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by

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

V. Ranchhod[1] and T. Dinkelman[2]

Abstract

We generate a longitudinal dataset using the rotating panel component of the nationally representative Labour Force Surveys from 2001 to 2003. 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 may be desirable for studying income mobility over a significant period of time but is not ideal for studying the rate at which people find jobs. It is possible that 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, Western Cape. 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. They do contain much more information on work and labour market transitions between waves than the KIDS since retrospective job histories are collected from the young aduts. These data would be appropriate for analysing labour market dynamics among young people; however, we would not be able to learn more about these dynamics for all adults since the oldest CAPS respondents are now 26 years of age.

In this paper, we aim to 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 (LFS) between September 2001 and September 2003 can be matched to help us in this descriptive 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 challenges of this procedure.

Our data complement the recently released Statistics South Africa individual level panel, which also draws on multiple waves of the LFS. While the official release (based on name matches) almost surely has fewer false matches, these data have been stripped of household identifiers. This seriously limits the types of analyses the data can be used for, as no information about other household residents is linked to the individual. Questions about spousal effects and home production, the effects of pension income on schooling and labor supply, or even simple aggregations of household income for per capita poverty classifications are unanswerable with the Statistics South Africa panel. With our panel, such household level variables can be constructed, allowing researchers to analyses different sorts of questions.

We begin this paper by describing how we created the 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 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 transitions 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 Bhorat 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 September

2003, (i.e. LFS2001:2 to LFS2003:2), 20% of dwellings were out-rotated from each wave[3] 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, wave 6 in September 2002, wave 7 in March 2003 and wave 8 in September 2003.

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

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: First match each wave *t* with wave *t+1* using only the household identifiers, where *t*= 4, 5, 6 or 7.

Step 2: Exclude all households present in wave *t* but not in wave *t+1*, (or vice versa), as it is impossible to match these observations across waves. This excludes all respondents in dwellings rotated out of the sample from wave *t* or introduced into the sample in wave *t+1*. [4]

Step 3: 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 4: 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

[3] As stated in the official meta-data releases of Statistics South Africa.

[4] Statistics South Africa indicated that household identifiers were generally maintained across waves for revisited properties. For properties containing multiple dwellings, household identifiers were not necessarily maintained across waves.

uniquely identify these observations based on their demographic characteristics in the corresponding wave *t* or *t+1*.

Step 5: 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 6: 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 7: 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 8: The matches in steps 5, 6 and 7 are appended to generate the full panel, which we refer to as the 'expanded match'.

Step 9: 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[5]:

"NEA"	: not economically active, = 1 is 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 "$panel_{ij}$" where 'i' and 'j' refer to the number corresponding to wave *t* and wave *t+1* respectively. We thus have $panel_{45}$, $panel_{56}$, $panel_{67}$ and $panel_{78}$. Table 2 shows sample sizes. Our average match rate is approximately 52% using the expanded criteria and 38% using the strict criteria.[6] The final pooled sample across the four waves is very large: 117,553 observations using the strict criteria and 161,289 observations using the expanded criteria.

[5] We made use of the classifications provided by Statistics South Africa here. The variables are called "status1", "status2" and "sectorwk".

[6] This compares reasonably well 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 households common to both waves & not new to household		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	106,455	109,410	80,782	75,342	37,161	27,723	0.49	0.37
Panel 56	109,410	102,535	88,587	84,526	44,041	30,280	0.52	0.36
Panel 67	102,535	100,834	81,831	76,489	40,582	30,930	0.53	0.40
Panel 78	100,834	105,025	76,121	72,710	39,505	28,620	0.54	0.39
All Panels	419,234	417,804	327,321	309,067	161,289	117,553	0.52	0.38

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. 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 non-Africans, 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’.[7] Probit results were consistent with information in Table 3 telling us who is more likely to be matched. 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 probability, with an even stronger relationship amongst those who owned their homes but did not yet have it fully paid off. [8]

[7] These regressions included in the appendix at the end of the paper.

[8] 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.

