

# Labour Market Transitions in South Africa: What can we learn from matched Labour Force Survey data?

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## Abstract

We generate a longitudinal dataset using the rotating panel component of the nationally representative Labour Force Surveys from 2001 to 2004. We then estimate the transition probabilities across different labour market states over a six month period. We find that unemployed searchers are more likely to find employment than the non-searching unemployed. Informal sector workers are more likely to find formal sector employment than the searching unemployed. Whites are more likely to find and remain in formal sector jobs. However, some part of the Black – White unemployment gap arises from unemployed Whites leaving the labour force at a higher rate.

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## 1. Introduction

South Africa has a chronically high unemployment problem. This has been observed in several cross-sectional surveys starting with the PSLSD/SALDRU survey conducted in 1993. Much research has been devoted to understanding various dimensions of employment and unemployment. However, a lack of longitudinal data has prevented researchers from estimating flows from unemployment into employment and from unemployment to withdrawal from the labour force. Not knowing how much turnover there is in the labour market makes it difficult to identify whether there is a core set of people who never work (the unemployable) or whether a high proportion of workers experience short spells of unemployment. Questions about the effectiveness of search behaviors are also difficult to answer without observations on the same person over time. These are simple questions of fundamental importance in understanding the dynamics of the South African labour market.

At present, there are two geographically focused longitudinal datasets in the public domain. The Kwa-Zulu Natal Income Dynamics Study (KIDS) followed SALDRU respondents and re-interviewed them in 1998 and 2004. KIDS has been extensively used to analyse dynamic labour market movements. There are three limitations to these data. First, the focus on Kwa-Zulu Natal limits generalisability of findings. Second, sample sizes are small, which restricts statistical power and reduces the precision of corresponding estimates. Third, a five year gap between waves is not ideal for studying the rate at which people find jobs. A person could have several spells of employment and unemployment over a five year period which would not be captured in a five year long difference.

The second panel data set is the Cape Area Panel Study (CAPS): a survey of young adults living in Cape Town. Data are available on a sample of youth initially aged 14 to 22 for waves conducted in 2002 and 2004. These data are also limited in geographic generalisability. Moreover, we would not be able to learn about labour market dynamics for all adults since the oldest CAPS respondents are now 26 years of age.

In this paper, we describe labour market transitions for a sample of adults (ages 15-58) drawn from across South Africa. We present one way in which the rotating panel component of the Labour Force Surveys between September 2001 and March 2004 can be matched to help us in this task. To the best of our knowledge, no researcher has used this version of the data. For this reason, we carefully explain the matching algorithm that creates the panel and discuss some of the challenges with this procedure.

We describe the resulting matched panel, and then present transition matrices that document the rates at which people in various labour market states transit into other states. As a robustness check on the validity of the panel, we check whether the transition rates are consistent with the change in the levels of employment and unemployment that are observed across individual waves. Specifically, we compare sample proportions in each labour market state in wave  $t+1$  to estimated proportions in each labour market state in that wave. The estimated proportions are the panel transition rates multiplied by the

initial labour market stock variable in the full wave  $t$  cross section. On average across the four panels, our predictions are less than 1% point away from the full cross-sectional estimates in wave  $t+1$  in each of the five labour market states that we use. This provides us with some confidence in the matching algorithm.

We use the matched panel to generate transition rates for demographic groups defined by race, age and gender. We find Africans and African females in particular are more likely to lose employment over a 6 month period and much less likely to find employment. Gender and race differences in labour market transition rates are large. The chances of finding or maintaining employment are particularly low amongst African youth. Interestingly, we find that transition rates from informal to formal sector jobs are almost uniformly higher across all groups than transitions into formal jobs from other labour market states.

## 2. Prior work on labour market flows

Information using cross-sectional data has been used extensively to show how demographic factors such as education, gender, race and location correlate with employment and unemployment (see Borat et al (2001), Kingdon and Knight (2001a) and Klasen and Woolard (1999)) Youth unemployment is growing (Casale, Muller & Posel (2004)), racial differences in employment rates remain significant, (Rospabe (1999), Brookes and Hinks (2004), and Kingdon and Knight (2004)) and gender differences in participation and employment have become increasingly relevant over time (Casale and Posel (2002) and Grun (2004)). Our research helps us to better understand all of these many aspects of the South African labour market.

Only a few studies have explicitly considered modeling labour force dynamics. Wittenberg (2002) does so using non-parametric techniques and cross-sectional data. However, most of our knowledge of employment and poverty dynamics comes from the KIDS survey, which is described in May et al (2000). Keswell (2000) analyses earnings mobility and employment transitions, using the KIDS dataset. Dinkelman (2004) uses a search framework to investigate the effects of household context on the efficacy of search. Cichello et al (2005) provide a thorough analysis of earnings and employment dynamics using KIDS.

## 3. The Data

The core data come from repeated waves of the South African Labour Force Surveys (LFS) released by Statistics South Africa. These are biannual, nationally representative surveys, conducted in March and September each year. Between September 2001 and March 2004, (i.e. LFS2001:2 to LFS2004:1), 20% of dwellings were out-rotated from each wave<sup>3</sup> and the sample was refreshed with a new 20% of dwellings. We use these repeat observations to construct a panel. For the rest of the paper, wave 4 is the LFS conducted in September 2001, wave 5 was conducted in March 2002, and so forth as described in Table 1.

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<sup>3</sup> As stated in the official meta-data releases of Statistics South Africa.

