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Drivers of Inequality in South Africa

by
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Abstract

The first democratic elections in 1994 brought about the promise for equal opportunity and an overall improvement of living standards for the majority of the South African population. The newly elected government promised to combat high levels of poverty as well as inequality inherited from the apartheid regime. However, 20 years after the democratization of South Africa, levels of inequality remain stubbornly high. Therefore, this paper analyzes the role of income from different sources in order to investigate which one(s) continue to drive those high levels of inequality. We use data from the 1993 Project for Statistics on Living Standards and Development (PSLSD) to present a detailed snapshot of the level and texture of inequality that was prevalent at the end of the apartheid regime.

Furthermore, we use recent data from the National Income Dynamics Study (NIDS) from 2008 and 2014 to assess the role of different income sources in overall inequality and compare these contemporary snapshots to the results from 1993. We do so by applying two different decomposition methods to inequality measured by the Gini coefficient. The first is static, explaining the role of income sources in driving income inequality at each of the three points in time. The second is dynamic, explaining the role of changing income sources in changes in income inequality over time. We find that over the past 20 years, labour income has been the major contributor to overall inequality. The results indicate that a drop in inequality from labour market sources led to a decrease in overall income inequality. A more nuanced decomposition technique within the dynamic decomposition allows us to extract the effect of changes in household demographics on inequality from these results. This shows that when factors of household composition are accounted for, changes in all of the different income sources have led to a decrease in inequality between 2008 and 2014 in particular and over the entire post-apartheid period in general.

Keywords: income distribution; South Africa; inequality drivers; labour markets

1 Introduction

Levels of inequality have remained high in the recent history of South Africa and analyzing the drivers of these income inequalities are of importance to both researchers and policy makers. There is a well-established literature that looks at the drivers of inequality in South Africa by decomposing income inequality by groups (race and space in particular) or by income sources using South Africa's available household surveys (see Leibbrandt et al., 2012, Leibbrandt et al., 2010). Decompositions of inequality by income source allow us to determine what income source(s) lead to the overall high levels of inequality and provide a foundation on how to address inequalities in those income sources particularly.

This paper will start by updating existing work of inequality decomposition using the latest round of National Income Dynamics Study (NIDS) data from 2014/2015. We will compare the 1993 Project for Statistics on Living Standards and Development (PSLSD) data, the 2008 NIDS data and the most contemporary picture in detail. Furthermore, the application of some recently developed dynamic decompositions will allow for an assessment of how changes in income sources but also in relevant demographic factors have influenced changes in inequality over time.

The decomposition methods utilized in existing literature are useful but only loosely indicative of drivers of inequality. This paper will complement current research by following a methodology developed by Lerman and Yitzhaki (1975), we will model the changes in the distribution of per capita income with a particular focus on the role of different income sources before applying micro-simulations as outlined by Azevedo et al. (2013). Micro-simulations allow an assessment of the effect of changes in income sources but also in relevant household characteristics on the changes in inequality over time.

Our results show a drop in overall inequality between 1993 and 2014 despite a temporary increase in inequality between 1993 and 2008. The Gini coefficient increased between 1993 and 2008 from 0.681 to 0.69 and dropped to 0.655 in 2014. The decrease between 2008 and 2014 seems to be driven largely by a decrease in inequality in income from labour market sources. The static decomposition by Lerman and Yitzhaki (1975) shows a strong correlation between labour market incomes and total household income and reports a decrease in inequality within this income source. Furthermore, the static approach indicates that government grants had a decreasing effect on inequality and that remittances have at least the potential to lower inequality. Applying a more nuanced approach, the dynamic decomposition method allowed us not only to evaluate the effect of changes in different income sources on the overall Gini but also to account for changes in household composition. While the effects of the share of adults in the household are small, they seem to be driving inequality slightly upwards. The share of employed adults, however, had a decreasing effect between 1993 and 2008. Once these household composition variables are accounted for, the change in the Gini coefficient is largely driven by changes in the different income sources. The strongest driver was found to be labour income which increased inequality by 6.6% between 1993 and 2008 and contributed 6.7% to a decrease in inequality between 2008 and 2014. However, the inequality increasing forces of labour income between 1993 and 2008 were largely offset by redistributive efforts by the government through government grants. Other important changes were driven by investment income, while remittances seem to have had only small effects.