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

	Wave 4	Wave 5	Wave 6	Wave 7	Wave 8	Panel 45	Panel 56	Panel 67	Panel 78
% male	47.3	47.7	47.8	47.6	47.7	46.3	46.4	46.2	46.5
% African	79.2	78.1	78.0	77.8	77.5	77.3	75.8	76.2	76.0
% Coloured	11.4	11.4	11.6	11.6	11.7	12.5	12.9	12.9	13.2
% Indian	2.0	2.2	2.3	2.4	2.3	2.4	2.4	2.3	1.9
% White	7.3	8.2	8.1	8.2	8.5	7.8	8.9	8.5	9.0
% Urban	53.7	54.4	53.5	53.6	53.5	55.2	56.5	55.1	55.2
% Age < 25	53.6	52.7	53.3	53.1	52.6	55.2	54.8	54.3	54.8
% 24 < Age < 60	39.2	39.8	39.2	39.3	39.6	37.3	37.2	37.6	37.3
% 60 < Age	7.2	7.5	7.5	7.6	7.7	7.6	8.0	8.1	8.0
% NEA	37.5	35.4	38.1	37.7	38.2	40.6	39.3	40.8	40.6
% Unemp_D	10.5	10.3	9.8	9.9	11.7	9.9	9.7	9.4	9.0
% Unemp_S	15.1	15.8	15.4	16.0	13.6	14.1	15.0	14.5	15.1
% Empl_informal	11.6	12.5	10.8	10.5	10.3	10.8	11.0	9.7	9.6
% Empl_formal	25.3	25.9	25.9	25.9	26.2	24.7	25.1	25.6	25.8

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. Alternatively, if unobservable characteristics are reasonably proxied for by observable characteristics, then the IPW will correct for this. For example, suppose that starting to receive a pension is correlated with both migration and retirement, and that age-eligibility is a reasonable proxy for pension recipiency. If we cannot observe pension recipiency but include age-eligibility instead we could appropriately correct for this.

For most analyses, however, it is likely that unobservable differences should matter. People presumably 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 search for jobs are the ones most likely missing from the matched panel. It would be difficult to find reasonable proxies for `search type' in remaining observables.

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.[9] 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 four panels were pooled to generate these tables and all estimates are weighted using person weights released by Statistics South Africa[10], 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 2.65 in the column labeled 'NEA' and in the row labeled 'Empl_for' in Table 4a, indicates that 2.65% 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, 3 entries have an absolute difference of greater than 1 % point, with the largest difference of 1.47 % points in the proportion of not economically active remaining not economically active. On the other hand, 15 of the 25 entries have an absolute value of less than 0.5 % points. 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[11].

[9] 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."

[10] We used the person weight in wave *t* as the relevant person weight.

[11] 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
	Numbers	30,880	9,959	15,476	9,620	25,705
	NEA	75.69	19.68	12.63	12.55	2.92
	Unempl_d	8.8	36.56	19.57	10.57	2.33
Wave t+1	Unempl_s	8.56	29.39	48.13	13.72	6.12
	Empl_inf	4.29	9.58	9.46	48.71	5.38
	Empl_for	2.65	4.78	10.21	14.44	83.25
		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
	Numbers	22,738	6,529	10,173	6,004	17,187
	NEA	77.16	19.4	12.08	12.88	2.64
	Unempl_d	8.41	36.58	19.26	10.59	1.94
Wave t+1	Unempl_s	8.01	29.47	49.19	13.26	5.55
	Empl_inf	3.89	9.47	8.78	48.12	4.79
	Empl_for	2.53	5.08	10.68	15.14	85.08
	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
	NEA	-1.47	0.28	0.55	-0.33	0.28
	Unempl_d	0.39	-0.02	0.31	-0.02	0.39
Wave t+1	Unempl_s	0.55	-0.08	-1.06	0.46	0.57
	Empl_inf	0.4	0.11	0.68	0.59	0.59
	Empl_for	0.12	-0.3	-0.47	-0.7	-1.83

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 $X_{t+1} = A_t \, . \, X_t$, 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:

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

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				Expanded Match				Ave: all_waves	
	Wave 45	Wave 56	Wave 67	Wave 78	Wave 45	Wave 56	Wave 67	Wave 78	Strict	Expanded
NEA	-1.02	-0.48	-0.86	-0.21	-1.06	-0.47	-0.77	0.05	-0.64	-0.56
unempl_D	-0.49	0.46	0.93	2.06	0.44	0.43	0.71	2.26	0.74	0.96
unempl_S	1.78	-0.07	0.14	-2.70	1.43	0.27	0.21	-2.61	-0.21	-0.18
empl_inf	-0.53	-0.71	-0.77	-0.40	-0.32	-0.41	-0.22	-0.10	-0.60	-0.26
empl_for	0.25	0.78	0.57	1.25	-0.49	0.16	0.06	0.41	0.71	0.03
Total	0.00	-0.02	0.00	0.00	0.00	-0.02	0.00	0.00	-0.01	-0.01

Note:
With inverse probability reweighting
The totals column is not exactly zero due to rounding errors at various stages of the calculations

On the whole, differences are not large. With the exception of a few categories in panel_{78}, 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 four 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 20% leave the labour market, while about 30% are actively searching for jobs. Approximately 1 in 7 finds employment, although 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, just 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 14.44 %, 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.