**Table 1: Year and Month of Labour Force Survey waves**

Year	Month	Wave
2001	September	Wave 4
2002	March	Wave 5
2002	September	Wave 6
2003	March	Wave 7
2003	September	Wave 8
2004	March	Wave 9

Matching observations across waves is not straightforward. Difficulties arise due to out-migration, mortality, in-migration of household members, and the fact that the person identifiers within households are not maintained across waves. Thus, person  $i$  in household  $j$  in wave  $t$  is not necessarily the same person as person  $i$  in household  $j$  in wave  $t+1$ . This problem is similar to the one that researchers have experienced in the US when trying to extract longitudinal data from the Current Population Survey (CPS). Some insights and suggestions on various matching alternatives are discussed in Madrian and Lefgren (1999). Following their discussion, we matched people with the same dwelling identifier across waves, based on their demographic characteristics and reports about whether they had recently taken up residence in a particular dwelling. Since no researcher in South Africa have yet published any findings using this dataset, we carefully document our matching procedure, describe the final panels that we generate, and discuss some of the potential pitfalls in employing such a methodology.

### 3.1 The matching algorithm

- Step 1: Drop all observations from properties with more than one dwelling on it. This was done as Statistics South Africa indicated that property numbers were generally maintained across waves, but that in multiple dwelling properties, the dwelling numbers may have been interchanged.
- Step 2: Exclude all individual level observations in wave  $t+1$  where the respondent is reported to have moved into the residence in the past 6 months. This should exclude people who moved into the dwelling between wave  $t$  and wave  $t+1$ .
- Step 3: Exclude individuals in a particular wave where multiple observations in a household have the same race, gender and ages differing by at most one year. For example, if there were two African females aged 16, or aged 15 and 16, or aged 16 and 17 in a household in wave 5, both are excluded from the set of possible matches in wave 5. This is done to reduce the possibility of false matches, since we would not be able to uniquely identify these observations based on their demographic characteristics in the corresponding wave  $t$  or  $t+1$ .
- Step 4: Remaining observations can potentially be matched across waves. We matched observations across wave  $t$  and wave  $t+1$  using household identifier, gender, race and  $age_t = age_{t+1}$ , where the subscript on age denotes the corresponding wave. Perfectly matched observations are removed from the set and stored.

- Step 5: For remaining observations, we match again on household identifier, gender, race and  $age_t + 1 = age_{t+1}$ . This allows for an individual's age to increase by one in the six months between waves. This second set of matches is also removed from the set and stored.
- Step 6: To allow for a small amount of misreporting of age, we matched the final remaining unmatched observations in the set of potential matches using household identifier, gender, race and  $age_t - 1 = age_{t+1}$ .
- Step 7: The matches in steps 4, 5 and 6 are appended to generated the full panel, which we refer to as the 'expanded match'.
- Step 8: To test whether our results are sensitive to potentially false matches, we then imposed additional consistency requirements on the expanded matches. We excluded matches with  $age_t - 1 = age_{t+1}$ , or with  $education_t$  greater than  $education_{t+1}$ , or with a change in marital status from married, divorced or widowed in wave  $t$  to 'never married' in wave  $t+1$ , or with an observed decrease in the person's ability to read or write between waves. This subset is called the 'strict match' panel.

To analyze transitions, each respondent aged 15 or older is classified into one of five mutually exclusive and exhaustive labour market states. This generates the following five corresponding indicator variables<sup>4</sup>:

- “NEA” : not economically active, = 1 if a person is not working, not looking for work, and not willing to accept a 'reasonable' offer, = 0 otherwise.
- “Unempl\_d” : discouraged unemployed, =1 if a person is not working, not looking for work, but is willing to accept a 'reasonable' offer, = 0 otherwise.
- “Unempl\_s” : searching unemployed, =1 if a person is not working, but is actively searching for work, = 0 otherwise.
- “Empl\_inf” : employed in the informal sector, =1 if a person is working, and reports that the employment takes place in the informal sector, = 0 otherwise.
- “Empl\_for” : employed in the formal sector, =1 if a person is working, and reports that the employment takes place in the formal sector, = 0 otherwise.

### 3.2 Sample sizes

We label each panel as “panel<sub>ij</sub>” where ‘i’ and ‘j’ refer to the number corresponding to wave  $t$  and wave  $t+1$  respectively. We thus have panel<sub>45</sub>, panel<sub>56</sub>, panel<sub>67</sub>, panel<sub>78</sub> and panel<sub>89</sub>. Table 2 shows sample sizes. Our average match rate is approximately 46% using the expanded criteria and 34% using the strict criteria.<sup>5</sup> The final pooled sample across the five waves is very large: 135 413 observations using the strict criteria and 184 712 observations using the expanded criteria.

<sup>4</sup> We made use of the classifications provided by Statistics South Africa here. The variables are called “status1”, “status2” and “sectorwk”.

<sup>5</sup> This compares somewhat poorly with the US Current Population Survey match rate obtained in Madrian and Lefgren (1999), which ranged between 71% and 65%.