In the next section, Section 2, we review the NIDS data in detail and compare the characteristics of NIDS with the PSLSD data. We will continue in Section 3.1 by outlining and applying the so-called static decomposition method by Lerman and Yitzhaki (1975) and extended by Stark et al. (1986) to the PSLSD data set from 1993, NIDS data of 2008 and 2014/2015 before applying a dynamic approach using micro-simulations to the time frame from 1993 to 2008 and 2008 to 2014 respectively in Section 3.2. Finally, Section 4 concludes.

2 Descriptive Statistics

The data sets we use in this paper stem from the 1993 Project for Statistics on Living Standards and Development (PSLSD) and the National Income Dynamics Study (NIDS). Using these different data sets allows us to compare levels of inequality prevalent at the end of the apartheid period and over the last 20 years by applying both static and dynamic decomposition methods.

Both datasets offer detailed information collected on income from different sources. The PSLSD was a household level survey in which one individual answered all questions regarding the household (Leibbrandt et al., 2012). The household questionnaire comprised areas such as demography, household services and expenditure, including health and education, land access and use, employment and other income, health and educational status and anthropometry (SALDRU, 1994). Similarly, the NIDS dataset offers great detail in the information collected on income from different sources as well as information on a household and an individual level. NIDS may be slightly more reliable with regard to individual data, given that NIDS contains questionnaires not only for the household as a whole but also individual questionnaires for all resident members of the household. As opposed to the one time study of the PSLSD, NIDS is a nationally representative panel survey of South African individuals (NIDS, 2013). Every two years, the study collects information on households and individuals with regards to a wide range of topics including labour market participation, individual and household income from employment and non-employment sources as well as data on wealth, individual health and well-being and education.

Leibbrandt et al. (2012) compare and contrast the PSLSD and NIDS datasets in much detail and conclude that the two datasets are largely comparable with the exception of data collected on agricultural income and imputed rent. Particularly agricultural income plays only a small role in overall household income and therefore, we will abstain from using these income categories in our analysis. In order to compare changes over time, this paper will use the 1993 PSLSD data[1] and compare it to NIDS Wave 1 data collected in 2008[2] as well as the data collected in 2014/2015[3]. For simplicity, we will refer to 2014 incomes from here on as all numbers will be represented in 2014 prices.

[1] see SALDRU 1993.
[2] see SALDRU 2008.
[3] see SALDRU 2014-2015.

With the information provided by PSLSD and NIDS, household income can be disaggregated into income from labour market sources, such as a salary paid by an employer or income from self-employment, and income from several non-employment sources, namely income from government grants (such as child support grants, pensions and other government support), income from remittances (including contributions in kind as well as monetary transfers made to an individual in the household) and income from investment sources such as loans, stocks, annuities and rental income.

Table 1: Income Components in per capita terms - NIDS 2008 and 2014

Variable	**1993**	**2008**	**2014**
Total Household Income			
Mean of HH Income	1328.17	2062.68	2398.57
Gini of HH Income	0.681	0.690	0.655
Labour Income			
Mean of Labour Income	1078.18	1659.86	1971.98
Share in total HH Income	83.6%	74.5%	73.0%
Proportion of HHs receiving Labour Income	60.5%	64.4%	72.6%
Gini of Labour Income	0.73	0.76	0.73
Income from Government Grants			
Mean of Govt Grants	86.17	161.31	187.34
Share in total HH Income	3.4%	15.6%	16.4%
Proportion of HHs receiving Govt Grants	23.5%	56.3%	68.0%
Gini of Government Grants	0.92	0.78	0.76
Income from Remittances			
Mean of Remittance Income	50.56	86.69	93.94
Share in total HH Income	4.6%	3.6%	6.1%
Proportion of HHs receiving Remittances	22.2%	13.9%	38.3%
Gini of Remittances	0.91	0.97	0.91
Investment Income			
Mean of Investment Income	113.28	154.81	145.31
Share in total HH Income	8.3%	6.3%	4.5%
Proport. of HHs receiving Investment In.	3.5%	5.6%	23.3%
Gini of Investment Income	0.99	0.97	0.98
N_unweighted	39,180	28,225	37,965
N_weighted	39 020 805	49 295 750	54 941 051

Source: Authors' calculations using PSLSD and NIDS weighted.

Table 1 provides descriptive statistics on the different income components as well as on household income in general. All components are represented in 2014 prices in per-capita terms. There is evidence for a significant increase in total household income per capita and as such, income from all income components has increased from 1993 to 2014 in real terms. There has been a slight decrease in overall income inequality with the Gini coefficient falling from 0.681 to 0.655 between 1993 and 2014, despite an increase of the Gini to 0.69 in 2008.