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.

Table 6a
Transition rates : African Adults

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	6,396	5,676	9,142	7,265	13,117
	NEA	55.22	16.74	9.73	9.84	1.99
	Unempl_d	15.87	36.76	20.05	10.54	2.6
Wave t+1	Unempl_s	13.67	29.56	48.76	13.43	7.01
	Empl_inf	11.29	12.31	11.98	53.55	7.03
	Empl_for	3.95	4.64	9.47	12.64	81.37
		100	100	100	100	100

Table 6b
Transition rates : Coloured Adults

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	1,830	489	991	800	4,321
	NEA	71.41	24.96	16.28	10.07	2.64
	Unempl_d	7.36	20.36	11.26	3.9	1.61
Wave t+1	Unempl_s	10.43	32.7	43.1	13.06	4.44
	Empl_inf	5.35	7.28	8.54	50.79	3.26
	Empl_for	5.45	14.7	20.81	22.18	88.05
	Total	100	100	100	100	100

Table 6c
Transition rates : White Adults

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	1,234	157	213	323	4,944
	NEA	71.28	45.89	27.07	14.91	3.83
	Unempl_d	6.84	19.08	12.35	1.61	0.66
Wave t+1	Unempl_s	3.38	9.72	24.96	4.73	1.47
	Empl_inf	4	6.46	6.38	23.28	3.22
	Empl_for	14.5	18.85	29.25	55.47	90.83
	Total	100	100	100	100	100

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.[12] Of the searching unemployed, more than 1 in 3 whites find employment, predominantly in the formal sector (82%)[13], while slightly less than 1 in 3 Coloureds find employment, with 71% of these jobs in the formal sector. In contrast, less than 1 in 4 African searchers find employment, with less than half of the newfound employment in the formal sector (44%). A similar pattern holds in

[12] The one exception being not economically active Coloureds, who are more likely to find formal sector jobs than their African counterparts, but are less likely to find **some** type of employment. The difference occurs as Africans in this category are more than twice as likely to find informal sector employment than Coloureds.
[13] Obtained by 29.25/(29.25+6.38)

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, 45.89% of whites leave the labour force, while 24.96% of Coloureds and only 16.74 % 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.[14]

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.

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[15] is approximately equal, African youth are far less successful in finding employment.

[14] 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.

[15] As measured by the proportion of those who transit out of the NEA category between the two waves.

Table 7a
Transition rates : African Youth

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	17,393	3,099	3,883	979	819
	NEA	83.52	22.78	16.87	30.91	7.2
	Unempl_d	7.15	40.44	22.33	16.87	10.14
Wave t+1	Unempl_s	6.65	28.76	49.73	18.63	18.97
	Empl_inf	2.15	5.81	5.35	27.37	4.65
	Empl_for	0.53	2.21	5.71	6.22	59.04
	Total	100	100	100	100	100

Table 7b
Transition rates : Coloured Youth

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	1,723	386	842	118	872
	NEA	77.58	17.64	12.68	6.81	4.22
	Unempl_d	5.65	25.7	16.36	20.27	4.65
Wave t+1	Unempl_s	12.19	40.41	51.43	14.7	14.56
	Empl_inf	0.76	3.07	2.73	23.64	2.63
	Empl_for	3.82	13.18	16.8	34.58	73.94
	Total	100	100	100	100	100

Table 7c
Transition rates : White Youth

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	1,085	47	99	30	422
	NEA	84.92	36.96	24.38	24.39	8.32
	Unempl_d	2.28	14.81	3.38	0	2.51
Wave t+1	Unempl_s	4.64	18.76	26.17	13.05	5.7
	Empl_inf	0.39	0	3.62	7.6	1.67
	Empl_for	7.77	29.47	42.45	54.96	81.81
	Total	100	100	100	100	100

The following 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, 43% are ‘discouraged’, while another 40% are actively searching. Only 3.2% find formal sector employment. For Coloured entrants, 25% are discouraged, 54% are actively searching, while 17% have found formal employment. Even among whites, who experience by far the most positive entry into the labour market, only 51.5% have found formal sector jobs, while 15% are ‘discouraged’ and 30.7% 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.