**Table 2: Sample sizes**

	Cross Section		# people in to possibly match (Steps 1-3 above)		Number of individual matches		Match rate: As a proportion of possible matches	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)=(5)/(3)	(8)=(6)/(3)
	Wave t	Wave t+1	Wave t	Wave t+1	Expanded	Strict	Expanded	Strict
Panel 45	106,439	109,414	80774	75,329	33,258	24,963	0.41	0.31
Panel 56	109,414	102,483	88520	84,529	40,296	27,760	0.46	0.31
Panel 67	102,483	100,835	81806	76,437	38,704	29,546	0.47	0.36
Panel 78	100,835	98,750	76122	72,712	37,399	26,472	0.49	0.35
Panel 89	98750	98256	74963	71172	35,055	26,672	0.47	0.36
All Panels	517,921	509,738	402,185	380,179	184,712	135,413	0.46	0.34

### 3.3 Issues arising with the match

#### 3.3.1 Non-random matching on observables

The first potential pitfall from using this data is matches may not represent a random sample of the population.<sup>6</sup> Table 3 provides summary statistics of our matched sample using the expanded criteria alongside the corresponding statistics from the related full cross-section. The match algorithm is systematically more likely to match females and Coloured and Whites, individuals in urban areas, youth younger than 25 and the elderly aged 60 or above. Of those older than 15, we are more likely to match respondents who are ‘not economically active’ and less likely to match respondents in any other category.

To the extent that attrition arises for observable reasons, we can correct for this by re-weighting the matched sub-sample. For example, if shack dwellers are more likely to move and are thus less likely to be matched, we can adjust the weighting of those shack dwellers who we do manage to match. Thus, non-random matching on observables is not an insurmountable problem *per se*, as we can use inverse probability weighting (IPW) methods to obtain unbiased estimates (see Wooldridge 2001, pp 587-590).

For each full cross section, we estimate probit regressions for the probability of being matched across waves and re-weight the matched sample using the (IPW) method. This was done for each of the ‘expanded matches’ and the ‘strict matches’.<sup>7</sup> Probit results were consistent with the information in Table. In addition, several other variables indicative of stability were significant predictors of the match probability. Married people, those with more education and those in smaller households are more likely to be matched. Respondents in different provinces had different propensities to be matched. Mud dwellings correlated negatively with the match rate, while dwellings made of brick correlated positively. Not surprisingly, home ownership is a strong predictor of match

<sup>6</sup> Note that the relatively low match rate is not a problem in and of itself, since the absolute number of matches is still very large.

<sup>7</sup> These regressions are excluded for brevity but are available from the authors upon request.

probability, with an even stronger relationship amongst those who owned their homes but did not yet have it fully paid off.<sup>8</sup>

**Table 3: Descriptive statistics of the panels in relative to the cross-sections**

	Wave Number						Panel Number				
	4	5	6	7	8	9	45	56	67	78	89
% male	47.3	47.7	47.8	47.6	47.7	47.5	46.3	46.4	46.2	46.5	46.2
% African	79.15	78.1	78.0	77.8	77.5	77.7	78.3	76.7	76.8	76.5	76.2
% Coloured	11.4	11.4	11.6	11.6	11.7	11.4	12.4	12.9	12.9	13.0	12.9
% Indian	2.03	2.2	2.3	2.4	2.3	2.4	2.0	2.2	2.0	1.7	1.7
% White	7.3	8.2	8.1	8.2	8.5	8.4	7.3	8.2	8.3	8.7	9.2
% Urban	53.66	54.4	53.5	53.6	53.5	54.1	54.0	55.4	54.5	54.6	53.6
% Age < 25	53.6	52.7	53.3	53.1	52.6	52.21	55.5	55.3	54.6	55.0	54.4
% 24 < Age < 60	39.2	39.8	39.2	39.3	39.6	40.01	36.9	36.8	37.3	37.0	37.4
% 60 < Age	7.2	7.5	7.5	7.6	7.8	7.78	7.6	8.0	8.1	8.1	8.3
% NEA	37.5	35.4	38.1	37.7	38.2	38.2	41.0	39.6	41.2	41.0	41.7
% Unemp_D	10.5	10.3	9.8	9.9	11.7	11.7	10.3	9.9	9.7	9.3	11.5
% Unemp_S	15.1	15.8	15.4	16.0	13.6	13.6	14.4	15.3	14.7	15.3	12.7
% Empl_informal	11.6	12.5	10.8	10.5	10.3	9.8	10.5	10.8	9.5	9.3	9.1
% Empl_formal	25.3	25.9	25.9	25.9	26.2	26.8	23.9	24.4	25.0	25.1	25.0

Notes:

The statistics for the 'wave' columns refer to the entire cross-section

The statistics for the 'panel' columns refer to the matches using the expanded criteria

In the panel columns, the age and labour market status statistics refer to the percentages in wave  $t$ .

Proportions of each race do not necessarily add up to 1 as some respondents report their race as "other"

The labour market status statistics refer to people aged 15 and higher

### 3.3.2 Non-random matching on unobservables

A more difficult issue arises with non-random matching on unobservable characteristics. This is similar to a selective attrition problem in *bona fide* longitudinal samples. If these characteristics are orthogonal to variables used in any particular analysis, estimates will still be unbiased in expectation.

However, it is likely that unobservable differences do indeed matter. People probably do move in search of jobs, if they become unemployed, or if they find a job in a different area – hence, the type of people who are most likely to have experienced a transition are the ones most likely missing from the matched panel.

<sup>8</sup> Questions on home ownership, type of dwelling and quality of walls were only asked in waves 4, 6 and 8. We thus used the wave  $t+1$  information for the wave  $t$  probit if necessary, by matching on households. We do not believe that this is problematic for the purpose of generating the weights.

In our study of labour market transitions, this non-random matching on unobservables affects how we interpret results. Assuming that a transition in labour market status is positively correlated with migration and that we have not corrected for this using the IPW technique our estimated transition probabilities are likely lower bounds of the true population level transition probabilities. In other words, the stability of individuals who are matched may lead us to over-estimate persistence.

