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Labour Market Dynamics in South Africa

Evidence from KwaZulu Natal Province

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Abstract

Six years into South Africa's fledgling democracy one is prompted to ask: *what has been achieved, if anything*? In this paper, I will attempt to provide some answers, if tentative, concerning economic mobility as it pertains to labour markets in KwaZulu-Natal using the KwaZulu Income Dynamics Study (KIDS) data. To do so I adopt both univariate and multivariate techniques. Univariate estimates of earnings mobility are presented under Markovian assumptions, first in the form of transition matrices and then in the form of first order autoregressive models. To shed light on other correlates of mobility, I then turn to an analysis of transitions between labour market states using a multinomial logit framework. Key findings are: (i) females experience a 61% increase in their transition probability from self-employment to being "out of the labour force"; (ii) race appears to be insignificant in predicting transitions out of unemployment and into employment, but is significant in predicting jobloss: in short, it would appear that being an African person has become unimportant for getting a new job, but is still important for losing one; (iii) belonging to a revolving credit association increases one's chances of finding a new job by 45%; (iv) years of experience (proxied for by age in years) is significant for finding a new job if you were unemployed in 1993, but for new entrants into the labour force, education replaces experience; and (v) an additional year of education is important for remaining employed and increases one's chances of moving up the earnings distribution by 5%.

I. Introduction

"Relative social mobility" is a situation in which there is no overall change in the income distribution, but there is a marginal change in the welfare of individuals, as is the case when two people in the income distribution simply exchange places. Relative social mobility therefore implies that the incidence of poverty (however it may be measured) remains unchanged, which begs the question: *why should we be concerned about social mobility in the first place?* In answering this question, Atkinson, Bourguignon and Morrisson (1992) distinguish between "instrumental" motives and "intrinsic" motives for mobility. An example of the former is the equity/efficiency argument, i.e., where the mobility of entities between various states is purely instrumental in achieving a desired social outcome (such as a more equitable distribution of income). By contrast, the latter motive holds that mobility has some sort of intrinsic value such as the notion that mobility accords with some broad notion of liberty and freedom. This distinction is an important one, especially for societies (such as South Africa), which have had very rigid social structures. To be sure, the main task of the Mandela administration was to implement a legislative overhaul by repealing old laws and passing new ones in order to set in motion the process of change, a change of immense intrinsic value.

In certain cases, simply changing laws can have an unanticipated instrumental effect on inequality. Consider the reasons advanced by Lundberg and Startz (1996) for the emergence of low-wage-low skill poverty traps. They argue that if workers can invest in productive skills that are not perfectly observable, black workers will have less of an incentive to undertake such investments. The logic is that since such investments are not observable, the only way they can be rewarded is if test scores change as a result of undertaking the investment.[1] But if employers accord a lower weight to the test scores of black workers [2](Aigner and Cain, 1977), the workers best response will be to not undertake the investment. This has the effect of shifting the wage schedule for black workers downward while the slope of the wage schedule of white workers (who do undertake investments) becomes even steeper. The low-wage-low-productivity-low-skill poverty trap in which black workers are caught is a self-fulfilling prophecy. One might think that an overhaul of the legal framework along

[1] In other words, the decision not to invest on the part of the worker, and the decision to pay low wages on the part of the employer, can be thought of as mutual best responses. See Bowles (1999a) for a similar take on *Apartheid* labour market conventions in South Africa where the decision to accept low wages and pay low wages are interpreted as mutual best responses on the part of unskilled black workers and white employers respectively; as long as mo st of the latter adhered to the convention, it would remain a stable equilibrium.

[2] In their classic study of racial wage discrimination, Aigner and Cain (1977) advanced the theory that since test scores are noisy signals for worker quality (and thus wage setting), racial stereotyping emerges as the device used to set the wage schedule. White workers, they argued, were not as removed from their managers since they too were white. Individual test scores could therefore be verified by the manager simply "knowing" the worker, given the limited social distance between them. The same could not be said for black workers and therefore their individual test scores could not be used as a basis for setting the wage schedule.

with the introduction of legislation such as the "Employment Equity Act" would eradicate the problem. Possible perhaps, but far from realistic!

It is our contention that new legislation, while very important in facilitating the emergence of political and social freedoms, has very little instrumental value in terms of delivering economic freedoms, because of *two* mutually reinforcing phenomena: poverty traps *and* wealth inequality. In short, despite the repeal of much apartheid legislation that actively discriminated against black South Africans, the overwhelming majority of whom are classified as poor, these same individuals remain trapped in their poverty, unable to escape owing to previous and existing wealth inequalities. In the colourful language of Charles Simkins, South Africa's poor remain poor because of the *footprints of Apartheid*.

The importance of wealth inequality to understanding the continued co-existence of destitution and opulence has been recognised in the theoretical literature over the last decade. One important view is that owing to their wealth status, the poor might be credit rationed, leading to underinvestment in human capital on their part (Galor and Zeira, 1993; Giannini, 1998)[3]. This limits their prospects for job mobility and consequently, their earnings mobility will also be quite limited (Banerjee and Newman, 1993).[4]

If wealth inequality is an important determinant of the persistence of widespread poverty, unemployment, and earnings inequality, then what should the role of policy be in tackling these problems? As suggested

[3] As Galor and Zeira (1993) and Giannini (1998), 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[3]. There exists therefore, some threshold initial wealth level below which agents are stuck in a poverty trap, and above which agents are propelled to high levels of accumulation. Relatively egalitarian societies (where there are large middle classes) do better in terms of accumulation, than do relatively inegalitarian ones.

[4] Banerjee and Newman (1993) show that given the initial distribution of wealth, a low wage rate and little upward mobility obtains if there is initially a large group of poor agents who have no alternatives but to engage in wage labour. Conversely, a high wage rate and large upward mobility obtains if there is initially a small group of poor agents.

above, policies that combat (labour market) discrimination might go some way to reducing some inequality. However, as Bowles (1999b) argues, if such policies are combined with appropriate social policy designed specifically to improve community governance (or social capital) by changing the incentive structures that characterises local interactions where there are unequal rewards for different behaviours, an optimal mix of state, market, and community problem solving might be achieved. Stated differently, if government action is limited to changing laws, accompanied by token attempts at enforcement and minimal (sustainable) asset redistribution, low mobility traps may proliferate, solely because the reward structures for local interactions are not incentive-compatible.

Yet the reverse case might also be true. Consider the following though experiment: Sustainable asset redistribution will eventually lead to a larger frequency of anonymous interactions as markets expand and people, once constrained in their choices, become able to interact with whomever they please. But as markets grow larger, so does the need for 3rd party enforcement of contracts, which obviates the need for socially desirable norms such as trust, reciprocity and fairness.[5] An absence of socially desirable norms (such as having honest work ethics) and selective third party enforcement of contracts implies a worsening of the incentive structure governing interactions. Under such conditions, the costs of monitoring or controlling for the unobservables of the parties to an interaction, raises the incentives for increased reliance on statistical discrimination based on such easily observed characteristics such as race, gender, language and age. Worse, if (market) interactions expand as a result of economic growth, the benefits of which accrue to only a small fraction of the population, which may now also include a small number of those previously disadvantaged (as is the case when both between and within group inequality rises), the rate at which socially desirable norms are eroded could rise quite considerably. If it is true that socially desirable norms have positive externalities (social capital) which exert an upward

[5] By raising this possibility we do not mean to imply that markets are inconsistent with the maintenance of socially desirable norms such as trust. Indeed, the two can be quite harmonious, but probably only where contracts are incomplete, as Bowles and Gintis (1997) argue, and where traders who have some characteristic, physical attribute or experience in common, dominate the market. (Coleman's (1988) example of trust among Jewish owned jewellery dealers in New York City comes to mind)).

influence on job mobility (and therefore also earnings mobility), the destruction of such norms may constrain labour market opportunities. Frustrated by their stagnation, this could lead workers to shirk more (or at least increase the incentives to shirking). In the presence of "flexible" labour markets and zero employment rents, but comprehensive unemployment benefits, both worker productivity and firm level technical efficiency could decrease, thus further constraining growth. If (asset) redistribution still does not take place, a vicious circle of low growth, low social capital and low productivity might occur.