Table 8a
Transition rates : African Adults Male

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	1,867	1,724	3,954	2,471	7,758
	NEA	60.56	11.61	8.15	6.27	1.46
	Unempl_d	11.37	32.33	16.44	9.3	2.35
Wave t+1	Unempl_s	13.78	36.49	50.82	16.17	6.98
	Empl_inf	8.72	12.54	11.83	47.33	6.81
	Empl_for	5.57	7.03	12.76	20.93	82.4
	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	4,529	3,952	5,188	4,794	5,359
	NEA	52.9	19.2	11	11.85	2.83
	Unempl_d	17.83	38.89	22.94	11.23	3.01
Wave t+1	Unempl_s	13.62	26.23	47.11	11.89	7.05
	Empl_inf	12.41	12.19	12.11	57.05	7.39
	Empl_for	3.24	3.49	6.84	7.98	79.71
	Total	100	100	100	100	100

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. Females who are in the labour force in a particular state are more likely to leave than males in the same state. 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, with women considerably more likely to find and keep informal sector employment. Of men who enter the labour force, 22.1% find informal sector employment, while another 14.1% find formal sector employment. For women, the corresponding numbers are 26.3% and 6.9%. 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, almost 80% find employment in the informal sector, as compared to 61% of men. Regardless of initial state, African females are more likely to be employed in the informal sector than in the formal sector, relative to males in the same initial state.

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 over 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 (3.217% vs. 3.200%)[16], but males are considerably less likely to find informal sector employment (9.65% vs. 17.1%). The remainder become unemployed. Of those who were unemployed in wave *t*, females are 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. Less than 1 in 10 females and 1 in 8 males who are actively searching for employment are employed six months later.

[16] 3.217% = 0.47/(100-85.31), 3.200%=0.59/(100-81.66)

Table 9a
Transition rates : African Youth Male

		Wave t				
		NEA	Unempl_d	Unempl_s	Empl_inf	Empl_for
	Numbers	8,670	1,180	1,805	547	495
	NEA	85.31	22.12	16.62	30.28	6.97
	Unempl_d	5.7	36.68	21.55	15.86	10.18
Wave t+1	Unempl_s	6.01	30.37	49.36	18.88	21
	Empl_inf	2.52	7.36	6.18	27.02	5.28
	Empl_for	0.47	3.48	6.28	7.96	56.57
	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	8,723	1,919	2,078	432	324
	NEA	81.66	23.22	17.1	31.74	7.6
	Unempl_d	8.66	42.88	23.02	18.21	10.07
Wave t+1	Unempl_s	7.32	27.72	50.06	18.3	15.57
	Empl_inf	1.77	4.8	4.62	27.84	3.6
	Empl_for	0.59	1.39	5.2	3.91	63.17
	Total	100	100	100	100	100

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. In addition, the matched panel we have been able to create complement existing longitudinal data sources.

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Appendix Table: Probit coefficients (marginal effects) for probability of match