### 3.3.3 False Matches

The third challenge arises as there are undoubtedly some false matches in our panel. If we reasonably believe that most people in a particular labour market state are likely to be in that same state six months later, than random false matching is likely to exaggerate our estimated transition probabilities.<sup>9</sup> For this reason, we constructed the two samples, using both the expanded criteria and strict criteria. If results to the same analyses using these two matching criteria differ significantly, then false matches are likely to be a big problem. If, however, similar results are obtained using both panels, then we can be more confident of the validity of our matching algorithm.

Tables 4a and 4b contain mean transition rates for people aged 15 to 58 in wave  $t$ , for the matches using the expanded and strict criteria respectively. All five panels were pooled to generate these tables and all estimates are weighted using person weights released by Statistics South Africa<sup>10</sup>, multiplied by the inverse of the match probability obtained from the probit regressions discussed above.

The columns represent a person's wave  $t$  status, and the rows a person's wave  $t+1$  status. Thus, the entry of 2.72 in the column labeled 'NEA' and in the row labeled 'Empl\_for' in Table 4a, indicates that 2.72% of the not economically active population aged 15 to 58 were employed in the formal sector six months later.

Table 4c presents differences between these estimates. In general, results are fairly consistent. Of the 25 entries, only 2 entries have an absolute difference of greater than 1 percentage point. On the other hand, 19 of the 25 entries have an absolute value of less than half a percentage point. On aggregate, we find this outcome reassuring. False matches could well be a problem, but their magnitude is unlikely to be sufficient to completely invalidate our results<sup>11</sup>.

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<sup>9</sup> Ashenfelter, Deaton and Solon (1986) argue that this "may not matter very much since there is likely to be a positive correlation between the behavior of different households in similar (in this case, identical) accommodations."

<sup>10</sup> We used the person weight in wave  $t$  as the relevant person weight.

<sup>11</sup> To be more correct, false matches that are excluded by the difference between the strict and expanded matching criteria are unlikely to bias our estimates significantly. False matches that are common to both will continue to bias both sets of estimates.

**Table 4a****Transition rates (%) across labour market states from panel: expanded match**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	35,839	12,129	17,544	10,589	28,726
	NEA	75.74	18.98	12.9	12.84	2.93
	Unempl_d	8.91	37.65	19.61	10.67	2.35
	Unempl_s	8.53	29.32	48.11	14	6.17
	Empl_inf	4.1	8.95	9.04	47.63	5.21
	Empl_for	2.72	5.1	10.33	14.87	83.33
	Total	100	100	100	100	100

**Table 4b****Transition rates (%) across labour market states from panel: strict match**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	26,709	7,973	11,598	6,658	19,402
	NEA	76.56	18.49	12.41	12.63	2.62
	Unempl_d	8.8	37.51	19.12	10.61	2.05
	Unempl_s	8.17	29.73	49.22	13.32	5.63
	Empl_inf	3.86	8.83	8.67	47.72	4.73
	Empl_for	2.62	5.44	10.58	15.73	84.97
	Total	100	100	100	100	100

**Table 4c****Difference in transition rates between expanded and strict matches**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	NEA	-0.82	0.49	0.49	0.21	0.31
	Unempl_d	0.11	0.14	0.49	0.06	0.3
	Unempl_s	0.36	-0.41	-1.11	0.68	0.54
	Empl_inf	0.24	0.12	0.37	-0.09	0.48
	Empl_for	0.1	-0.34	-0.25	-0.86	-1.64

**3.3.4 A Robustness Check**

A further robustness check is suggested by Wittenberg (2002): “The equilibrium stocks can be deduced from the various flow rates”. If our estimates are sensible, we can take the wave  $t$  levels for the entire cross section, combine these with our estimated transition rates between wave  $t$  and wave  $t+1$ , and predict the wave  $t+1$  levels. If these predictions

are very different from the observed levels in the wave  $t+1$  cross-section, then we are likely to have systematically biased estimates. This is only a weak test, since we could have simultaneously biased but offsetting estimates that could still generate the correct predicted levels. Nevertheless, the test does provide us with at least one mechanism by which we can challenge the credibility of our estimates.

Formally, we have  $X_{t+1} = A_t \cdot X_t$ , where  $X_t$  is a 5 x 1 vector containing the proportion of the population in each labour market state at time  $t$ ,  $X_{t+1}$  is defined in similar fashion, and  $A_t$  is a 5 x 5 transition matrix as specified above. Our transition matrices above are estimates, denoted by  $\hat{A}_t$ . Assuming that the cross-sectional estimates generate unbiased estimates of the true population levels, we calculate the predicted levels using  $\hat{A}_t$  and  $X_t$  from the cross section, denoted by  $X_{t,CS}$ . We then calculate the difference between the predicted proportions and observed proportions in the full cross-section in wave  $t+1$  (denoted by  $X_{t+1,CS}$ ), and investigate the magnitude of these differences. This vector of differences is denoted  $D_{t+1}$ . Thus:

$$D_{t+1} = \hat{A}_t \cdot X_{t,CS} - X_{t+1,CS}$$

This exercise is performed for each wave separately. The differences between the proportions in the full cross section, and the predicted proportions in each labour market state are presented in Table 5:

**Table 5: Differences between predicted and cross-sectional percentages (in percentage points)**

	Strict Match: Panel number:					Average
	45	56	67	78	89	Strict
NEA	-1.07	-0.41	-0.78	-0.89	-0.56	-0.74
unempl_D	-0.65	0.62	0.95	-0.05	0.29	0.23
unempl_S	2.10	-0.01	0.22	0.02	0.96	0.66
empl_informal	-0.74	-1.09	-0.91	-0.47	-0.53	-0.75
empl_formal	0.36	0.86	0.51	1.39	-0.15	0.59
Total	0.00	-0.02	-0.01	0.00	0.00	-0.01

	Expanded Match: Panel number:					Average
	45	56	67	78	89	All
NEA	-1.05	-0.45	-0.73	-0.76	-0.64	-0.73
unempl_D	0.30	0.62	0.69	0.19	0.53	0.47
unempl_S	1.75	0.41	0.34	0.09	1.14	0.75
empl_informal	-0.65	-0.78	-0.32	-0.15	-0.44	-0.47
empl_formal	-0.34	0.18	0.00	0.63	-0.59	-0.03
Total	0.00	-0.01	-0.02	0.00	0.01	0.00

On the whole, differences are not large. With the exception of one category in panel<sub>45</sub>, the difference is less than 2 % points. On average, across the four panels, the difference is less than 1% point for each category, regardless of which set of matched observations we

use. These seem to be reasonable ‘ballpark’ estimates of true transition rates. Since the expanded match criteria do not yield strikingly different results and has many more observations, we use this dataset for the remainder of the paper.

#### 4. Transition rates

We are primarily interested in describing the rates at which people find jobs, lose jobs, and enter and leave the labour force. We first discuss the aggregate transition rates, and then investigate how these differ by various demographically sub-populations, defined by age, race and gender. The five panels are pooled for this component of the analysis.

##### 4.1 Aggregate transitions

Aggregate transitions in Table 4a clearly indicate some degree of persistence in the labour market, since any individual in a given state in wave  $t$  is most likely to still be in that state in wave  $t+1$ . However, there is also lots of movement across states. Roughly one quarter of individuals NEA in wave  $t$  enter the labour force by  $t+1$ , although less than one third of these find employment of any sort. Of the discouraged unemployed, almost 19% leave the labour market, while about 30% are actively searching for jobs. Approximately 1 in 7 finds employment, although close to two thirds of the jobs are in the informal sector. In contrast, searching unemployed are more likely to find employment (approximately 1 in 5 find employment), but the differential is almost entirely generated by a greater rate of finding formal sector jobs. Thus, the payoff to searching is likely to manifest not only in terms of the probability of finding a job, but also in the quality of the job.

We also observe that searching unemployed are less likely to be discouraged, or leave the labour force, than the non-searching unemployed. Turning now to those employed in the informal sector, over 1 in 3 are not employed six months later. Informal sector employment does not entail much job security. Of particular interest is the percentage of informal sector employees who find formal sector employment in wave  $t+1$ . At 14.87 %, this is greater than the proportion of either group of the unemployed. This is consistent with an hypothesis whereby skills, networks and information obtained during informal sector employment actually assist workers in subsequently obtaining formal sector employment. Such a possibility has not yet been investigated in the South African literature.

##### 4.2 Racial differences in adult transition rates

We next perform the same analysis for African, Coloured and White adults separately. Indians were excluded due to relatively small sample sizes. Adults are aged 25 to 58 in wave  $t$  inclusive. The lower bound of 25 is imposed to exclude individuals still in school. The upper bound is imposed because of labour force participation around retirement age. Ranchhod (2006) argues that labour force participation rates of females exhibit a sharp discontinuity at age 60 due to the person potentially becoming eligible to receive the old age pension. We wanted to exclude such observations as they would exaggerate our

transition probabilities. Some respondents aged 59 in wave  $t$  turn 60 by wave  $t+1$ , so we imposed a cutoff at age 58. Results are presented in Table 6a, 6b and 6c below.

**Table 6a**

**Transition rates : African Adults**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	7,534	7,009	10,344	8,048	14,602
	NEA	56.22	16.25	9.81	10.39	2.08
	Unempl_d	15.56	37.99	20.2	10.76	2.64
	Unempl_s	13.25	29.44	48.78	13.63	7.02
	Empl_inf	10.98	11.48	11.61	52.33	6.84
	Empl_for	3.99	4.84	9.6	12.89	81.42
		100	100	100	100	100

**Table**

**6b**

**Transition rates : Coloured Adults**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	2,127	568	1,124	863	4,979
	NEA	72.53	24.33	16.95	9.7	2.66
	Unempl_d	7	21.12	11.94	3.67	1.66
	Unempl_s	9.24	31.56	41.6	12.88	4.3
	Empl_inf	5.01	7.17	9.02	50.31	3.02
	Empl_for	6.22	15.82	20.49	23.44	88.36
Total		100	100	100	100	100

**Table 6c**

**Transition rates : White Adults**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	1,423	160	247	363	5,544
	NEA	72	43.35	28.49	15.25	3.6
	Unempl_d	6.61	21.53	13.07	1.56	0.66
	Unempl_s	3.64	8.36	26.38	4.48	1.48
	Empl_inf	3.62	5.3	5.08	24.16	3.18
	Empl_for	14.12	21.46	26.98	54.54	91.09
Total		100	100	100	100	100

Results for each race group are qualitatively similar to the aggregate findings. Searchers are more likely to find employment relative to the non-searching unemployed, and those employed in informal sector jobs are more likely to find formal sector work than the

searching unemployed. Those with jobs are also less likely to become not economically active. Informal sector employment is considerably less stable than formal sector employment.