Labour income holds the largest share of total household income among the different income sources. A majority of households receive income from labour market sources and the proportion of households receiving labour income has steadily increased from 60.5% in 1993 to 64% of all households in 2008 and 73% in 2014. The Gini coefficient for this component is relatively large and has fallen slightly by 0.032 points from 0.764 to 0.732 between 2008 and 2014. Considering the strong dependency on this type on income, this slight decrease in the Gini of income from labour market sources as well as the fact that, compared to 1993, much more households receive this type of income may be the driver of the overall decrease in income inequality within the observed time period. We return to investigate this in more detail.

Interestingly, within the same time period, income from government grants has increased as has the proportion of households receiving this type of income. The proportion of households receiving some form of government support rose significantly from 23.5% in 1993 to 56.3% in 2008 and as far as 68% in 2014. Income from government grants reports a relatively large Gini coefficient which most likely stems from the fact that there are many households reporting zero income from this source. Overall, the Gini of income from government grants decreased slightly from 0.777 in 2008 to 0.758 in 2014. However, the Gini has fallen by 0.16 points since 1993 which is indicative of the fact that so many more households receive grant income by 2014. Therefore, grant income plays a much larger role in total household income with its share having risen from only 6% in 1993 to 16.4% in total household income by 2014.

In addition, the proportion of households receiving remittances has increased significantly between 1993 and 2014, despite a large drop in 2008. Previously, 22% of households received income in the form of inter-household transfers in cash and in kind. This proportion dropped to a low of 14% in 2008. In 2014, 38% of households received this form of income. There are less households reporting zero income from remittances, therefore, the distribution of this type of income has become more equal. This would also explain the decrease from a Gini of 0.97 to 0.91 between 2008 and 2014. The overall share of remittances in total household income is still relatively small and has increased between 1993 and 2014 from 3.1% to 6.1% in total household income.

Lastly, we observe a strong increase in the proportion of households receiving income from investment sources between 1993 and 2014. When previously only 3.5% of households reported income from investment, 23% report this type of income in 2014. Investment income remains highly unequal over the observed time period with a Gini coefficient close to one in all three years. The fact that the share of investment in total household income has decreased, however, would indicate that other income components, namely labour income and government grants, have grown stronger than investment income and play a more important role in the income composition of the households.

Table 1 discussed the development of income in real terms in 1993, 2008 and 2014. In order to interpret these changes, however, it is imperative to study changes in the underlying demographic variables as well. Thus, Table 2 presents descriptive statistics for household composition variables. Household size has decreased from 4.38 in 1993 to 3.5 people in an average household in 2008 and then to 3.2 persons on average in 2014. Households

Table 2: Household Composition from 1993 to 2014

Variable	**1993**	**2008**	**2014**
Household Size	4.38	3.53	3.21
	0.03	*0.03*	*0.03*
Number of Adults in HH	2.81	2.70	2.59
	0.02	*0.02*	*0.02*
Number of Employed in HH	1.08	0.96	1.02
	0.01	*0.01*	*0.01*
Share of Adults in HH	0.73	0.88	0.95
	0.00	*0.01*	*0.01*
Share of Employed in HH	0.37	0.38	0.46
	0.00	*0.00*	*0.00*

Source: Authors' calculations using PSLSD and NIDS weighted.
Note: Standard errors are in italics.

are constituted largely of adults, rather idiosyncratically defined as persons aged 15 years and older. This threshold has been chosen since it presents the start of the working age in South Africa. Although both numbers fall in absolute terms, the share of adults in the household increased steadily between 1993 and 2014 from 0.73 to 0.95. This implies that the number of household members decreased more sharply than the fall in adults. The number of employed adults has fluctuated around an average of one person per household over the period of 1993 to 2014. Due to the decrease in overall household size, however, this implies that a share of 37% was employed in the household in 1993 compared to a share of 46% in 2014. It is important to note that any form of employment activity was accounted for, not only a formally paid job for an employer but also any form of self-employment and other labour market activities were counted into this variable.

The discussion of the variables in this chapter has shown that the PSLSD and the NIDS datasets offer detailed information on income components and household demographics to investigate their role in the development of income inequality over time. The remainder of this paper proceeds to assess the drivers of inequality first by applying a static approach to analyze the effects of different income sources on overall income inequality. These results will be extended by using micro-simulations that allow a dynamic analysis of these changes over time.