	Matched Expanded Criteria				Matched Strict Criteria			
	Wave 4	Wave 5	Wave 6	Wave 7	Wave 4	Wave 5	Wave 6	Wave 7
Unempl_d	-0.042	-0.036	-0.034	-0.058	-0.044	-0.032	-0.051	-0.043
	[0.008]**	[0.008]**	[0.008]**	[0.009]**	[0.007]**	[0.007]**	[0.008]**	[0.008]**
Unempl_s	-0.037	-0.036	-0.039	-0.049	-0.038	-0.026	-0.053	-0.032
	[0.007]**	[0.007]**	[0.007]**	[0.008]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**
Empl_informal	-0.033	-0.028	-0.035	-0.038	-0.048	-0.026	-0.051	-0.038
	[0.008]**	[0.008]**	[0.008]**	[0.009]**	[0.007]**	[0.007]**	[0.008]**	[0.008]**
Empl_formal	-0.036	-0.025	-0.032	-0.045	-0.027	-0.017	-0.037	-0.023
	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.006]**	[0.007]**	[0.007]**
pensionable age	-0.033	0.016	0.02	-0.018	-0.013	0.016	0.023	-0.016
	[0.013]*	[0.012]	[0.013]	[0.013]	[0.012]	[0.012]	[0.013]	[0.013]
Age	-0.011	-0.009	-0.011	-0.009	-0.005	-0.004	-0.004	-0.007
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Age < 20	0.048	0.064	0.04	0.063	0.068	0.066	0.077	0.063
	[0.009]**	[0.008]**	[0.008]**	[0.009]**	[0.008]**	[0.008]**	[0.008]**	[0.009]**
Age squared	0	0	0	0	0	0	0	0
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
Age cubed	0	0	0	0	0	0	0	0
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
Coloured	0.075	0.069	1	0.087	0.069	0.069	0.964	0.091
	[0.008]**	[0.007]**	[0.000]**	[0.008]**	[0.008]**	[0.007]**	[0.031]**	[0.008]**
Indian	0.065	0.052	0.077	-0.033	0.084	0.039	0.071	-0.014
	[0.013]**	[0.012]**	[0.008]**	[0.013]*	[0.013]**	[0.012]**	[0.008]**	[0.013]
White	0.065	0.046	0.031	0.048	0.099	0.082	0.054	0.089
	[0.008]**	[0.008]**	[0.013]*	[0.008]**	[0.008]**	[0.008]**	[0.013]**	[0.008]**
Race_other	-0.402	-0.45	0.072		-0.3	-0.296	0.105	
	[0.023]**	[0.024]**	[0.008]**		[0.020]**	[0.023]**	[0.008]**	
male	-0.012	-0.02	-0.026	-0.021	-0.016	-0.018	-0.027	-0.026
	[0.004]**	[0.004]**	[0.004]**	[0.004]**	[0.003]**	[0.003]**	[0.004]**	[0.004]**
urban	0.038	0.025	0.021	0.016	0.031	0.019	0.017	0.015
	[0.005]**	[0.005]**	[0.005]**	[0.005]**	[0.004]**	[0.004]**	[0.005]**	[0.005]**
province==2	0.008	-0.01	-0.047	-0.058	0.008	0.002	-0.035	-0.058
	[0.009]	[0.008]	[0.009]**	[0.009]**	[0.009]	[0.008]	[0.008]**	[0.008]**
province==3	-0.021	-0.046	-0.066	-0.111	-0.029	-0.038	-0.069	-0.091
	[0.010]*	[0.010]**	[0.010]**	[0.010]**	[0.009]**	[0.009]**	[0.009]**	[0.009]**
province==4	0.017	0.026	-0.023	-0.011	0.009	0.014	-0.029	-0.025
	[0.010]	[0.010]**	[0.010]*	[0.010]	[0.010]	[0.009]	[0.009]**	[0.010]*
province==5	-0.081	-0.08	-0.111	-0.16	-0.072	-0.057	-0.098	-0.13
	[0.009]**	[0.009]**	[0.009]**	[0.009]**	[0.008]**	[0.008]**	[0.008]**	[0.008]**
province==6	0.069	0.035	0.01	-0.024	0.057	0.028	0.011	-0.022
	[0.010]**	[0.009]**	[0.010]	[0.010]*	[0.009]**	[0.009]**	[0.009]	[0.009]*
province==7	-0.074	-0.053	-0.068	-0.071	-0.065	-0.06	-0.068	-0.078
	[0.009]**	[0.009]**	[0.009]**	[0.009]**	[0.008]**	[0.008]**	[0.008]**	[0.008]**
province==8	0.03	0.008	-0.017	-0.011	0.015	0.001	-0.03	-0.006
	[0.010]**	[0.010]	[0.010]	[0.010]	[0.009]	[0.009]	[0.009]**	[0.009]
province==9	0.043	0.032	0.013	0.007	0.034	0.037	0.025	0.016
	[0.010]**	[0.009]**	[0.009]	[0.010]	[0.009]**	[0.009]**	[0.009]**	[0.009]
Widowed	-0.011	-0.025	-0.017	-0.012	-0.021	-0.036	-0.032	-0.021
	[0.010]	[0.009]**	[0.010]	[0.010]	[0.009]*	[0.009]**	[0.009]**	[0.010]*