The pattern that emerges across race groups is remarkable. In each of the five states in wave  $t$ , Whites are more likely to find or keep employment than Coloureds, who in turn are generally more likely to find or keep employment than Africans.<sup>12</sup> Of the searching unemployed, almost 1 in 3 whites find employment, predominantly in the formal sector (84%)<sup>13</sup>, while slightly fewer than 1 in 3 Coloureds find employment, with 69% of these jobs in the formal sector. In contrast, fewer than 1 in 4 African searchers find employment, with less than half of the newfound employment in the formal sector (45%). A similar pattern holds in reverse if we look at the probability that an individual of a particular race group in a given state in wave  $t$  is classified as unemployed in wave  $t+1$ .

The rates at which the different race groups leave the labour force conditional on being unemployed in wave  $t$  also tell an interesting story. Of the discouraged unemployed, 43.35% of whites leave the labour force, while 24.33% of Coloureds and only 16.25% of Africans leave. Of the searching unemployed, over 1 in 4 whites leave the labour force, while less than 1 in 10 Africans do so. This is unlikely to be a reflection of discrimination in the labour market, as whites are more likely to find employment when they are unemployed. A plausible explanation is that whites have a greater asset base, or access to greater familial resources, which allows them to withdraw at a faster rate. Thus, at least part of the racial differentials in levels of unemployment reflects the greater rates at which the unemployed whites leave the labour force.

#### 4.3 Racial differences in youth transitions

Youth are defined as individuals aged 15 to 24 inclusive in wave  $t$ . Here, we are primarily interested in the success rates in finding employment of first time entrants in the labour market. Amongst youth within a racial group, we note the familiar pattern that those who are not economically active are the least likely to be employed in wave  $t+1$ , followed in ascending order by the discouraged unemployed, the searching unemployed, the informal sector workers, and the formal sector workers (see Table 7 a-c). However, informal sector African youth are in fact more likely to leave the labour force than the unemployed African youth.<sup>14</sup>

Comparing across races, Africans are again least likely to keep a formal sector job, or to find one within a 6 month period. Amongst African youth in a formal sector job in wave  $t$ , 2 in 5 are no longer employed as such in wave  $t+1$ . Corresponding numbers for Coloured and whites are approximately 1 in 4 and 1 in 5 respectively.

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<sup>12</sup> The one exception being not economically active Coloureds, who are still more likely to find jobs than their African counterparts conditional on labour market entry.

<sup>13</sup> Obtained by  $26.98/(26.98+5.08)$

<sup>14</sup> We do not comment on the unemployed white youth, nor on the informal sector white and Coloured youth, as our sample sizes in these categories in wave  $t$  are rather small.

Entry into the labour force is also marked by large racial differences. While the rate at which African and white youth enter the labour market<sup>15</sup> is similar, African youth entrants are far less successful in finding employment. Whereas 58% of white youth enter directly into some form of employment, the corresponding number for African youth is only 15%. This itself masks the difference in composition between formal and informal sector employment.

**Table 7a**  
**Transition rates : African Youth**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	20,296	3,749	4,454	1,062	938
	NEA	83.16	21.8	17.2	30.17	6.9
	Unempl_d	7.48	41.13	22.05	17.08	9.75
	Unempl_s	6.83	28.94	49.74	19.34	18.54
	Empl_inf	1.98	5.4	4.78	26.32	5.02
	Empl_for	0.55	2.72	6.23	7.1	59.8
	Total	100	100	100	100	100

**Table 7b**  
**Transition rates : Coloured Youth**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	2,028	476	941	116	969
	NEA	76.93	17.09	13.12	9.15	4.14
	Unempl_d	6.11	25.65	15.6	21.06	4.31
	Unempl_s	12.18	41.42	52.84	12.59	13.7
	Empl_inf	0.7	3.18	2.4	20.61	2.52
	Empl_for	4.08	12.66	16.04	36.58	75.33
	Total	100	100	100	100	100

**Table 7c**  
**Transition rates : White Youth**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Wave t+1	Numbers	1,182	56	118	29	508
	NEA	85.22	33.42	26.32	22.97	8.26
	Unempl_d	1.72	14.45	4.37	0	3.42
	Unempl_s	4.54	18.18	27.13	13.74	6.74
	Empl_inf	0.55	3.11	2.94	5.57	1.7
	Empl_for	7.97	30.84	39.24	57.72	79.87
	Total	100	100	100	100	100

<sup>15</sup> As measured by the proportion of those who transit out of the NEA category between the two waves.

The proportions are striking, but should be interpreted with the caveat that for Coloured and whites they are estimated using only a couple of hundred observations. Nevertheless, of African youth who enter the labour market, 44% are ‘discouraged’, while another 41% are actively searching. Only 3.3% find formal sector employment. For Coloured entrants, 26% are discouraged, 53% are actively searching, while 17.7% have found formal employment. Even among whites, who experience by far the most positive entry into the labour market, only 47.3% have found formal sector jobs, while 10% are ‘discouraged’ and 27% are actively searching.

Finally, we compare transition rates between unemployed Coloureds and Africans. In each of these categories, Coloureds are more likely to find employment, and much more likely to find formal sector employment. In sum, being young and entering the job market is likely to entail a lot of disappointment, regardless of race. This is especially true for young Africans.