3 Gini Decompositions

3.1 Static Approach

This subsection utilizes an approach introduced by Shorrocks (1982) and extended by Lerman and Yitzhaki (1975) and Stark et al. (1986)[4] for a static decomposition of the Gini coefficient. The index presented here is a Gini coefficient decomposed into the different sources of income. We call this a static approach as income inequality is decomposed by different income sources as it is observed at a particular moment in time. However,

[4]This paper will follow the notation of Stark et al. (1986).

by taking the derivative with respect to a small percentage change in income from a particular source, Stark et al. (1986) analyzed the effect of a marginal change in an income source on the overall Gini coefficient at that point in time holding all other income sources constant. This section will briefly analyze the methodology of this static approach before comparing the decomposition of 1993 PSLSD data to NIDS 2008 and 2014.

The decomposition of the Gini coefficient is instrumental in analyzing the role of different income sources in more depth so as to gain a deeper understanding of the underlying factors of South Africa's persistently high levels of inequality. Following Stark et al. (1986), the overall Gini coefficient G_0 can be presented as follows.

$$G_0 = \sum_{k=1}^{K} R_k \cdot G_k \cdot S_k \tag{1}$$

where S_k and G_k are the share and the Gini coefficient of income component k respectively.[5] R_k represents the so-called Gini correlation of component k with total household income, it shows similar characteristics as the Pearson's and Spearman's correlation coefficients.

As such, equation (1) yields the decomposition of the Gini coefficient by income source (Stark et al., 1986). It allows us to examine three important concepts:

1. the share of the respective income source in overall household income, S_k
2. the inequality within the different income sources, G_k, and
3. the (Gini) correlation R_k between income component k and total household income.

By definition, the share of an income source in overall household income S_k and the Gini coefficient of any income source G_k are always positive and bounded between 0 and 1. The Gini correlation R_k, however, will be positive when an income component contributes positively to the overall Gini, that is when y_k is an increasing function of total income y_0. Correspondingly, R_k will be negative when income component y_k is a decreasing function of total income y_0. R_k is bounded by $-1 \leq R_k \leq 1$ and will be equal to zero when y_k and y_0 are uncorrelated.

In addition to the three concepts outlined above, the assessment of the effect of a small change in any one of the income components k on the overall Gini will be of interest. For this purpose, assume that an exogenous change in any income component j by a factor e occurs. Then, income from j is assumed to change according to $y_j(e) = (1 + e)y_j$ and

$$\frac{\partial G_0}{\partial e} = S_j(R_j \cdot G_j - G_0). \tag{2}$$

Equation (2) is a partial derivative which simulates a marginal change in a particular income source while holding income from other sources constant. Further, dividing (2) by G_0 yields

$$\frac{\partial G_0/\partial e}{G_0} = \frac{S_j \cdot R_j \cdot G_j}{G_0} - S_j. \tag{3}$$

[5]The decomposition and the methodology are discussed in more detail in Appendix A.

Thus, the change in overall inequality due to a small change in income component j is equal to the initial share of j in total inequality less the share of component j in total household income (Stark et al., 1986). Given the characteristics of R_j, this yields two possible outcomes for the overall Gini coefficient. If income component j has a negative or zero correlation between j and total household income y_0, an increase in income from component j will have an equalizing effect, thereby lowering inequality. This is due to the fact that S_j, the share of income from component j, as well as the Gini indices for j and total income, G_j and G_0, are always positive. The other possible outcome is when R_j represents a positive Gini correlation. Assuming that $G_j > G_0$, then $\frac{R_k \cdot G_k}{G}$ which leads to an increase in inequality associated with component j. $G_j > G_0$ is a necessary condition for an inequality-increasing effect of income component j given that R_j is always smaller or equal to 1.

In summary, this approach allows us to analyze the three concepts laid out above as well as the effect of a change in j on total income inequality. Nevertheless, the method proposed by Stark et al. (1986) comes with one major limitation. When assessing the change in one income component, income from all other components is held constant. However, the validity of this assumption is debatable as households tend to either compensate by increasing income from other sources or possibly decreasing efforts to obtain other income when income from one component j changes. As such, the approach by Stark et al. (1986) provides a valuable snapshot of inequality within one period as well as its decomposition but fails to adequately assess the effect of changes in income components on overall inequality. This is due to its one-dimensional approach which limits its potential to analyze how changes in different income sources drive aggregate changes in income inequality over a period of time.