It is our view that post-*Apartheid* South Africa falls somewhere between these two extremes, characterised by sustainable redistribution on the one hand, (for example, the old-age pension scheme) and unsustainable redistribution, low growth and growing unemployment on the other.[6] Moreover, these perils feed off one another.

II. Policy Relevance

If perceptions of the fairness of relative social mobility are related to social and political cohesion, especially in societies with a history of large (socially engineered) inequality, such as South Africa[7], isolating the predictors of "movers" and "stayers" can be invaluable in moving a step closer to the more difficult goal of understanding whether egalitarian reforms will be supported in the future. The need for such an analysis is especially important if we have reason to suspect that the poor might have overly optimistic expectations about their future position in the income distribution. Such a model, which is consistent with observed intergenerational persistence of inequality in the USA, has been employed

[6] Redistribution is "sustainable" if it alters the incentive structure governing prisoners dilemma type interactions such that the degree of reciprocal fairness increases, thus lowering the probability of a reversal of the original redistribution in the future. See Bowles and Gintis (1997) and the dialogue in Eric Olin Wright (1997) for more on this.

[7] Note that social mobility may come about through transitory shocks or because of changing rewards for different skills, as in the case of "intra"generational mobility; or - as in the case of "inter"generational mobility - could also come about through group effects and individual characteristics apart from skill that contribute to earnings, such as a positive work ethic (Bowles and Gintis, 2000b). For a model of the relationship between distribution, growth, mobility and political attitudes, see David Hojman (2000) and for a model of the determinants of active labour market policy, see Gilles Saint-Paul (1998).

in explaining why the electorate continually vote down (or seek to prevent constitutionally) any redistributive policies which impose high tax rates on future generations (Benabou and Ok, 1998). But people do not always behave in this manner. Egalitarian redistribution such as unemployment insurance may be supported for purely selfish motives, even by those who expect to spend more than their fair share towards such insurance over their lifetime (Moene and Wallerstein, 1997). More importantly, they may also support egalitarian reforms because of "reciprocal fairness" – a tendency for human beings to display other-regarding behaviour (contrary to the self interested individual of neo-classical economics), both in co-operating with others and in punishing those who deviate from established norms of reciprocity and fairness (Fehr, 1996).[8]

There are many practical reasons why an understanding of earnings or income dynamics might be immediately relevant from an equity/efficiency standpoint. An understanding of the role played by purely stochastic factors in determining observed income levels is crucial in policy debates such as the design of anti-poverty programmes. Reliance on observed (temporary) income from cross sectional surveys as opposed to lifetime income measures, invariably leads to an overestimation of the incidence of poverty (Behrman, 2000). The same can be said for estimates of correlation coefficients, both within and between generations (Solon, 1989; 2000).

Atkinson *et al* (1992) also note the relevance of mobility to the design of pension schemes as well as the use of "averaging" for income tax purposes. A society with a large degree of persistence, they note, will generate lower overall government revenues if average incomes (over a number of years) are used as a basis for revenue generation.

[8] Such behaviour is supported both by the quite substantial experimental evidence from public goods games as well as evidence from artificial life simulations. In terms of the latter, of particular importance, is the finding of evolutionary stability of "tit-for-tat" strategies among randomly paired agents (see Gintis, 2000 as well as Bowles and Gintis, 1997 for a review of this evidence).

III. Methods and Preliminary Evidence

Two key approaches to measuring the extent of mobility are used in this study. The first are transition matrix-based approaches and the second is the Galton-Markov model of regression toward the mean. What follows are brief outlines of each approach and a discussion of their application to the KIDS data.

In general, a transition probability matrix (**P**) is an **n** × **n** matrix, where **n** refers to the number of categories and ($\mathbf{p}_{jk}$) is the element in the *j*th row and *k*th column of **(P)** and refers to the probability that an entity moves from the *j*th category to the *k*th category between the two time periods. The sum of the rows must be equal to 1 whereas the sum of the columns need not necessarily be 1. Preliminary estimates (adjusted for life-cycle effects) of such transition probabilities – where the categories represent an individual's position in the earnings distribution in 1993 (rows) and 1998 (columns) – are shown below in tables 1-15. The diagonal elements show probabilities of persistence, whereas the off-diagonal elements are probabilities of transition (upward or downward) in the earnings distribution. The probability of remaining in the bottom tercile (if you were there in 1993) is 0.68 while the corresponding probability of staying in middle tercile is 0.56. The degree of persistence in the top tercile is even greater. A total of 71.4% of these types of households could expect to preserve their advantage over the five-year period.

The gender and regional dimensions of persistence as reported in tables 2-6 reveal an even starker picture of persistence, as indicated by the even thicker tails of the diagonal. The probability of remaining in the bottom tercile for females (males) is 0.77 (0.59), while the corresponding probability for females (males) in the top tercile is 0.78 (0.69). Moreover, the probability of persistence in the first and third terciles, conditional on living in a rural area, are 0.75 and 0.76. The same probabilities, conditional on living in an urban area however, are 0.44 and 0.70, suggesting markedly more mobile individuals at the bottom of the earnings distribution in 1993[9].

[9] A cautionary note: owing to the small sample of individuals at the bottom of the (age adjusted) earnings distribution in 1993, it is not prudent to accord too much weight to the difference in persistence probabilities for the bottom tercile.

By contrast, "middle class" earners in urban areas exhibit much higher levels of persistence as reported in table 5.

In general, persistence findings for the full sample, with the exception of those in the top tercile, are also reasonably robust to controls for shocks. As reported in tables 7-10, a negative shock - defined as whether or not an individual was part of a household that experienced a death, serious illness, theft, major crop failure, and widespread death or disease of livestock - decreases the probability of persistence in the top quintile from 0.78, for those who didn't experience a negative shock, to 0.62 (for those who did). By contrast, belonging to a household that experienced a positive shock (such as new or increased remittances and grants, inheritances, gifts and lottery winnings, payment by a firm, and marriage) increases the persistence probability in the top quintile from 0.69 to 0.87, as reported in tables 9 and 10.

Tables 11-12 shows similar estimated transition probabilities for each of the two race groups captured by the KIDS data. Since Africans represent the majority of the valid sample (77%), it is not all that surprising that the persistence patterns for this sub-sample resemble those of the full sample reported in table 1. The probability of remaining in the bottom tercile for Africans who were poor in 1993 is 0.70 whereas the probability of remaining in the top tercile is 0.67. This compares to a persistence probability of 0.76 for Indians in the top tercile. Assuming that the Indian sub sample is representative, this finding would suggest that Indians are more likely (than Africans) to preserve any advantage they may have acquired in the labour market by 1993.

A limitation of the above discussion of transition probabilities is that they say nothing of the extent of overall earnings mobility or immobility: in short the problem has to do with how to reduce a transition matrix to a scalar measure of the degree of mobility or immobility. Various measures are proposed in the literature but not all consistently rank different transition matrices.[10] One such scalar measure, first suggested by Shorrocks (1978) which captures the inverse of the harmonic mean length of stay in a particular state (scaled by n/(n-1)) is the "trace measure of mobility" or $\mathbf{M}_{TR}$

[10] See the discussions in Behrman, 2000 as well as the work of Geweke *et al* (1986) and Shorrocks (1978).

