Short-run differences between static and dynamic measures of earnings inequality in South Africa

Arden Finn & Vimal Ranchhod

Abstract

A substantial literature has evolved in South Africa over the last twenty years that has estimated the levels and trends in income and earnings inequality. The evidence is overwhelming that South Africa both was, and remains, one of the most unequal societies in the world, although most of these measures are obtained using cross-sectional data. We contribute to this literature by investigating a dynamic measure of earnings inequality, using the nationally representative QLFS panel. These are high frequency data where individuals are surveyed up to four times in a twelve month period. The key mechanism by which these might differ from cross-sectional measures is through labour market churning. Our estimates of inequality in earnings drop by a small but meaningful amount when we move from a static measure, with an average Gini coefficient of 0.626, to a one-year average earnings measure with a Gini coefficient of 0.608. The decrease is not larger because, while the South African labour market does display a substantial amount of churning, this churning is concentrated amongst unskilled and low wage earners who fluctuate between unemployment and low-earnings employment. In contrast, well paid and highly skilled individuals tend to have much greater levels of job security, which mitigates the potential differences between the two measures.

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Short-run differences between static and dynamic measures of earnings inequality in South Africa[1]

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1. Introduction

Inequality levels in South Africa are widely recognized as amongst the highest in the world. At the same time, there is evidence of a substantial degree of churning in the labour market. A question arises as to how much this churning would affect dynamic measures of inequality over a short time horizon, relative to similar static measures. In this paper, we make use of longitudinal data from the QLFS panel over the period 2010 to 2014. The data are high frequency, with respondents being observed up to four times over a twelve month period.

To date, a substantial literature has developed in South Africa that relates to measuring the levels and trends in inequality, using multiple datasets and methods. Ranchhod and Leibbrandt (2016) provide a reasonable overview of the evolution of this literature. Prior to 1994, serious data limitations meant that very few empirical studies were done that could speak to national level inequality for the pre-1994 era.[4]

The empirical measurement literature then developed quite rapidly in the post-apartheid era. Leibbrandt, Bhorat and Woolard (2001) make use of income data from two separate cross-sectional datasets, the Income and Expenditure survey of 1995 (IES95), and the 1993 PSLSD survey. Their overall point, after much investigation, is that wage inequality is by far the major contributor to income inequality, and that an important factor to consider is unemployment/non-employment.

Hoogeveen and Özler (2006) moved the literature forward by comparing income and expenditures from the IES95 to the IES00, again two cross-sections, which were conducted in 1995 and 2000 respectively. They found that inequality increased during this period, mostly due to an increase in the inequality measured within the African subpopulation. For example, for the entire sample the mean log deviation increased from 0.56 to 0.61 during

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[4] Some of the commonly cited studies are Nattrass (1977), Treiman et al (1996), Whiteford and McGrath (1994) and Whiteford and Seventer (2000).

this period, while the Gini coefficient increased from 0.565 to 0.577. In contrast, Leibbrandt, Woolard and Woolard (2009) looking at a similar time period but using the 1996 and 2001 Census data, estimate Gini coefficients of 0.68 and 0.73 respectively. They thus estimate similar trends but substantially different levels of inequality.

The overall empirical literature is too large to describe here. These include the papers by Simkins (2004), Leibbrandt, Levinsohn and McCrary (2010), Ardington, Lam, Leibbrandt and Welch (2005), Leibbrandt, Woolard, Finn and Argent (2010), van der Berg and Louw (2004), van der Berg, Louw and Yu (2008), Yu (2010) and Leibbrandt, Finn and Woolard (2012); and even this list is not exhaustive. They differ in terms of the datasets employed, the assumptions underlying how to deal with missing data and whether the analysis is done at the household or individual level. In terms of findings, there remains debate about the actual levels of inequality and the rate at which it is changing.

Van der Berg (2010: 12), in the literature review section of his paper, succinctly summarizes the state of the literature in South Africa as follows: "Thus there was probably a strong upward trend in inequality as measured by the Gini coefficient in the second half of the 1990s, and largely stable inequality since. Inequality is clearly very high, but how high is not clear... Ginis simply differ greatly even for the same year due to data comparability and measurement issues”.