The results of the decomposition method by Stark et al. (1986) are provided in Table 3 for 1993, 2008 and 2014. Equation (1) has shown that the Gini coefficient is the sum of the products of the first three columns of Table 3 for each component k. These products of $S_K \cdot R_k \cdot G_k$ are reported as the (absolute) contribution in column (4). The results in Table 3 show that income from labour market sources is the biggest driver of inequality. In 1993, labour income contributed 84.4% to overall inequality which increased to 87.2% in 2008 and 90.2% in 2014 as can be seen in Column (5) of Table 3 . The Gini coefficient of labour income was 0.73 in 1993, 0.759 in 2008 and 0.731 in 2014. Labour income is also the most strongly correlated of all income sources with the Gini coefficient. The Gini correlation, or R_k is close to one for all three years under observation. In this context it is important to point out that the drop in the Gini of labour income between 2008 and 2014 seems to have contributed to the large decrease in overall income inequality as measured by the Gini coefficient. While the Gini of labour income decreased by 0.03 between 2008 and 2014, the relative contribution increased by 3%. As labour is the largest contributor to overall inequality, the drop in the Gini of the income source explains partially why overall inequality has decreased. Most importantly, it is clear from the decomposition that during the period under observation, labour income seems to be the driver behind household income inequality.

The second largest driver of inequality is income from investment sources. This is despite the fact that between 1993 and 2014, the relative contribution of investment income to overall income inequality decreased from 11.7% in 1993 to 10.1% in 2008 and further to 9.2% in 2014. The key to this influential role of investment sources is the fact that the Gini coefficient of this source is among the highest of all the income sources and close to absolute inequality with values close to one. The discussion of the descriptive statics above has shown that between 2008 and 2014 a small but increasing proportion of households report income from investment. The high Gini coefficient reflects the many households reporting zero income from this source. Both, investment income and income from labour market sources have strongly dis-equalizing effects in all periods. This is shown by the elasticities reported in the last column of Table 3. Following from equation (3), a 1% change in income from labour markets leads to an absolute increase in the Gini of 0.024 in 1993, of 0.047 in 2008 and an of 0.064 in 2014. While the dis-equalizing effect of investment is stronger in 1993, at 0.029 points in the Gini, the decreasing share S_k of investment income leads to a drop in the change of the Gini in response to a 1% change in investment income. In 2008, a marginal increase in investment would lead to an increase of the Gini of 0.016 and in 2014, the Gini would increase by 0.015.

The effects discussed so far are mostly offset by the equalizing forces of government grants and remittances. The results of the static decomposition suggest that the absolute and relative contributions of income from remittances and government grants are rather low yet (potentially) lowering the overall Gini coefficient. Government grants report relatively high Gini coefficients of 0.924 in 1993, 0.776 in 2008 and 0.758 in 2014. The large drop in the Gini of government grants is most likely owed to increased efforts of the democratic governments since 1994 to address poverty and inequality inherited from the apartheid era through an extensive roll-out of government grants. The persistently high Gini may indicate that many households do not qualify for support from social grants or are ineligible for grant support due to a lack of documents that would support their claim (Leibbrandt et al., 2010). As such, there are a number of households that report zero income in this category. However, suggesting that income from government grants is relatively well targeted we find that for the post-apartheid years, the negative correlation of income from government grants leads to negative absolute and relative contributions of government grants in 2008 and 2014. This highlights the equalizing effect of grants on total income inequality even if these effects are rather small. In 2008, government grants lowered the overall Gini by 0.002 points (0.3%) and in 2014 by 0.007 point (1%). The elasticity reported in the last column of Table 3 shows that a 1% increase in social grants had a potentially equalizing effect in 1993 already. A marginal increase in government grants would lower inequality measured by the Gini by 0.026 in 1993 compared to 0.057 in 2008 and 2014, holding all other incomes constant.