(P) = [(n - trace(**A**) - 1)/(n - 1)] . However, Geweke *et al* (1986) found a counter exmple for which the trace measure violated the assumption of monotonicity.[11] A more serious problem with this approach however, is that it does not account for variations in the amount of mobility – it treats two individuals that experienced some mobility as conceptually identical and therefore does not capture the depth of movements away from the diagonal. A more appropriate measure in this regard, is the "determinant measure of mobility" $\mathbf{M}_{\boldsymbol{D}}$ **(P) =** $1 - \left|\text{Det } (\mathbf{A})\right|^{1/(n-1)}$. Geweke *et al*(1986) showed that as long as all the eigenvalues of **P** are real and nonnegative, the trace measure will be internally consistent. Moreover, if any function mapping **P** into a scalar can be expressed as a strictly monotonically decreasing function of the moduli of the eigenvalues of **P,** then so is the determinant measure. Since we have not tested explicitly for the latter, we consequently report both measures. Table 16 reports a summary of $\mathbf{M}_{\boldsymbol{D}}$ and $\mathbf{M}_{\boldsymbol{TR}}$ for all the transition matrices reported above.

The first point to note is that the trace and determinant measures differ by ten index points, when the transition matrix in question is unadjusted for life cycle effects and has no additional controls. Both measures also accord an unexpectedly high rate of mobility to the full sample (M_{TR} = 0.71 and M_D = 0.81) as indicated by the measures reported in the last row of table 16. Simply controlling for life cycle effects reduces the trace measure to 0.52 and the determinant measure to 0.57 (see row 1). The results also show that men are considerably more mobile than women. Note that the life cycle effect appears particularly acute for women as it accords a rate of mobility of 0.46 when age controls are used compared to 0.77 when age controls are absent. Finally, shocks whether positive or negative, unambiguously lowers both the indices of mobility.

We now turn to models of regression toward the mean. The usual specification of the first-order Galton-Markov model is

$$w_{it} = \boldsymbol{b}_0 + \boldsymbol{b}_1\, w_{it\text{-}1} + u_{it} \qquad (1)$$

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[11] Shorrocks (1978) showed that monotonicity requires that $M(P) > M(P^*)$ if $p_{jk} \geq p^*_{jk}$ for all $j \neq k$, and $p_{jk} > p^*_{jk}$ some $j \neq k$. Note that P and P^* are two transition matrices and $M(P)$ reads a mobility index is a function mapping P into a scalar.

where w represents the natural log of earnings (income) for individual (household) i at time t and u is the error term which is assumed to be independent of the previous period earnings (income) and is distributed independently and identically across periods (for individual i) and across individuals (for date t). Atkinson *et al* (1992) show that the Galton-Markov model is one of regression toward the mean in the sense that if $\boldsymbol{b} < 1$, then the expected value of earnings, at time t for person i differs from that expected by a person with mean earnings $m_w(t\text{-}1)$ by an amount $\boldsymbol{b}(w_{it\text{-}1} - m_w(t\text{-}1))$. People above the mean can therefore expect to preserve their advantage but to a reduced extent, whereas people below the mean may expect to see their earnings move closer to the mean.

Tables 17-19 present the results from estimating the Galton-Markov model using the KIDS panel data set. The model was estimated for various sub-samples of the data using either the natural log of earnings (for individuals) or income (for households). In addition to these regressions, the model was also estimated for all variables normalised by the mean of the relevant distribution. The most interesting finding thus far, is that the estimated $\boldsymbol{b}$'*s* of the log transformed variables for both individual earnings and household income are the same (1.49). This should not be the case as it suggests that immobile earnings might be driving immobile household incomes, which seem implausible given the problems of attrition bias, incomplete earnings histories and cross sectional censoring (Note the variation in sample sizes between table 17 and table 18). The estimated $\boldsymbol{b}$'*s* when all variables are normalised by their sample means shows a completely different picture. Household incomes appear to be much more mobile (as low as 0.62 for the full sample) whereas individual earnings exhibit strong persistence (as high as 0.95 suggesting that either the real incomes of the rich are increasing or those of the poor are decreasing). In addition, there appears to be a bifurcation of incomes suggesting the presence of non-linearities in the transition process. Individuals and households in the bottom and top of the income distribution seem to exhibit much larger persistence, whereas those in the middle of the income distribution experience greater mobility. A closer examination of the quintile transition matrices shown in tables 13-15 confirms this. Table 13, which shows the transition probabilities for females, suggests very high levels of persistence in the first and fifth quintiles; 0.54 and 0.63, whereas the probabilities of persisting in the second and fourth quintiles are 0.38 and

0.48 respectively. Finally, persistence in the middle quintile is the lowest among all the diagonal elements; 0.36.[12]

Two important areas yet to be addressed, especially in the case where individual earnings are the relevant definition of w, is attrition bias, by which we mean the failure to collect information that exists (as is the case when time t-1 has been accorded a data point but period t has not) and the problem of incomplete earnings histories (which is related to an individual leaving or entering the labour force). The fact that these two problems cannot be separated in any meaningful way (in the absence of well-designed filter questions) adds to the larger problem of censoring within each cross section of the panel.[13] In order to have a better understanding of movers and stayers in the two cross sectional earnings distributions, we need to study the behaviour of individuals out of the labour force as well as those captured by the earnings data. In the next section, we attempt to model entry into and exit from the labour market by estimating a multinomial logit model.

[12] An important qualification concerning non-linearities: from the evidence presented thus far, one cannot tell with certainty if indeed the transition process is truly non-linear or rather the outcome of a floor/ ceiling effect imposed by the very design of transition matrices. To untangle this, a detailed decomposition at the percentile level is needed. A more likely possibility is some combination of a non-linear process as well as a floor-ceiling effect. We proceed under the assumption that at the very least, this is true, and defer verification of this assumption for present purposes.

In order to capture such non-linearities we present a multinomial logit regression framework below, in estimating the probability of transitioning to the middle or top terciles. The logit model is appropriate since it allows for a non-linear functional form based on the logistic distribution.

[13] Elsewhere, we have tried to address this problem at the cross sectional level by estimating Tobit earnings functions (Burns and Keswell, 2000), but such an approach is not readily applied to panel data. A recent strand of econometric work in this area such as Hu (2000) does try to deal with this problem by suggesting an efficient way of "trimming" the data (thus restoring symmetry) and implementing a generalised method of moments. However, for the purposes of this paper, no attempts have been made to account for attrition bias and cross sectional censoring.

IV. A Multivariate Model of Labour Market Entry and Exit

An individual is assumed to have preferences defined over the set of alternatives $j = \{1, 2, 3, 4\}$ where 1 = " wage employment", 2 = "self employment", 3 = "out of the labour force" and 4 = "unemployment" and derives utility $U_{ij} = \max(U_{i1}, U_{i2}, U_{i3}, U_{i4})$ from these choices.[14] In other words,

$$\mathbf{U}_{ij} = \boldsymbol{\beta}_j' \mathbf{x}_{jt} + \mathbf{e}_{jt}$$

The observed outcome of labour market state is given by y = choice j if U (alternative j) > U (alternative k) for all $j \ldots k$. The error terms represent individual heterogeneity and are assumed to be independently and identically distributed. The probability of choice j is therefore given by

$$\Pr(y = j) = \frac{e^{b_j' x_t}}{\sum_{j=1}^{4} e^{b_j' x_t}}, \; j = 1, \ldots, 4$$

The vector $\mathbf{x}$ includes time-invariant individual characteristics (such as race and gender) as well as time-varying individual characteristics (such as age, years of education completed, body-mass index) and time-varying non-individual characteristics (such the occurance of a negative or positive shock to the household, and "social capital" conventionally defined).