This paper contributes to the inequality measurement literature in South Africa by using high frequency longitudinal data to estimate short run measures of inequality that account for transitory changes in earnings levels.[5] An illustrative example may help to show why this might be important. Consider a hypothetical two person economy where each person works for at most two periods. Suppose that in the first period, person A is employed and earns R100, while person B is unemployed and has no income. In the second period, they reverse roles with real wages being held constant. While in either period, a cross-sectional measure of inequality would indicate extreme inequality,[6] the two-period dynamic inequality would yield each person earning R50 on average in each period; a situation of perfect inequality. The crucial part of the above example is the labour market churning, and there exists some empirical evidence that the levels of short-run churning in South Africa are substantial.[7] Of course, the example does not necessarily hold in the real world, where there are millions of people and many are in stable employment or unemployment, but there are nonetheless

[5] Note that this is conceptually different to using longer run panel studies, such as NIDS or KIDS, to measure inequality, which are better suited to measuring income mobility or life cycle inequality.
[6] Indeed, the Gini would be 1 in either period.
[7] See Ranchhod and Dinkelman (2007) and Ranchhod (2013).

people who find and lose jobs all the time. Ultimately, the question about the effect of this on inequality measurement remains to be informed by empirical analysis.

To summarize our findings; we find that there is a substantial amount of churning over any given twelve month period, but that this is concentrated amongst low wage earners. This results in a small but meaningful reduction in our measured earnings inequality, from an average over the static Gini coefficients of 0.625 to a Gini coefficient of average incomes of 0.608.

The remainder of this paper is structured as follows. In Section 2 we describe the data and present some summary statistics. In Section 3 we present some results that investigate the levels and correlates of churning. Section 4 contains our estimates of the Gini coefficients using alternative income measures. Section 5 contains the results of some regression models where we investigate the factors that correlate with changes in income across the waves in our data. Section 6 concludes.

2. Data

We make use of the rotating panel components of Statistics South Africa's Quarterly Labour Force Surveys (QLFS). The rotating panel of this survey was designed so that there would be an overlap of 75% of households between consecutive waves. In other words, in each quarter, 25% of dwelling units rotate out of the survey, and are replaced by dwelling units that should, ideally, remain in the sample for the next four quarters. Although the sampling takes place at the dwelling unit or household level, we make use of link files to identify individuals who are interviewed in multiple waves.[8] We also make use of the demographic data from the QLFSs and wage data from the Labour Market Dynamics in South Africa (LMDSA) datasets from the first quarter of 2010 to the fourth quarter of 2014, thus allowing us to work with 20 quarters of data.

In Table 1 we present the sample sizes and simple descriptive statistics of working age individuals[9] who appear in at least two and at most four consecutive quarters in the data. The table pools the data from individuals over time, so that if a respondent was interviewed in two quarters, we treat it as if there are two observations. We will change this assumption when we calculate inequality measures and run some regressions, but for now we treat each person-time combination as an independent observation. The quarters that bookend

[8] These 'link' files were made available to us from StatsSA as part of a data quality exercise that we collaborated with them on. The match quality in the 'links' is likely to be very high, as the information used to identify people across waves included demographic information as well as the individual's name.
[9] We define this as those respondents who are between the ages of 15 and 64.

our analysis have the fewest respondents, with 38 400 and 36 296 in quarters one and 20 respectively. The remaining quarters from quarter 2 of 2010 to quarter 3 of 2014 have approximately 50 000 respondents each. This gives us a total of close to one million observations across the entire time period under analysis.

The average age of working age respondents is stable throughout the period of analysis, and is around 34 years. The same can be said for the number and proportion of males in the sample, as well as of those in the economic status categories of employed, unemployed, discouraged and not economically active.

Table 1. Sample sizes

Wave	Age	Male	Empl.	Unemp.	Disc.	NEA	Total
1	33.94	17,434	14,707	5,031	2,388	16,274	38,400
2	33.87	23,800	20,092	6,921	3,276	21,988	52,277
3	33.88	23,466	19,544	6,685	3,320	22,016	51,565
4	33.91	23,084	19,252	6,125	3,495	21,446	50,318
5	33.96	22,699	18,912	6,251	3,600	20,834	49,597
6	33.95	22,453	18,812	6,363	3,415	20,743	49,333
7	34.01	23,116	19,590	6,500	3,500	21,040	50,630
8	34.04	23,249	20,029	6,278	3,656	21,006	50,969
9	34.06	23,472	19,968	6,727	3,666	20,721	51,082
10	34.10	23,561	19,848	6,773	3,644	21,084	51,349
11	34.12	23,754	20,313	7,082	3,429	20,857	51,681
12	34.17	23,834	20,263	6,860	3,410	21,063	51,596
13	34.18	23,619	20,099	6,879	3,554	20,684	51,216
14	34.22	24,018	20,623	7,117	3,604	20,753	52,097
15	34.26	24,208	20,853	6,989	3,498	20,840	52,180
16	34.30	24,294	21,045	6,859	3,365	21,127	52,396
17	34.34	24,116	20,667	7,173	3,585	20,496	51,921
18	34.33	23,236	20,017	7,057	3,481	19,827	50,382
19	34.42	23,062	19,987	6,889	3,567	19,607	50,050
20	34.52	16,635	14,611	4,676	2,505	14,504	36,296
N							**995,335**

