Markov Model (high opportunity children)	0.18	0.45	0.27	0.10	0.08
Mover-Stayer Markov Model (low opportunity children)	0.30	0.46	0.18	0.05	0.22
Mover-Stayer Markov Model (same opportunity children)	0.25	0.41	0.23	0.11	0.11
African Females					
Mover-Stayer Markov Model (high opportunity children)	0.19	0.48	0.25	0.07	0.12
Mover-Stayer Markov Model (low opportunity children)	0.28	0.49	0.18	0.04	0.23
Mover-Stayer Markov Model (same opportunity children)	0.49	0.35	0.13	0.03	0.29
Panel B: 50 Year Olds and Older	Level 1	Level 2	Level 3	Level 4	Difference
All Races					
Unconditional Distribution	0.35	0.29	0.12	0.24	0.00
Basic Markov Model	0.29	0.25	0.13	0.33	-0.10
Mover-Stayer Markov Model (high opportunity children)	0.22	0.44	0.14	0.20	0.02
Mover-Stayer Markov Model (low opportunity children)	0.40	0.43	0.09	0.08	0.19
Mover-Stayer Markov Model (same opportunity children)	0.15	0.35	0.12	0.37	-0.14
African Females					
Mover-Stayer Markov Model (high opportunity children)	0.37	0.43	0.07	0.12	0.16
Mover-Stayer Markov Model (low opportunity children)	0.58	0.32	0.05	0.05	0.26
Mover-Stayer Markov Model (same opportunity children)	0.37	0.47	0.09	0.07	0.20

Notes: Mover-stayer steady state distributions are conditional on educational opportunity, measured in terms of the educational levels of children relative to their parents, where “B” is more opportunity, “C” is less opportunity and “D” is the same opportunity. More opportunity is when children obtain more schooling than their fathers. Less opportunity is when children obtain less schooling than their fathers. The same opportunity is when children obtain the same schooling than their fathers. The kth row in the table is $\mathbf{x}_k^{(n)} = P_k^{(n)}\mathbf{x}_k^{(0)} \to [S_k + (I - S_k)V_k]\mathbf{x}_k^{(0)}$, where V_k is the limiting matrix of M_k^n, the matrix of predicted transition probabilities from an ordinal logit regression of the occupational level of the child against age, age squared, completed schooling, dummies for race, gender, occupational level of the father, occupational level of the mother, age of the father, age of the mother, and educational opportunity and S_k is a diagonal matrix of the same dimension as M_k and $\mathbf{x}_k^{(0)}$ is parental distribution of occupations. 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.