The dependent variable y is defined as the observed labour market state $j = \{1\ldots4\}$in 1998, conditional on the labour market states in 1993. The model is therefore estimated for each of the four labour market states in 1993. In other words, separate estimates are carried out for households that

[14] Note that we use a choice theoretic framework in the above analysis. To the extent that the choice of labour market states isn't strictly an optimal response on the part of the individual, but rather the circumstance of a predetermined or exogenous outcome (such as being retrenched during a recession or exiting the labour market owing to on the job injury), then our model can easily be converted to a purely mechanical relation such as a latent regression approach, where the observed labour market state of an individual is given by certain individual specific (possibly time invariant) characteristics as well as a vector of other non-individual specific characteristics.

made transitions from being employed in 1993, to each of the 4 discrete observed outcomes in 1998. The same will be done for those who were unemployed, self – employed[15] and out of the labour force in 1993. The table below describes the valid sample.

		1998				
		Employed	Self Employed	Unemployed	OLF	*n*
1993	Employed	672	27	160	99	958
	Self Employd	47	37	33	52	169
	Unemployed	281	41	418	62	802
	OLF	300	44	511	756	1611
	n	1300	149	1122	969	3540

Tables 20-21 report the multinomial logit estimates for four variations of the model on the transitional probabilities from employment in 1993 to each of the three other states in 1998. Table 22 reports the estimates of a model of transtioning from self employment to the three other

[15] The category self-employed includes both petty commodity trade and production (of which there are 20 sub-categories captured by the KIDS panel) as well as subsistence and commercial agriculture. In other work, we are investigating how to incorporate these sub-categories of occupational choice in the above model. One approach is to use a nested multinomial logit framework but the success of this approach depends largely on sufficient variation of the LHS variables, which is a problem in the KIDS panel. For example, the reported data on self-employment in agriculture in 1993 is very low. An added problem is that the 1998 questionnaire did not distinguish between forms of self-employment. Presumably, this is has to do with the typical amount of time an individual/ household spends on farming. Since most farming takes place on a part time basis, but a great number of people rely on it for subsistence purposes (Carter and May, 1999), such activity does constitute self employment. We therefore have to devise a way of inferring which individuals in a household rely more on agricultural production and which spend most of their time in petty commodity trade and production. Moreover this has to be done using the production data in combination with the reported activity of the individual respondents. This becomes quite a cumbersome task and requires one to make assumptions about time spent in self employment (other than agriculture) which are not internally verifiable since the agricultural production data provides no variables on hours of work. As an exercise, we computed self-employment in agriculture by inferring hours worked in the 20 sub categories of self-employment. If an individual reported that s/he was self employment but spent less than 20 hours a week doing that activity, and if the household reported production data for agriculture, then this individuals main activity was read as "self employed in agriculture". The resulting LHS variable (which now had 1 additional labour market state) still did not contain enough variation to be estimated (even in the multinomial framework listed above).

states. Three varitions of the model of transitions from unemployment in 1993 are reported in table 23 and finally, table 24 reports 2 variations of the model of the OLF transitions.

Employment Transitions

Being African decreases the probability of transition to OLF by 6%. A one year increase in age also reduces this probabilty - by about 2% - however, this advantage disappears, the older one gets. Females face an exceptionally large increase in the probability of exit into OLF status (12%). The results in table 20 also suggest that individuals malnourished (or at risk of becoming so) face no such penalty. Indeed, the probability of exit decreases by 5%. An interesting finding, and one that is quite robust (as will become evident shortly) is that memebership in a financial group such as a stokvel in 1993 lowers the exit probability by about 6%.

Table 21 reports the results of a slightlydifferent specification for transitioning into self employment and unemployment. It shows that being African results in a 4% increase in the transition probability from employment to self employment. Also, overweight individuals [defined as having a body mass index (a proxy for current health status)[16] in excess of 25)], can expect to have a 2% increase in their a transition probability to self employment.

While race seems to confer an advantage to individuals who exit employment into OLF, it does the opposite for those who exit into unemployment: being african results in a 15% increase in the transition probability. By contrast, being overweight results in a decrease of 11% in the transition probability.

Self Employment Transitions

Table 22 reports the results of transitions out of self employment. As is evident from the table, owing land in 1993 increases the transition probabiliy from self employment into unemployment. As was the case for employment transitions, age plays a significant role for individuals who

[16] See Dasgupta (1999).

move from being self employed to OLF. Here too, the non-linear effect of an additional year of age is evident given the large negative value associated with age, compared to the positive value associated with its square. By far the most interesting finding however is the that females can expect a 61% increase in their transition probability to OLF. The vastly differing magnitude of this variable for the employment transition to OLF as discussed above, may in part, be owing to the geater degree of flexibility in entering and exiting self-employment modes of production (largely petty commodity production or agricultural activities) as opposed to formal employment. Furthemore, if it is true that incomes in self-employment activities are lower than those in formal employment, the opportunity cost faced by a woman making a decision to exit self-employment will be lower than that of a woman exiting formal employment. Finally, individuals who experienced a postive shock between 1993 and 1998 can expect an 28% increase in their transition probability to OLF.

Unemployment Transitions

Table 23 reports the estimated coefficients and marginal values for unemployment transitions. Three models with particularly interesting results are highlighted: these are the models of transition to employment. Note that race appears insignificant in all three specifications. This is in contrast to the models of employment transitions discussed above, where being African increased your chances of losing your job by as much as 15%. In short it would appear that race has become unimportant for getting a new job, but still remains very important for losing one. This finding is quite pertinent to the design of redistributive instruments such as unemployment insurance as it suggests that while labour markets in KwaZulu Natal might no longer be biased in favour of Indians and whites when it comes to hiring, previous advantage might still play a role in shielding workers from jobloss. If it is true that the pattern of retrenchments between 1993-1998 resulted in more African workers losing their jobs because of (a) sheer numbers - Africans occupy most of the unskilled labour positions and (b) Indians occupy a more than proportionate number of skilled labour positions, then a government concerned about egalitarian redistrbution should not only be concerned about expanding the set of redistributive instruments, but should also provide incentives for firms to alter the skill base of their employees. Subsidised on the job training is one promising area as it serves both as a form of social insurance and as a demand side intervention: better trained people advance quicker in their jobs, thus eroding the role played by race in downsizing in the long run, and if more Africans still lose their jobs, the skills learnt might decrease their unemployment spell[17].

Another interesting finding is the coefficient on the dummy variable for being a member of a stokvel in 1993. As is evident from table 23, belonging to such an association (which are essentialy revolving credit associations) increases one's probability of finding a new job by 45%. One interpretation of this finding is that belonging to such a group allows one to consumption smooth more effectively, thus freeing up valuable time (that might otherwise be spent on unproductive or low return activities) which can then be used to extend the amount of time and effort searching for new employment. Yet, in order for this explanation to be consistent, having access to such a windfall must also effectively reduce mean unemployment spells, so as to enable members to meet future payments to the stokvel. Otherwise, one would need to find some other way (possibly from pooling household resources) of meeting obligations to the group.

Another possibile interpretation is that merely beloging to such a group expands one's chances of finding new employment, given access to a broader network of (most likely) other employed individuals. Improved information here could be the driving force behind increasing the probability of finding a new job, but so could the simple benefit of interacting with others on a community level, i.e., the social capital effect. Finally, having access to periodic payments might aid in investing in skills or education. However, if this were true, one would expect that an increase in the number of years of education should be a significant predictor of getting a new job, if previously unemplyed. We do not find any evidence of this however. Note that the variable YRSEDU 93 is not statistically significant and does not become significant when different race or regional dummies are used. This finding is also robust to other model specifications not reported here.