#### 4.4 Gender differences between African adults

Employment levels and sectors differ by gender, so it is reasonable to expect transition rates to differ as well. We restrict attention to Africans for brevity. Results are presented in Tables 8a and 8b.

Within groups, there is a fair amount of persistence. Informal sector workers are more likely to find formal sector employment than the unemployed. Of those not employed in wave  $t$ , searchers are the most likely to find employment. Amongst men, the discouraged unemployed are more likely to find employment than the not economically active, but this difference in likelihood is approximately zero for women. For the most part, the transition rates within group are qualitatively similar to the aggregate transition rates.

Between groups, there are important differences. Unemployed males in either category are more likely to find employment than their female counterparts, while employed males are more likely to remain employed. In addition, males employed in the informal sector are much more likely to enter formal employment than informal sector female workers. At the same time, females in the informal sector are much more likely to remain in the informal sector.

There is a strong and systematic difference in the composition of employment. Conditional on employment in wave  $t+1$ , women considerably more likely to find and keep informal sector employment. Of men who enter the labour force, 22.7% find informal sector employment, while another 13.9% find formal sector employment. For women, the corresponding numbers are 25.9% and 7.4%. Thus, while not economically active women are more likely to enter the labour force, they are less likely to find employment. Moreover, of those women who find employment, 77.7% find employment in the informal sector, as compared to 61.9% of men. Regardless of initial state, African

females who find employment are more likely to be employed in the informal sector than in the formal sector, relative to males in the same initial state.

**Table 8a**  
**Transition rates : African Adults Male**

	Wave t				
	NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Numbers	2,153	2,110	4,423	2,791	8,758
Wave t+1					
NEA	61.82	11.26	7.91	6.46	1.51
Unempl_d	10.95	33.62	16.55	9.32	2.34
Unempl_s	13.25	36.23	51.29	15.87	6.92
Empl_inf	8.66	11.78	11.43	47.44	6.5
Empl_for	5.32	7.11	12.82	20.91	82.73
Total	100	100	100	100	100

**Table 8b**  
**Transition rates : African Adults Female**

	Wave t				
	NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
Numbers	5,381	4,899	5,921	5,257	5,844
Wave t+1					
NEA	53.86	18.62	11.3	12.7	3.01
Unempl_d	17.51	40.06	23.06	11.61	3.15
Unempl_s	13.24	26.22	46.82	12.32	7.18
Empl_inf	11.96	11.34	11.74	55.2	7.42
Empl_for	3.43	3.77	7.07	8.17	79.25
Total	100	100	100	100	100

This is remarkably consistent with the findings of Casale and Posel (2002), who found the identical changes in the levels in each state in the period from 1995 to 1999. Part of male/female difference undoubtedly arises from the importance of informal sector domestic work in South Africa which is predominantly female. However, greater access to informal sector employment would not necessarily explain why a smaller proportion of females, conditional only on their wave  $t$  state, find formal sector employment than males.

#### 4.5 Difference between African youths by gender

Finally, we investigate gender differences for African youth in Tables 9a and 9b. Patterns are broadly consistent with the prior results. One point of departure is that about 30% of both male and female informal sector workers are likely to withdraw completely from the labour force. One possibility is that such workers are doing so to continue their studies, which could well be justified given the poor employment probabilities they experience.

Unlike earlier subpopulations considered, African female youth are more likely to transit into a formal sector job directly from searching unemployment than from informal sector employment.

The formal – informal sector differences are no longer clear cut. Females are more likely to keep a formal sector job, but unemployed and informally employed females are still less likely to find one. Females are more likely to enter the labour force than males. Of those who enter the labour force, both genders find formal sector employment at approximately the same rate (3.4% vs. 3.1%)<sup>16</sup>, but males are considerably more likely to find informal sector employment (15.2% vs. 8.8%). The remainder becomes unemployed. Of those who were unemployed in wave *t*, females are slightly more likely to still be unemployed, and less likely to find employment. The finding here is that the employment prospects are exceptionally bleak for both demographic groups. Fewer than 1 in 10 females and about 1 in 8 males who are actively searching for employment are employed in either sector six months later.

**Table 9a**  
**Transition rates : African Youth Male**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	10,093	1,434	2,068	609	573
Wave t+1	NEA	84.95	20.12	16.21	29.67	6.97
	Unempl_d	5.96	38.61	21.06	16.05	9.14
	Unempl_s	6.28	30.98	49.88	18.23	20.49
	Empl_inf	2.29	6.29	5.48	26.79	5.94
	Empl_for	0.51	4	7.37	9.26	57.45
	Total	100	100	100	100	100

**Table 9b**  
**Transition rates : African Youth Female**

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	10,203	2,315	2,386	453	365
Wave t+1	NEA	81.31	22.88	18.05	30.87	6.77
	Unempl_d	9.05	42.75	22.92	18.5	10.71
	Unempl_s	7.4	27.64	49.62	20.88	15.42
	Empl_inf	1.65	4.83	4.17	25.65	3.55
	Empl_for	0.58	1.9	5.24	4.1	63.54
	Total	100	100	100	100	100

<sup>16</sup>  $3.389\% = 0.51/(100-84.95)$ ,  $3.103\% = 0.58/(100-81.31)$

## 5. Conclusions

Our primary aim in this paper was to draw attention to a data resource that could prove useful to researchers interested in the South African labour market. We described in detail one possible way in which longitudinal data could be matched across five waves of the Labour Force Surveys. We then performed some analyses to probe the data quality in our matched panels. While the resulting data is far from perfect, we believe it is sufficiently accurate to be useful in analysis of labour market transitions. Moreover, the current lack of alternative longitudinal datasets that cover the entire country enhances the value of such a resource. In the future, we look forward to nationally representative panel data that will emerge from the National Income Dynamics Study.