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations restricted to panel members between 15 and 64 years of age. Cross sectional weights applied.

In Table 2 we take a closer look at the characteristics of those respondents between the ages of 15 and 64 who were interviewed successfully in multiple waves. The proportion of male respondents was about two percentage points lower than the proportion of females. 35% of respondents had at least completed a matric education, while the proportion with primary schooling or lower was about 19%. 42% of respondents were employed across the 20 quarters, and 37.26% were classified as being 'not economically active'. Of the 995 335 respondents who were interviewed in more than one wave, over two-thirds were interviewed in all four possible waves, 20% were interviewed in 3 waves, and just under 12%

were interviewed in 2 waves. This means that we have close to 170 000 respondents for whom we have data over four consecutive quarters. Not all of these respondents will have reported labour market earnings in each quarter, but this is nonetheless a large enough sample size to mean that concerns about the power of our findings should be limited.

Table 2. Summary statistics of sample members

Age	34.13
Male	48.92
Education	
No schooling	3.74
Primary	15.42
Inc. Sec	44.43
Matric	25.69
Tertiary	10.73
Labour market status	
Employed	42.26
Unemployed	13.87
Discouraged	6.61
NEA	37.26
Number of waves	
2 waves	11.81
3 waves	19.97
4 waves	68.22
N	**995,335**

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations restricted to panel members between 15 and 64 years of age. Cross sectional weights applied.

3. Understanding the levels of churning

One of the ways in which inequality measured at four (albeit closely-spaced) different intervals in time could differ from a snapshot of inequality is if there is short-run churning in the labour market. Table 3 breaks down, for different categories, the proportion of respondents who were employed in one, two, three or four waves. This is restricted to those who were successfully interviewed in four consecutive waves, and who were employed in at least one of those waves. In this table we change our approach of assuming independence between each individual-quarter observation, and instead treat each respondent as a single record.

Overall, almost 71% of our restricted subset of respondents were employed in each of the four quarters in which they were interviewed. 10% were employed in three out of four quarters, 8% in two out of four quarters, and 11% in only one quarter. This provides evidence of some substantial churning in the labour market, as almost a third of the workforce was at some stage employed and at another stage unemployed over a single 12 month period.

Table 3. Number of waves employed by demographic categories

	Number of waves employed			
	1	**2**	**3**	**4**
All	11.28	8.10	9.90	70.73
Gender				
Male	10.02	7.47	9.63	72.88
Female	12.78	8.84	10.22	68.17
Race				
African	12.73	9.15	10.99	67.13
Coloured	11.06	8.19	9.21	71.54
Asian/Indian	4.95	4.26	6.14	84.65
White	4.37	2.60	4.87	88.15
Education				
No edu	16.63	10.15	12.98	60.24
Primary	15.22	9.97	12.83	61.98
Inc. Sec	14.30	10.56	11.92	63.22
Matric	9.62	7.29	9.09	74.00
Tertiary	4.00	2.74	4.34	88.92
Age category				
18-29	17.22	12.07	13.03	57.69
30-34	11.15	7.83	10.46	70.56
35-49	8.24	6.28	8.34	77.15
50-64	9.23	6.88	8.62	75.27
Geotype				
Urban	9.79	7.22	8.95	74.04
Rural	15.93	10.82	12.83	60.42

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations are weighted and are restricted to panel members between 15 and 64 years of age who were interviewed in four consecutive waves.

When we compare the number of waves that respondents were employed by various demographic characteristics we find some striking patterns. Women were about three percentage points more likely than men to have been employed in only one out of four waves. Close to 73% of men who were interviewed in four consecutive quarters were employed in each of those quarters, while the corresponding proportion of women stood at 68%. Less than 5% of white and Asian/Indian respondents were employed in only a single wave, while the corresponding proportions for Coloured and African respondents were 11% and 12.76% respectively. Conversely, only 67% of African respondents were employed at each quarter of interview, while the proportion of white respondents employed at each interview was close to 90%.