[17] This of course ignores other problems such skill specificity and the effects these might have on unemployment. It also assumes that mobility achieved in this way will be asymmetrical.

If greater social capital is the underlying process by which stokvel membership translates into an increase in the probability of finding a new job (i.e., greater interaction with others might confer skills which could be used in securing new employment), then the type of group one belongs to matters also. Belonging to the "African Independent Church" for example results in a 18% decrease in the probability of finding new employment.

Out of the Labour Force Transitions

The most interesting finding regarding OLF transitions concerns the effect of education on the probability of finding a new job. As is evident from table 24, having a secondary level of education increases the probability of fnding a new job by 5%, while having only a primary level of education decreases the probability by 5%. Given the insignificance of education in predicting a transition from a state of unemployment to new employment, the relevence of education for the OLF transitions signals that education replaces years of experiance (as proxied by age) for the sample of individuals who make such a transition. This interpretation is supported by the finding that age is statistically insignificant in the regression results reported in table 24, yet they are consistently significant for the unemployment transition models reported in table 23. Finally, individuals who live in the former KwaZulu homeland can expect an 8% decrease in their probability of finding new employment, if they were OLF in 1993.

Earnings Transitions

The multinomial logit results estimated for transitions in labour market states do not shed any light on the question of what matters for the advancement of employed individuals. Table 25 presents multinomial logit estimates of earnings transitions among terciles. An additional year of education results in a 5% increase in the transitional probability from the the bottom tercile to the top tercile while membership of a stokvel increases this probability by 7%.

Table 1. Full Sample (natural log of earnings adjusted for life cycle effects)

1998

1993		Bottom	Middle	Top	*n*
	Bottom	68.3	23.7	7.9	*139*
	Middle	15.7	55.7	28.6	*140*
	Top	11.3	17.3	71.4	*168*
	n	*136*	*140*	*171*	*447*

Table 2. Females (natural log of earnings adjusted for life cycle effects)

1998

1993		Bottom	Middle	Top	*n*
	Bottom	77.1	18.6	4.3	*70*
	Middle	21.1	56.1	22.8	*57*
	Top	13	8.7	78.3	*46*
	n	*72*	*49*	*52*	*173*

Table 3. Males (natural log of earnings adjusted for life cycle effects)

1998

1993		Bottom	Middle	Top	*n*
	Bottom	59.4	29	11.6	69
	Middle	12	55.4	32.5	83
	Top	10.7	20.5	68.9	122
	n	64	91	119	274

Table 4. Rural (natural log of earnings adjusted for life cycle effects)

1993		1998 Bottom	Middle	Top	*n*
	Bottom	74.5	21.7	3.8	106
	Middle	24.6	53.6	21.7	69
	Top	16	8	76	50
	n	104	64	57	225

Table 5. Urban (natural log of earnings adjusted for life cycle effects)

1993		1998 Bottom	Middle	Top	*n*
	Bottom	44.4	38.9	16.7	18
	Middle	7.5	62.5	30	40
	Top	7.4	22.2	70.4	81
	n	17	50	72	139

Table 6. Metropolitan (natural log of earnings adjusted for life cycle effects)

1993		1998 Bottom	Middle	Top	*n*
	Bottom	53.3	20	26.7	15
	Middle	6.5	51.6	41.9	31
	Top	13.5	18.9	67.6	37
	n	15	26	42	83

Table 7. Negative Shock = 0 (natural log of earnings adjusted for life cycle effects)

1993 \ 1998	Bottom	Middle	Top	*n*
Bottom	66.7	24.2	9.1	66
Middle	12.7	58.7	28.6	63
Top	9.3	12.4	78.4	97
n	61	65	100	226

Table 8. Negative Shock = 1 (natural log of earnings adjusted for life cycle effects)

1993 \ 1998	Bottom	Middle	Top	*n*
Bottom	69.9	23.3	6.8	73
Middle	18.2	53.2	28.6	77
Top	14.1	23.9	62	71
n	75	75	71	221

Table 9. Positive Shock = 0 (natural log of earnings adjusted for life cycle effects)

1993 \ 1998	Bottom	Middle	Top	*n*
Bottom	68.4	24.1	7.5	133
Middle	15.6	59	25.4	122
Top	11.7	19.3	69	145
n	127	132	141	400

Table 10. Positive Shock = 1 (natural log of earnings adjusted for life cycle effects)

		1998 Bottom	Middle	Top	*n*
1993	Bottom	66.7	16.7	16.7	6
	Middle	16.7	33.3	50	18
	Top	8.7	4.3	87	23
	n	9	8	30	47

Table 11. African sub-sample (natural log of earnings adjusted for life cycle effects)

		1998 Bottom	Middle	Top	*n*
1993	Bottom	69.6	22.2	8.1	135
	Middle	16.8	54.6	28.6	119
	Top	10.1	22.5	67.4	89
	n	123	115	105	343

Table 12. Indian sub-sample (natural log of earnings adjusted for life cycle effects)

		1998 Bottom	Middle	Top	*n*
1993	Bottom	25	75	0	4
	Middle	9.5	61.9	28.6	21
	Top	12.7	11.4	75.9	79
	n	13	25	66	104

Table 13. Female = 1 (natural log of real earnings by quintiles, unadjusted)

		1998					
		First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	n
1993	First quintile	54.1	37.8	2.7	5.4	0	37
	Second quintile	30	37.5	22.5	7.5	2.5	40
	Third quintile	13.9	27.8	36.1	19.4	2.8	36
	Fourth quintile	0	14.8	18.5	48.1	18.5	27
	Fifth quintile	5.7	8.6	0	22.9	62.9	35
	n	39	46	28	33	29	175

Table 14. Former Natal Province (natural log of real earnings by quintiles, unadjusted)

		1998					
		First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	n
1993	First quintile	54.5	30.3	6.1	9.1	0	33
	Second quintile	47.1	44.1	5.9	2.9	0	34
	Third quintile	19.2	11.5	42.3	19.2	7.7	26
	Fourth quintile	0	3	24.2	42.4	30.3	33
	Fifth quintile	6.1	7.6	9.1	13.6	63.6	66
	n	43	34	29	32	54	192

Table 15. Full Sample (natural log of real earnings by quintiles, unadjusted)

		1998					
		First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile	n
1993	First quintile	45.1	31	11.3	12.7		71
	Second quintile	32.9	32.9	23.7	9.2	1.3	76
	Third quintile	11.4	14.8	37.5	29.5	6.8	88
	Fourth quintile	1	8.3	21.9	41.7	27.1	96
	Fifth quintile	3.4	7.6	7.6	22.9	58.5	118
	n	72	77	89	109	102	449

Table 16. Trace and Determinant Estimates of Earnings Mobility

P	M_{TR} ***(P)***	M_D ***(P)***
Full Sample (natural log of earnings adjusted for life cycle effects)	0.52	0.57
Females (natural log of earnings adjusted for life cycle effects)	0.44	0.46
Males (natural log of earnings adjusted for life cycle effects)	0.58	0.59
Rural (natural log of earnings adjusted for life cycle effects)	0.48	0.50
Urban (natural log of earnings adjusted for life cycle effects)	0.61	0.61
Metropolitan (natural log of earnings adjusted for life cycle effects)	0.64	0.64
Negative Shock = 0 (natural log of earnings adjusted for life cycle effects)	0.48	0.49
Negative Shock = 1 (natural log of earnings adjusted for life cycle effects)	0.57	0.60
Positive Shock = 0 (natural log of earnings adjusted for life cycle effects)	0.52	0.53
Positive Shock = 1 (natural log of earnings adjusted for life cycle effects)	0.57	0.60
African sub-sample (natural log of earnings adjusted for life cycle effects)	0.54	0.56
Indian sub-sample (natural log of earnings adjusted for life cycle effects)	0.69	0.71
Female = 1 (natural log of real earnings by quintiles, unadjusted)	0.65	0.77
Former Natal Province (natural log of real earnings by quintiles, unadjusted)	0.63	0.71
Full Sample (natural log of real earnings by quintiles, unadjusted)	0.71	0.81