The second contribution of this paper was to estimate transition rates across various labour market states in South Africa. These transition rates should be interpreted with some caution. We did not test for statistically significant differences between groups, nor control for other covariates. In particular, we did not control for any year- or season-specific labour market shocks. In some cases, transition rate estimates are likely to be much less accurate due to small sample sizes.

Bearing in mind that transition rates off diagonal are probably underestimating movement in the labour market, we learn that transitions from informal sector employment into formal sector work across a 6 month period are almost uniformly and substantially higher for all groups than transitions into formal jobs from other states. Whether this is a reflection of type (the types who get informal jobs are motivated to move on to formal jobs) or of opportunity (getting an informal job is a stepping stone to a formal work relationship) is not something we can test in these data. Africans have far lower rates of movement into formal sector work than other race groups at all ages and women are most likely to find an informal sector job, if at all. We believe our paper takes a useful step forward in understanding South African labour market dynamics.

## References

Ashenfelter, O. Deaton, A. and Solon, G. (1986). "Collecting Panel Data in Developing Countries: Does it Make Sense?" Living Standards Measurement Study, Working Paper # 23. Available at "[http://www-wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/1999/03/31/000178830\\_98101902170529/Rendered/PDF/multi0page.pdf](http://www-wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/1999/03/31/000178830_98101902170529/Rendered/PDF/multi0page.pdf)"

Bhorat H., Leibbrandt M., Mayiza M., van der Berg S., Woolard I. (2001). Fighting Poverty: Labour Markets and Inequality in South Africa. UCT Press: Cape Town.

Black P. (2004) "Poverty at the household level: A review of theory and South African evidence", South African Journal of Economics 72 (3): 413-436 September

Brookes M., Hinks T. (2004) "The racial employment gap in South Africa" South African Journal of Economics 72 (3): 573-597 September

Casale D., Muller C., Posel D. (2004). "Two million net new jobs': A reconsideration of the rise in employment in South Africa, 1995-2003" South African Journal of Economics 72 (5): 978-1002 December

Casale D., Posel D. (2002). "The continued feminisation of the labour force in South Africa: An analysis of recent data and trends" South African Journal of Economics 70 (1): 156-184 March

Cichello P.L., Fields G.S., Leibbrandt M. (2005). "Earnings and employment dynamics for Africans in post-apartheid South Africa: A panel study of KwaZulu-Natal" Journal of African Economies, 14 (2): 143-190 June

Dinkelman T. (2004) "How household context affects search outcomes of the unemployed in Kwazulu-Natal, South Africa: A panel data analysis" South African Journal of Economics 72 (3): 484-521 September

Grun C. (2004) "Direct and indirect gender discrimination in the South African labour market" International Journal Of Manpower 25 (3-4): 321-342

Keswell M. (2001). "Intra-generational Mobility: A Study of Chance and Change in Post-apartheid South Africa". DPRU Conference 2001 Available at: [http://www.commerce.uct.ac.za/research\\_units/dpru//Conf2001PDF/KESWELL.PDF](http://www.commerce.uct.ac.za/research_units/dpru//Conf2001PDF/KESWELL.PDF)

Kingdon G.G. and Knight J. (2001a). "What have we learned about Unemployment from Microdatasets in South Africa?" DPRU Conference 2001 Available at: [http://www.commerce.uct.ac.za/research\\_units/dpru//Conf2001PDF/kingdon&knight.pdf](http://www.commerce.uct.ac.za/research_units/dpru//Conf2001PDF/kingdon&knight.pdf)

- Kingdon G.G., and Knight J. (2001b). "Why high open unemployment and small informal sector in South Africa?" Available at:  
[www.csae.ox.ac.uk/resprogs/usam/why%20small%20informal%20sector.pdf](http://www.csae.ox.ac.uk/resprogs/usam/why%20small%20informal%20sector.pdf)
- Kingdon G.G., and Knight J. (2004). "Race and the incidence of unemployment in South Africa", Review of Development Economics, 8(2), 198 – 222.
- Klasen S. and Woolard, I. (1999). "Levels, trends and consistency of employment and unemployment figures in South Africa", Development Southern Africa, 16: 3-35
- Madrian, B. C. and Lefgren, L. J. (1999) "A Note on Longitudinally Matching Current Population Survey (CPS) Respondents" NBER Working Paper No. T0247, November
- May, J., Carter, M. R., Haddad, L., and Maluccio, J. (2000). "KwaZulu – Natal income dynamics study (KIDS) 1993 – 1998: a longitudinal household dataset for South African policy analysis", Development South Africa, 17(4), 567 – 581
- Ranchhod, V. (2006). "The Effect of the South African Old Age Pension on Labour Supply of the Elderly" South African Journal of Economics 74:725-744
- Rospabe, S. (2002). "How did labour market racial discrimination evolve after the end of apartheid? - An analysis of the evolution of employment, occupational and wage discrimination in South Africa between 1993 and 1999" South African Journal of Economics 70 (1): 185-217 March
- Wittenberg M, (2002). "Job search in South Africa: A nonparametric analysis" South African Journal of Economics 70 (8): 1163-1197 December
- Wooldridge, J. M. (2001). (2002)" Econometric Analysis of Cross Section and Panel Data, The MIT Press