We also see that there was far more churning in the probability of employment for those with relatively few years of schooling compared to those respondents with at least a matric.

63% of those with incomplete secondary education were employed in all four waves. This proportion increases to 74% for those who attained a matric, and then jumps even more sharply to 89% for those with tertiary education. The results broken down by age category are unsurprising, as there is far more churning in the "youth" category of 18 to 29 year olds than there is in the older categories. The 35-49 year old category displays the least churning, with three quarters of respondents in employment in all four waves.

Another way of thinking about churning is to break down the number of waves a respondent was employed by earnings category. We created four earnings categories by averaging earnings for respondents who were interviewed in four consecutive waves.[10] Cut points of the 25th, 50th and 75th percentiles of the resulting distribution were chosen as the boundaries in the creation of four categories. The pattern in Table 4 is clear – there was far more labour market churning at the bottom of the earnings distribution than at the top. Those in the bottom quarter of the distribution – earning R1 723 or less – were more likely to be employed in only one wave than the other earnings categories. In addition, only 55% were employed in all four waves, compared to 68% for the second category, 78% for the third category, and 87% for the category of earnings with waves of R8 000 per month and above. The proportion of respondents employed in one, two or three waves falls at each discrete step up the distribution of wages, while this churning-wage level relationship is reversed for those who were employed in all four quarters.

Table 4. Number of waves employed by earnings categories

	Number of waves employed			
Earnings categories	**1**	**2**	**3**	**4**
Up to R1 723	18.44	12.71	13.62	55.22
R1 723 to R3 425	11.04	8.84	11.75	68.36
R3 425 to R8 000	7.33	6.40	8.68	77.58
R8 000 and up	4.63	3.16	4.91	87.29

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations are weighted and are restricted to panel members between 15 and 64 years of age who were interviewed in four consecutive waves.

Table 5, below, breaks the amount of 12-month churning down by relative positions in the earnings distribution by earnings decile. Deciles were created from the distribution of mean earnings over 4 consecutive waves for those respondents who were interviewed in 4 consecutive waves. The pattern we observe is very similar to that in the previous table, though it is more finely delineated. About 69% of respondents in the bottom 10% of the distribution of earnings were employed in four consecutive waves. The proportion

[10] For example, respondents who were interviewed four times had the sum of earnings divided by four, respondents who only reported one period of earnings simply received that single period of earnings.

employed in all four waves increases at each decile as we move up the earnings distribution, so that by the time we reach the top 10% of earners, over 93% of those who were observed were employed at each quarter of interview. This interplay between the level of wages and the amount of churning has clear implications for inequality – those who earned the lowest wages were also the least likely to be employed in four consecutive waves during a 12 month period.

Table 5. Churning by relative position in the earnings distribution

	Number of waves employed				
Decile	**1**	**2**	**3**	**4**	
1	10.42	9.10	11.94	68.54	100
2	6.18	6.55	10.45	76.82	100
3	5.34	6.07	9.70	78.89	100
4	4.51	4.95	10.12	80.42	100
5	3.22	4.17	8.54	84.06	100
6	3.26	4.61	7.03	85.10	100
7	2.62	3.24	6.35	87.79	100
8	2.61	2.59	4.54	90.25	100
9	1.88	1.64	3.48	93.01	100
10	1.81	1.27	3.71	93.20	100

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations are weighted and are restricted to panel members between 15 and 64 years of age who were interviewed in four consecutive waves.

4. Inequality using different measures of earnings

We now turn our attention to the level of inequality of earnings in the QLFSs between 2010 and 2014. The amount of churning in a single 12-month period, discussed above, should result in average inequality over the full duration of earnings being lower than a single snapshot of inequality. In Table 6 we calculate Gini coefficients for four different categories. In the first column we present inequality levels for each quarter/wave of the QLFS treated as a cross section. We see that the level of earnings inequality as measured by the Gini coefficient was high to begin with at around 0.6, before rising to around 0.68. The average Gini coefficient over the 20 quarters is 0.626.

In the second column we move from a cross-section to an analysis of inequality of those who were interviewed at least twice. We define “any panel member” as a respondent who appears more than once in the data. Restricting the sample in this way makes very little difference to our measures of earnings inequality when compared to the cross-sectional measures of the first column. This is unsurprising as all we are doing is pruning our large sample and then estimating cross-sectional inequality measures.