Note:

The transition probabilities in tables 1-15 have been adjusted for life cycle effects by calculating expected earnings as a function of age and age squared. The residuals from these regressions were then saved and used as the basis for calculating the predicted transition probabilities. All transition matrices with the exception of the last 3 rows represent transitions between terciles. The last 3 rows are based on transitions between quintiles. Real earnings is computed by deflating wages of the year in question by the average CPI for that year with 1995 as the base year. $M_{TR}(P) = M_D(P) = 1$ *implies complete earnings mobility.*

Table 17. Income Immobility Estimates based on 1st Order Markov Process

Sample	*Constant*	*b*	*n*
Full	0.82	0.21	1158
African	0.43	0.71	1000
African		1.07	1000
African Rural	0.31	0.76	758
		1.03	758
African Urban	0.54	0.57	146
		1.00	146
Indian Rural	3.02	**0.07	16
		0.15	16
Indian Urban	0.56	0.60	89
		0.84	89
Indian Metro	0.82	0.57	57
		0.85	57
Full (stayed)	0.82	0.20	1098
		0.35	1099
Full (moved)	0.62	0.53	60
		0.72	61
African Rural (stayed)	0.30	0.77	731
		1.03	732
African Urban (stayed)	0.52	0.60	130
		1.01	131
Indian Urban (moved)	-0.03	1.16	11
Indian	1.55	0.12	159
Indian Metro (moved)	**1.03	0.46	5
Indian Metro (stayed)	0.78	0.59	51
1st & 3rd terciles	1.01	0.20	764
		0.35	765
1st & 3rd terciles, African		1.28	640
1st & 3rd terciles, African Rural		1.27	486
1st & 3rd terciles, African Urban		1.10	93
1st & 3rd terciles, African Metro		1.54	63
1st & 3rd terciles, Indian		0.24	126
Indian Rural, 1st & 3rd		0.15	14

Notes:

*y is household income and is normalised by the mean of its distribution (assumed non-stochastic). **b** is an indicator of immobility; as beta approaches 0, there is regression toward the mean. . "stayed" and "moved" selects for households who changed location in the period 93-98. All estimates are significant at the 1% level unless otherwise indicated. * = Statistically insignificant, and ** = significant at 10% level.*

Table 18. ***Income Immobility Estimates based on 1st Order Markov Process***

Sample	***Constant***	β	***n***
Full	4.17	0.47	1151
		1.08	1152
African	4.69	0.38	993
1st & 3rd terciles	3.50	0.57	759
1st & 2nd terciles	5.15	0.25	767
2nd & 3rd terciles	5.85	0.29	776
African, 1st & 3rd terciles	4.09	0.47	647
Rural African, 1st & 3rd terciles	4.44	0.38	531
Urban African, 1st & 3rd terciles	4.29	0.35	431
Metro African, 2nd tercile	6.70	0.10	34
Urban African, 2nd tercile	6.64	0.11	52
Rural African, 2nd tercile	6.87	0.06	272
Indian	3.31	0.63	158

Notes:

y is the natural logarithm of household income. β *is an indicator of immobility; as beta approaches 0, there is regression toward the mean. ."stayed" and "moved" selects for households who changed location in the period 93 -98. All estimates are significant at least at the 5% level unless otherwise indicated. * = Statistically insignificant, and ** = significant at 10% level.*

Table 19. ***Earnings Immobility Estimates based on 1st Order Markov Process***

Sample	***constant***	$\boldsymbol{\beta}$	***n***
Full		1.14	460
Full (variables natural log transformed)		1.07	453
African	0.46	0.95	326
Indian	0.80	0.65	133
Rural	0.44	0.75	216
Urban	*0.44	1.09	145
Metro	1.08	0.26	98
Rural African	0.27	1.08	205
Former Homeland (KwaZulu)	0.53	1.01	233
Urban African	0.88	0.59	72
Male	0.61	0.83	281
Female	0.53	0.64	178
Full, 1st & 3rd terciles	0.67	0.86	312
African, 1st & 3rd terciles	0.51	1.13	202
African Rural, 1st & 3rd terciles	0.20	1.37	127
Primary labour market	0.66	0.75	406
Secondary labour market		0.86	57
African Secondary labour market - 1st & 3rd terciles		1.01	22
Indian Primary labour market - 1st & 3rd terciles	**0.84	0.72	108

Notes:

*y is individual earnings from formal and casual labour and is normalised by the mean of its distribution (assumed non-stochastic). Beta is an indicator of immobility; as beta approaches 0, there is regression toward the mean. ."stayed" and "moved" selects for households who changed location in the period 93-98. All estimates are significant at the 1% level unless otherwise indicated. * = Statistically insignificant, and ** = significant at 10% level.*

Table 20. Transitions from Employment: multinomial logit estimates

TR1	Out. Of Lab. Force[18]	Marginal values	Out. Of Lab. Force[19]	Marginal values
Constant	1.6685	0.1361	0.9752	0.0836
	(1.9)		*(1.84)*	
AFRICAN	-0.765**	-0.0631	-0.7614	-0.0638
	(0.38)		*(0.37)*	
AGE 93	-0.2935*	-0.0230	-0.2794	-0.0223
	(0.09)		*(0.09)*	
AGE 93^2	0.005*	0.0004	0.0046	0.0004
	(0.001)		*(0.001)*	
FEMALE	1.548*	0.1210	1.4833	0.1178
	(0.298)		*(0.293)*	
RURAL	0.0180	0.0022	0.0797	0.0071
	(0.33)		*(0.33)*	
OVERWEIGHT 98	-0.3376	-0.0254	0.0613	0.0056
	(0.36)		*(0.28)*	
MALNOURISHED 98	-0.6678***	-0.0518		
	(0.39)			
STOKVEL 93	-1.276***	-0.0631	-1.2475	-0.0617
	(0.72)		*(0.72)*	
AIC 93	-0.2309	-0.0016	-0.2572	-0.0036
	(0.7)		*(0.71)*	
TR1: n = 684, log likelihood = -488.0666, resrt log likelihood = -595.3758, chi sqr = 214.6184*, df = 27			**TR1: n = 684, log likelihood = -489.8257, df = 24 resrt log likelihood = -595.3758, chi sqr = 211.1003*,**	

TR1[20]	Self-employed	Marginal values	Out. Of Lab. Force	Marginal values
Constant	-3.8965	-0.1168	1.0143	0.0929
	(3.15)		*(1.84)*	
AFRICAN	2.0271***	0.0614	-0.777**	-0.0679
	(1.08)		*(0.37)*	
AGE 93	-0.0468	-0.0007	-0.2813	-0.0218
	(0.15)		*(0.09)*	
AGE 93_2	0.0005	0.0000	0.005*	0.0004
	(0.00)		*(0.00)*	
FEMALE	-0.6726	-0.0240	1.476*	0.1161
	(0.46)		*(0.29)*	
RURAL	0.1920	0.0058	0.0799	0.0066
	(0.48)		*(0.33)*	
OVERWEIGHT 98	0.5545	0.0167	0.0564	0.0040
	(0.44)		*(0.28)*	
STOKVEL 93	-0.2809	0.0083	-1.247***	-0.0591
	(0.79)		*(0.72)*	

TR1: n = 684, log likelihood = -492.3099, resrt log likelihood = -595.3758, chi sqr = 206.1319*, df = 21

[18] Note: for tables 20-27, * = significant at 1% level, ** = 5% and *** = 10%. .