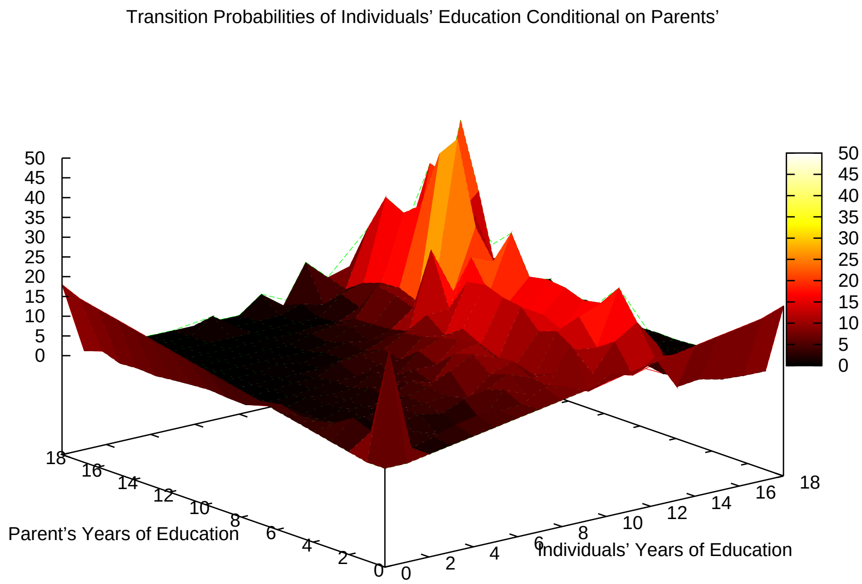

Figure 1: Unconditional Transition Probabilities: 3-D Surface Plots

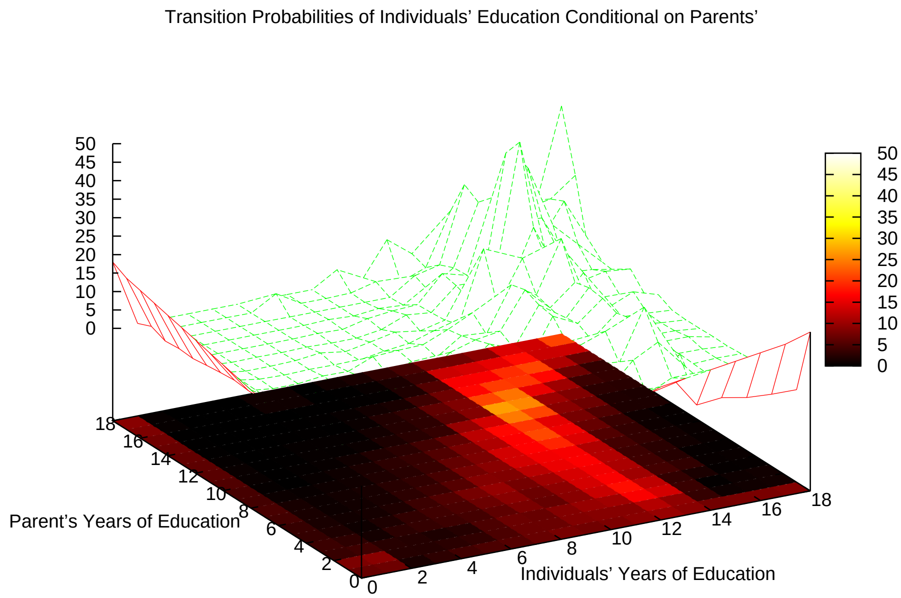

Figure 2: Unconditional Transition Probabilities: Heat plot

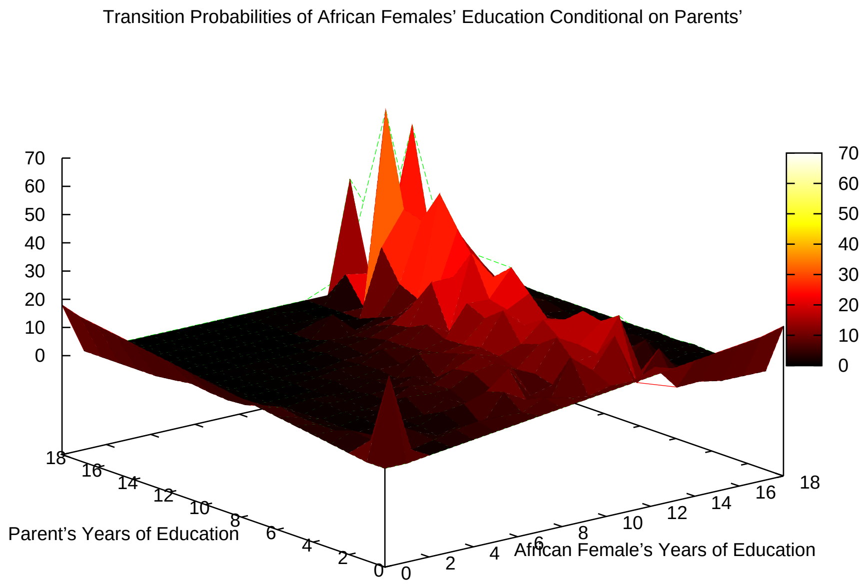

Figure 3: Unconditional Transition Probabilities: 3-D Surface Plots (African Females)

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southern africa labour and development research unit

The Southern Africa Labour and Development Research Unit (SALDRU) conducts research directed at improving the well-being of South Africa's poor. It was established in 1975. Over the next two decades the unit's research played a central role in documenting the human costs of apartheid. Key projects from this period included the Farm Labour Conference (1976), the Economics of Health Care Conference (1978), and the Second Carnegie Enquiry into Poverty and Development in South Africa (1983-86). At the urging of the African National Congress, from 1992-1994 SALDRU and the World Bank coordinated the Project for Statistics on Living Standards and Development (PSLSD). This project provide baseline data for the implementation of post-apartheid socio-economic policies through South Africa's first non-racial national sample survey.

In the post-apartheid period, SALDRU has continued to gather data and conduct research directed at informing and assessing anti-poverty policy. In line with its historical contribution, SALDRU's researchers continue to conduct research detailing changing patterns of well-being in South Africa and assessing the impact of government policy on the poor. Current research work falls into the following research themes: post-apartheid poverty; employment and migration dynamics; family support structures in an era of rapid social change; public works and public infrastructure programmes, financial strategies of the poor; common property resources and the poor. Key survey projects include the Langeberg Integrated Family Survey (1999), the Khayelitsha/Mitchell's Plain Survey (2000), the ongoing Cape Area Panel Study (2001-) and the Financial Diaries Project.

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