In the third column we restrict the sample even further to include only those respondents who were interviewed in four consecutive waves. Again, this makes very little difference to our measures of earnings inequality – the average Gini coefficient of 0.624 for this restricted sub-sample is almost identical to the Gini coefficients in the previous two columns. One addition that we make to this column is to include the Gini coefficient of average earnings as distinct from the average Gini coefficient of earnings. This simply involves calculating the mean earnings across the number of waves in which earnings were reported by each respondent, and calculating the Gini coefficient accordingly. The advantage of adopting this method is that we are able to incorporate the effect of changing earnings levels for respondents within a single year period. This churning (or mobility) on the earnings margin results in a lower measure of inequality – the Gini coefficient of average earnings is 0.608. The disadvantage of adopting this method is that it remains agnostic to the level of churning on the employment margin – a respondent who reports earning R1 000 and is employed in only one period out of four is treated the same way as a respondent who earns R1 000 in each of four consecutive periods.

One way of overcoming this problem is to restrict ourselves to panel members who reported earnings in all four waves in which they were interviewed, and this is what is done in the final column. Doing this means that we can focus on the effect of earnings variation on earnings inequality without worrying about respondents moving into and out of employment over a 12 month period. The restriction results in inequality measures that are generally lower during each quarter than the first three columns. The average Gini coefficient over the 20 waves is 0.614, and is quite a bit lower than the average Gini coefficient in the first three columns.

There is an important contrast to be made between the Gini coefficient of average earnings at the bottom of columns three and four, which are 0.608 and 0.601 respectively. The difference between the two is driven by the fact that those respondents who not employed at each time of interview are also those who earn relatively less than those who are employed in four consecutive waves. Restricting our sample to reflect only those who report their earnings in four consecutive quarters means that we exclude a relatively large mass of people towards the bottom of the earnings distribution, and this results in a relatively lower measure of earnings inequality.

Table 6. Inequality by group across waves and on average

Wave	Gini coefficient: All cross section	Any panel members	4 wave panel members	Wages in all 4 waves
1	0.587	0.589	0.593	0.587
2	0.602	0.594	0.594	0.587
3	0.594	0.594	0.592	0.579
4	0.591	0.591	0.590	0.578
5	0.597	0.597	0.600	0.590
6	0.606	0.607	0.612	0.607
7	0.590	0.591	0.597	0.588
8	0.574	0.574	0.578	0.569
9	0.568	0.567	0.567	0.553
10	0.599	0.599	0.599	0.572
11	0.633	0.630	0.634	0.618
12	0.655	0.652	0.659	0.643
13	0.666	0.662	0.662	0.656
14	0.680	0.679	0.677	0.674
15	0.680	0.678	0.659	0.658
16	0.673	0.675	0.666	0.652
17	0.669	0.672	0.664	0.662
18	0.666	0.669	0.650	0.644
19	0.652	0.652	0.652	0.652
20	0.636	0.637	0.631	0.619
Average Gini	**0.626**	**0.625**	**0.624**	**0.614**
Gini of average earnings			**0.608**	**0.601**
Alternative Gini of average earnings			**0.624**	

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations are weighted and are restricted to respondents between 15 and 64 years of age. Column 3 restricts to those who were interviewed in four consecutive waves, and column 4 to those who reported earnings in four consecutive waves.

There is another way in which we can try to incorporate churning on both the employment and earnings margins, and this is shown in the final row of Table 6 as the "alternative Gini of average earnings". As shown previously, around 30% of those who reported earnings at least once were not in fact employed in all four waves in which they were interviewed. We now calculate the average earnings over four quarters by dividing cumulative earnings by 4. This means that if a respondent earned R1 000 in the first quarter and was then unemployed for the subsequent three quarters, the average earnings would be R250. This changes our focus from thinking about the amount of earnings in a single quarter to the amount of earnings over a 12-month period. As expected, the Gini coefficient rises when this method is used, and stands at 0.624. Not only are we including the relatively low earners in our calculation, but we are adjusting for their labour market churning as well.

5. Regression results

Our final table, below, presents output from OLS regressions in which we model some of the factors associated with earnings changes between quarters. This echoes some of the income mobility literature in which the change in income/earnings appears on the left hand side of the estimating equation, and the lagged (first period) income/earnings enters as one of the regressors.