[19] Two other regressions were run for transition from employment to self-employment and unemployment. These results are not reported here. However, f or transition from employment to self employment, race (African was significant at the 5% level. For transition from employment to unemployment, race (African), rural and OVERWEIGHT were all significant at 1% level.

[20] Regression run for transition from emp loyment to unemployment (not reported here).
African, rural and OVERWEIGHT were all significant at 1% level, while female was significant at 5% level.

Table 21. TR1: Transitions from Employment

TR1	Self-employed	Marginal values	Unemployed	Marginal values	Out. Of Lab. Force	Marginal values
Constant	-5.556**	-0.1154	0.2322	0.0353	1.2312	0.0749
	(2.84)		*(1.06)*		*(1.42)*	
AFRICAN	1.831***	0.0343	1.307*	0.1658	-0.774**	-0.0580
	(1.07)		*(0.31)*		*(0.34)*	
AGE 93	0.0026	0.0008	-0.1175**	-0.0122	-0.294*	-0.0157
	(0.14)		*(0.06)*		*(0.07)*	
AGE 93_2	0.0000	0.0000	0.0011	0.0001	0.005*	0.0003
	(0.00)		*(0.00)*		*(0.00)*	
FEMALE	-0.4109	-0.0108	0.2812	0.0255	1.251*	0.0691
	(0.42)		*(0.19)*		*(0.26)*	
RURAL	0.3638	0.0075	-0.1135	-0.0172	0.1958	0.0117
	(0.46)		*(0.21)*		*(0.299)*	
OVERWEIGHT 98	1.05*	0.0239	-0.909*	-0.1194	0.1958	0.0179
	(0.43)		*(0.24)*		*(0.27)*	

TR1: n = 958, log likelihood = -719.3566, resrt log likelihood = -845.6983, chi sqr = 252.6834*, df = 18

Constant	-5.177***	-0.1069	0.0120	0.0064	1.2180	0.0760
	(2.82)		*(1.06)*		*(1.43)*	
AFRICAN	2.098**	0.0399	1.196*	0.1495	-0.681**	-0.0522
	(1.03)		*(0.29)*		*(0.29)*	
AGE 93	-0.0090	0.0005	-0.114**	-0.0116	-0.296*	-0.0159
	(0.14)		*(0.06)*		*(0.07)*	
AGE 93_2	0.0001	0.0000	0.0011	0.0001	0.005*	0.0003
	(0.00)		*(0.00)*		*(0.00)*	
FEMALE	-0.3895	-0.0104	0.2860	0.0258	1.25*	0.0694
	(0.42)		*(0.19)*		*(0.26)*	
SHOCK-	-0.2971	-0.0073	0.326***	0.0402	0.1742	0.0074
	(0.4)		*(0.19)*		*(0.25)*	
OVERWEIGHT 98	0.998**	0.0227	-0.881*	-0.1151	0.1900	0.0175
	(0.43)		*(0.24)*		*(0.27)*	

TR1: n = 958, log likelihood = -718.0144, resrt log likelihood = -845.6983, chi sqr = 255.3678, df = 18

Table 22.Transitions from self-employment: multinomial logit estimates

TR2	Employed	Marginal values	Unemployed	Marginal values	Out. Of Lab. force	Marginal values
Constant	0.4418	-0.4082	3.1882	0.1904	5.593***	0.8802
	(3.27)		*(3.31)*		*(3.24)*	
AFRICAN	-0.1022	-0.1217	1.7174	0.2955	0.3281	-0.0413
	(0.68)		*(1.18)*		*(0.84)*	
AGE 93	0.0997	0.0635	-0.2485	-0.0107	-0.601*	-0.1092
	(0.17)		*(0.16)*		*(0.17)*	
AGE 93_2	-0.0024	-0.0010	0.0027	0.0000	0.008*	0.0017
	(0.002)		*(0.002)*		*(0.002)*	
FEMALE	-0.4875	-0.2537	0.0863	-0.1519	2.9292*	0.6061
	(0.54)		*(0.598)*		*(0.82)*	
SHOCK+	0.5292	-0.0937	1.3330	0.0851	1.992**	0.2791
	(0.92)		*(0.92)*		*(0.92)*	
YRSEDU 93	0.0107	-0.0038	-0.0068	-0.0085	0.1030	0.0204
	(0.08)		*(0.09)*		*(0.098)*	
LAND (PRIVATE) 93	0.2168	-0.0467	1.4608**	0.2435	0.1676	-0.0748
	(0.82)		*(0.74)*		*(0.89)*	
OVERWEIGHT 98	-0.2549	-0.0992	0.0066	-0.0505	0.9836	0.2103
	(0.52)		*(0.62)*		*(0.64)*	

TR2: n= 169, log likelihood = -169.3598, restricted log likelihood = -231.5426, chi sqr = 124. 3656*, df = 24

*Notes: *= significant at 1% level; **=significant at 5% level; ***=significant at 10% level*

Table 23. Transitions from Unemployment: multinomial logit estimates

TR3	Self-	Marginal value	Employed	Marginal value	Out Lab. force	Marginal value
ONE	-4.1937	-0.3248	-1.5843	-0.1788	-0.3752	0.0706
	(-2.65)		*(1.68)*		*(2.39)*	
AGE 93	0.1291	0.0072	0.1527	0.0395	-0.21***	-0.0239
	(0.14)		*(0.09)*		*(0.12)*	
AGE 932_2	-0.1359	-0.0047	-0.25***	-0.0695	0.36*	0.0402
	(0.17)		*(0.13)*		*(0.15)*	
FEMALE	-0.1248	-0.0084	-0.4596	-0.1797	1.89*	0.1709
	(0.48)		*(0.30)*		*(0.65)*	
INDIAN	1.2830	0.0139	1.7077	0.2410	3.08*	0.1707
	(1.45)		*(1.09)*		*(1.21)*	
METRO	-0.08***	-0.0486	0.85**	0.2068	0.1561	-0.0194
	(0.72)		*(0.43)*		*(0.69)*	
YRSEDU 93	0.0299	0.0055	-0.0486	-0.0119	-0.0373	-0.0014
	(0.08)		*(0.05)*		*(0.08)*	
STOKVEL 93	2.28***	0.0939	2.38**	0.4268	1.3686	-0.0030
	(1.27)		*(1.07)*		*(1.32)*	
Constant	-1.6689	-0.2173	0.6466	0.1356	2.6922	0.2052
	(2.96)		*(1.98)*		*(2.65)*	
AFRICAN	-1.3571	-0.0204	-1.7278	-0.2451	-3.032*	-0.1624
	(1.44)		*(1.09)*		*(1.17)*	
AGE 93	0.0773	0.0039	0.1196	0.0344	-0.226**	-0.0233
	(0.14)		*(0.096)*		*(0.13)*	
AGE 93_2	-0.0009	0.0000	-0.0021	-0.0006	0.0038*	0.0004
	(0.00)		*(0.00)*		*(0.00)*	
FEMALE	-0.2565	-0.0152	-0.5407***	-0.1863	1.7094*	0.1591
	(0.49)		*(0.31)*		*(0.66)*	
OVERWEIGH	0.7991***	0.0503	0.3994	0.0285	0.8345**	0.0436
	(0.49)		*(0.33)*		*(0.47)*	
STOKVEL 93	2.101***	0.0795	2.3722**	0.4408	1.1404	-0.0197
	(1.28)		*(1.08)*		*(1.32)*	
AIC93	-0.4536	-0.0068	-0.803***	-0.1806	0.1156	0.0442
	(0.82)		*(0.49)*		*(0.73)*	
TR3 (n = 591, log likelihood = -292.6934, restricted log likelihood = -344.9887, chi sq = 104.5907*, df = 21)						
Constant	-1.7192	-0.2129	0.6305	0.1329	2.6349	0.2012
	(2.95)		*(1.98)*		*(2.66)*	
AFRICAN	-1.9184	-0.0732	-1.6715	-0.2011	-3.2014*	-0.1733
	(1.51)		*(1.11)*		*(1.24)*	
AGE 93	0.0843	0.0044	0.1202	0.0343	-0.2214***	-0.0230
	(0.14)		*(0.096)*		*(0.13)*	
AGE 93_2	-0.0010	0.0000	-0.0021	-0.0006	0.004**	0.0004
	(0.00)		*(0.00)*		*(0.00)*	
FEMALE	-0.3303	-0.0218	-0.5312***	-0.1810	1.696*	0.1585
	(0.495)		*(0.31)*		*(0.66)*	
RURAL	0.7607	0.0729	-0.0917	-0.0666	0.2390	0.0157
	(0.56)		*(0.31)*		*(0.54)*	
OVERWEIGH	0.8522***	0.0538	0.3932	0.0256	0.8417***	0.0442
	(0.496)		*(0.33)*		*(0.48)*	
STOKVEL 93	2.2122***	0.0859	2.3875**	0.4412	1.1949	-0.0166
	(1.29)		*(1.09)*		*(1.32)*	
AIC93	-0.4259	-0.0036	-0.8086***	-0.1839	0.1085	0.0436
	(0.82)		*(0.49)*		*(0.73)*	
TR3 (n = 280, log likelihood = -291.2720, restricted log likelihood = -344.9887, chi sq = 107.4334*, df = 24)						