Divorced	-0.022	-0.068	-0.045	-0.051	-0.074	-0.091	-0.083	-0.082
	[0.013]	[0.012]**	[0.012]**	[0.013]**	[0.012]**	[0.010]**	[0.012]**	[0.012]**
Never Married	-0.055	-0.054	-0.053	-0.056	-0.017	-0.023	-0.012	-0.012
	[0.006]**	[0.006]**	[0.006]**	[0.006]**	[0.006]**	[0.006]**	[0.006]*	[0.006]
Marital_unknown	0.038	-0.417	0.299	-0.283	0.191	-0.246	0.305	-0.181
	[0.220]	[0.082]**	[0.180]	[0.120]*	[0.222]	[0.089]**	[0.201]	[0.115]
hhsize	-0.008	-0.012	-0.011	-0.012	-0.008	-0.011	-0.011	-0.012
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Dwelling_owned + paid off	0.103	0.162	0.126	0.157	0.101	0.136	0.113	0.132
	[0.007]**	[0.007]**	[0.007]**	[0.008]**	[0.006]**	[0.006]**	[0.007]**	[0.008]**
Dwelling_owned + not paid off	0.137	0.186	0.153	0.189	0.137	0.174	0.144	0.172
	[0.009]**	[0.008]**	[0.009]**	[0.010]**	[0.009]**	[0.009]**	[0.009]**	[0.011]**
renting	0.002	0.019	0.032	0.05	0.029	0.035	0.041	0.049
	[0.008]	[0.008]*	[0.009]**	[0.009]**	[0.008]**	[0.008]**	[0.009]**	[0.010]**
wall_brick	0.008	0.053	0.025	0.031	0.009	0.042	0.035	0.033
	[0.008]	[0.008]**	[0.008]**	[0.009]**	[0.008]	[0.007]**	[0.008]**	[0.009]**
wall_cement	0.013	0.071	0.037	0.038	0.004	0.057	0.049	0.04
	[0.009]	[0.008]**	[0.008]**	[0.009]**	[0.008]	[0.008]**	[0.008]**	[0.009]**
wall_iron	0.021	0.046	0.04	0.032	0.019	0.059	0.026	0.03
	[0.011]	[0.010]**	[0.010]**	[0.011]**	[0.010]	[0.010]**	[0.010]*	[0.011]**
house_shack	-0.037	-0.066	-0.062	-0.079	-0.034	-0.063	-0.048	-0.059
	[0.010]**	[0.009]**	[0.010]**	[0.010]**	[0.010]**	[0.009]**	[0.009]**	[0.010]**
house_other	-0.041	-0.058	-0.058	-0.083	-0.033	-0.038	-0.049	-0.063
	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.007]**	[0.006]**	[0.007]**	[0.007]**
house_hut	-0.009	-0.001	-0.008	0.015	-0.019	-0.015	-0.01	0.011
	[0.009]	[0.008]	[0.008]	[0.009]	[0.008]*	[0.008]*	[0.008]	[0.009]
education_unknown	0.001	0.02	-0.011	0.009	-0.102	-0.055	-0.109	-0.129
	[0.016]	[0.017]	[0.018]	[0.019]	[0.013]**	[0.015]**	[0.016]**	[0.016]**
years of education	0.009	0.007	0.008	0.008	0.001	0.008	0.002	-0.002
	[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]	[0.001]**	[0.001]**	[0.001]*
matric	-0.013	-0.007	-0.006	-0.003	0.009	0.006	0.025	0.059
	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.006]	[0.007]**	[0.007]**
can read	0.041	-0.006	0.075	0.021	-0.028	-0.089	-0.015	0.01
	[0.024]	[0.027]	[0.029]**	[0.031]	[0.024]	[0.027]**	[0.029]	[0.030]
can write	-0.017	0.034	-0.052	0.012	-0.007	-0.034	-0.036	0
	[0.024]	[0.026]	[0.029]	[0.031]	[0.023]	[0.026]	[0.028]	[0.030]
Observations	80688	88486	81729	76042	80688	88486	81729	76042

Standard errors in brackets
* significant at 5%; ** significant at 1%

Notes:
Race_other was dropped from the wave 7 regressions as it predicted failure perfectly.
Age missing was similarly dropped.
Omitted categories:

Labour market status:	Not economically active
Race:	African
Provinces:	Western Cape
Marital status:	Married / Living together as husband/wife
Dwelling ownership:	Rent free accomodation
Wall_type:	Mud walls
House type:	Brick

The Southern Africa Labour and Development Research Unit

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

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

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