Table 7. Regressions explaining changes in earnings

Variables	(1) ΔW1W2	(2) ΔW2W3	(3) ΔW3W4	(4) ΔW1W4
Lagged earnings	-0.305***	-0.288***	-0.263***	-0.506***
	-0.003	-0.003	-0.003	0.003
Coloured	558.7***	546.6***	339.7**	786.3***
	-186.7	-175.7	-159.5	(207.9)
Asian/Indian	312.4	441.3	877.6***	1,077***
	-312.4	-294	-266.8	(347.8)
White	1,660***	2,270***	2,183***	3,828***
	-181.7	-170.9	-155.3	(202.3)
Age	56.34	61.56*	-28.47	28.92
	-36.09	-33.97	-30.83	(40.19)
Age squared	-0.267	-0.332	0.642*	0.298
	-0.431	-0.406	-0.368	(0.480)
Female	-836.7***	-776.8***	-750.8***	-1,346***
	-115.5	-108.7	-98.67	(128.6)
Urban	463.2***	397.4***	267.8**	633.3***
	-148.1	-139.4	-126.5	(164.9)
Primary	86.32	45.2	496.7	544.1
	-381.4	-359	-325.8	(424.7)
Inc. Sec.	528.1	381.6	654.5**	1,008**
	-366.5	-344.9	-313	(408.1)
Matric	1,364***	933.8***	1,127***	2,022***
	-373.9	-351.9	-319.4	(416.4)
Tertiary	3,578***	3,512***	3,433***	6,209***
	-381.9	-359.5	-326.3	(425.3)
Constant	-1,245	-1,184	467.5	-730.0
	(802.1)	(754.9)	(685.2)	(893.2)
Observations	50,564	50,564	50,564	50,564
R-squared	0.171	0.162	0.156	0.314

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Source: QLFSs from quarter 1 2010 to quarter 4 2014. Observations are weighted and are restricted to panel members between 15 and 64 years of age who reported earnings in four consecutive waves.

The negative and statistically significant coefficient on the base period (lagged) earnings implies that the growth rate of earnings was higher at the bottom of the earnings distribution than it was at the top over the 12-month period. This is analogous to the "pro-poor" interpretation of income mobility regressions in the mobility literature. If we focus our attention on column four, in which the dependent variable is the change in earnings between the first and fourth wave of observation, we see that the Coloured, Asian/Indian and white dummy variables are all economically and statistically significantly different to the African base category. The white premium, in particular, is large and stands at close to R4 000. The change for female earners over the 12-month period was smaller than it was for men, even when controlling for race, age, location and education. Finally, the wage increase for those with tertiary education compared to the base category of no education stood at about R6 200, and was more than three times the premium associated with having a matric.

6. Conclusion

We started this paper by motivating that static measures of income inequality may be different from dynamic measures that incorporate short run changes in employment and earnings. Our findings are somewhat nuanced. Overall, the Gini coefficients of average earnings over a twelve month period are lower than those obtained from the static measures of the same data, by about 0.018 units. On the one hand, this is meaningful from an inequality perspective. On the other hand, the measured Gini of 0.608 units on average earnings remains exceptionally high by global standards.

The rest of our analyses indicated that the reason for this is that the churning is heavily concentrated amongst less skilled workers who tend to earn relatively low wages. In contrast, highly skilled high income earners are also much more likely to have stable employment.

The policy implications are that an inequality reduction policy needs to consider not just employment rates and wages amongst relatively unskilled sub-populations, but also needs to take into account the job stability amongst these groups.

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The **Research Project on Employment, Income Distribution and Inclusive Growth (REDI3x3)** is a multi-year collaborative national research initiative. The project seeks to address South Africa's unemployment, inequality and poverty challenges.

It is aimed at deepening understanding of the dynamics of employment, incomes and economic growth trends, in particular by focusing on the interconnections between these three areas.

The project is designed to promote dialogue across disciplines and paradigms and to forge a stronger engagement between research and policy making. By generating an independent, rich and nuanced knowledge base and expert network, it intends to contribute to integrated and consistent policies and development strategies that will address these three critical problem areas effectively.

Collaboration with researchers at universities and research entities and fostering engagement between researchers and policymakers are key objectives of the initiative.

The project is based at SALDRU at the University of Cape Town and supported by the National Treasury.

Consult the website for information on research grants and scholarships.

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Research Project on Employment, Income Distribution & Inclusive Growth

Towards an integrated response to unemployment, inequality and poverty