Table 24. Transition from Out of the Labour Force: multinomial logit estimates

TR4	Self-employed	Marginal values	Unemployed	Marginal values	Employed	Marginal values
ONE	-2.2856	-0.0559	-3.659***	-0.2550	-0.9046	-0.0237
	(2.67)		*(1.96)*		*(1.9)*	
AFRICAN	2.1877	0.0545	2.05**	0.1328	2.61*	0.1053
	(1.5)		*(0.87)*		*(0.73)*	
KWAZULU	-0.2475	-0.0035	-0.3407	-0.0166	-2.03*	-0.0884
	(1.1)		*(0.69)*		*(0.63)*	
AGE 93	0.0003	-0.0003	0.136***	0.0098	0.0213	0.0004
	(0.11)		*(0.08)*		*(0.08)*	
AGE 93_2	-0.0009	0.0000	-0.002***	-0.0002	-0.0013	0.0000
	(0.00)		*(0.00)*		*(0.00)*	
SECONDARY EDU	-0.2718	-0.0080	-0.5274	-0.0411	1.02*	0.0475
	(0.64)		*(0.44)*		*(0.38)*	
LAND (PRIVATE) 93	-0.5099	-0.0162	0.0803	0.0034	0.97*	0.0435
	(0.65)		*(0.35)*		*(0.39)*	
TRUST GROWTH	-0.0826	-0.0006	-0.57**	-0.0400	-0.3149	-0.0118
	(0.45)		*(0.29)*		*(0.34)*	
TR4 (n = 591, log likelihood = -399.7690, restricted log likelihood = -502.7837, chi sq = 206.0294*, df = 21)						
ONE	-2.5569	-0.0639	-4.2**	-0.2958	0.1125	0.0238
	(2.52)		*(1.87)*		*(1.78)*	
AFRICAN	2.1874	0.0545	2.05**	0.1327	2.61*	0.1054
	(1.5)		*(0.87)*		*(0.73)*	
KWAZULU	-0.2476	-0.0035	-0.3408	-0.0166	-2.03*	-0.0885
	(1.09)		*(0.69)*		*(0.63)*	
AGE 93	0.0002	-0.0003	0.14***	0.0097	0.0214	0.0005
	(0.11)		*(0.08)*		*(0.08)*	
AGE 93_2	-0.0009	0.0000	-0.002***	-0.0002	-0.0013	0.0000
	(0.00)		*(0.00)*		*(0.00)*	
PRIMARY	0.2723	0.0080	0.5278	0.0411	-1.02*	-0.0476
	(0.64)		*(0.44)*		*(0.38)*	
LAND (PRIVATE) 93	-0.5099	-0.0162	0.0803	0.0034	0.97*	0.0435
	(0.65)		*(0.35)*		*(0.39)*	
TRUST GROWTH	-0.0826	-0.0006	-0.57**	-0.0400	-0.3149	-0.0118
	(0.45)		*(0.29)*		*(0.34)*	
TR4 (n = 591, log likelihood = -399.7708, restricted log likelihood = -502.7837, chi sq = 206.0294*, df = 21)						

Table 25. Earnings Transitions: from bottom and top

Bottom	Middle	Marginal value	Top	Marginal value
Constant	-2.401	-0.430	-0.712	-0.003
	(3.21)		*(7.3)*	
AGE 93	0.022	0.004	-0.061	-0.002
	(0.17)		*(0.42)*	
AGE 932_2	-0.017	-0.003	-0.008	0.000
	(0.21)		*(0.57)*	
YRSEDU 93	0.26*	0.045	0.28***	0.005
	(0.098)		*(0.17)5*	
FEMALE	0.017	0.018	-2.53***	-0.060
	(0.53)		*(1.33)*	
URBAN	0.265	0.038	1.794	0.041
	(0.88)		*(1.27)*	
STOKVEL 93	-0.555	-0.118	2.98**	0.074
	(1.27)		*(1.55)*	

poor : n = 101, log likelihood = -66.41875, rest log likelihood = -81.06500, chi sq = 29.29250*, df = 12

Bottom	Middle	Marginal value	Top	Marginal value
Constant	-9.21***	-1.389	-46.215	-0.005
	(4.91)		*(33.84)*	
AGE 93	0.47***	0.071	2.933	0.000
	(0.28)		*(2.18)*	
AGE 932_2	-0.67***	-0.101	-4.769	-0.001
	(0.395)		*(3.5)*	
YRSEDU 93	0.19***	0.029	0.159	0.000
	(0.11)		*(0.26)*	
FEMALE	0.272	0.041	-0.449	0.000
	(0.64)		*(1.35)*	
WORKER93	-0.465	-0.070	-1.088	0.000
	(0.64)		*(1.49)*	
STOKVEL 93	-0.078	-0.012	4.494	0.000
	(1.43)		*(5.55)*	

poor : n = 79, log likelihood = -44.65117 re st log likelihood = -55.97088, chi sq = 22.63942, df = 12**

Top	Bottom	Marginal value	Middle	Marginal value
Constant	3.104	0.094	7.28**	1.094
	(4.78)		*(3.76)*	
AGE 93	-0.299	-0.014	-0.31***	-0.045
	(0.22)		*(0.18)*	
AGE 932_2	0.377	0.018	0.334	0.047
	(0.26)		*(0.21)*	
YRSEDU 93	-0.028	0.000	-0.17**	-0.026
	(0.14)		*(0.08)*	
FEMALE	1.23***	0.081	-0.775	-0.135
	(0.69)		*(0.57)*	
STOKVEL 93	-0.514	-0.024	-0.470	-0.067
	(1.12)		*(0.65)*	

rich : n = 160, log likelihood = -113.1901 rest log likeli hood = -122.3860, chi sq = 18.39195, df = 12

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