Income from remittances shows a negative relative effect of a marginal percentage change on inequality as well but is contributing positively to the overall Gini in 2014. The relative contribution of remittances to overall income inequality in 1993 was marginal at 0.5% and increased to 3% in 2008, only to decrease again to 1.6% in 2014. Over the same period of time, the share of remittances in total household income has remained fairly stable between 3.1% and 3.8% of total household income. The correlation with the Gini, R_k, increased between 1993 and 2008 and decreased between 2008 and 2014. Overall, the Gini correlation is relatively low but remains positive between 0.11 and 0.59. However, the Gini coefficient within this income source is very high, fluctuating between 0.91 in

Table 3: Static Decomposition of the Gini Index by Income Sources

	Income share S_k	Gini correlation R_k	Gini index G_k	Contribution $S_k \cdot R_k \cdot G_k$	%-Contribution $\frac{S_k \cdot R_k \cdot G_k}{G}$	Elasticity $\frac{\partial G/\partial e}{G_0}$
1993 - PSLSD						
Labour Income	0.820	0.959	0.730	0.575	0.844	0.024
	0.011	*0.003*	*0.004*	*0.009*	*0.015*	-
Government Grants	0.061	0.418	0.924	0.024	0.035	-0.026
	0.004	*0.038*	*0.004*	*0.004*	*0.005*	-
Remittances	0.031	0.115	0.913	0.003	0.005	-0.026
	0.002	*0.050*	*0.005*	*0.002*	*0.002*	-
Investment	0.088	0.915	0.988	0.079	0.117	0.029
	0.010	*0.012*	*0.001*	*0.010*	*0.014*	-
Total	1.000	1.000	0.681	0.681	1.000	-
2008 - NIDS Wave 1						
Labour Income	0.825	0.962	0.759	0.602	0.872	0.047
	0.017	*0.005*	*0.009*	*0.017*	*0.024*	-
Government Grants	0.054	-0.047	0.776	-0.002	-0.003	-0.057
	0.004	*0.034*	*0.007*	*0.001*	*0.002*	-
Remittances	0.036	0.590	0.970	0.021	0.030	-0.006
	0.014	*0.168*	*0.011*	*0.014*	*0.020*	-
Investment	0.085	0.846	0.970	0.070	0.101	0.016
	0.012	*0.022*	*0.003*	*0.011*	*0.016*	-
Total	1.000	1.000	0.690	0.690	1.000	-
2014 - NIDS Wave 4						
Labour Income	0.838	0.964	0.731	0.591	0.902	0.064
	0.017	*0.004*	*0.011*	*0.020*	*0.025*	-
Government Grants	0.047	-0.187	0.758	-0.007	-0.010	-0.057
	0.003	*0.021*	*0.006*	*0.001*	*0.001*	-
Remittances	0.038	0.307	0.914	0.011	0.016	-0.022
	0.003	*0.040*	*0.004*	*0.002*	*0.003*	-
Investment	0.077	0.796	0.978	0.060	0.092	0.015
	0.017	*0.047*	*0.004*	*0.016*	*0.025*	-
Total	1.000	1.000	0.655	0.655	1.000	-

Note: Authors' calculations using NIDS and PSLSD weighted, Standard errors are in italics.
Decomposition with Lerman and Yitzhaki's approach (1985).

1993 and 2014 and 0.97 in 2008. This is due to the fact that many households report zero income in this income category which drives up the Gini coefficient within the income source. The marginal change analysis show that remittances have potential to lower the Gini coefficient. A 1% increase in remittances would lead to a 0.026 decrease in inequality as measured by the Gini in 1993, a decrease of 0.006 in 2008 and a decrease of the Gini by 0.022 in 2014. Thus, the elasticities reveal a stronger redistributive effect of this income source than the static decomposition alone.

The main shortcoming of the approach proposed by Stark et al. (1986) is in its static analysis. While this decomposition allows a detailed analysis of the contribution of different income sources in a given year, it is limited in its evaluation of the effect of changes in one income source on changes in total inequality. The elasticities measured here are given that all other household decisions regarding income are held constant which remains a questionable assumption. For example, if the arrival of a state old age pension pushes a household up the income distribution, the decomposition reflects the situation after the arrival of the pension. The elasticities are an attempt to correct for this weakness. However, they can only simulate a small or marginal change in income from a source, holding all other sources constant. Thus, the estimated elasticities are limited as simulations of the influence on the income distribution of sources that changed quite markedly over the post-apartheid period. To overcome this, we proceed to a more contemporary approach that uses micro-simulations to assess the effect of changes in one income source on overall inequality.

3.2 Micro Simulations

Even though the static decomposition offers a useful snapshot of inequality from a cross-sectional point of view, it only provides limited insights in the effects of changes in each income source to changing inequality. We therefore introduce an approach by Barros et al. (2006) and Azevedo et al. (2013) that tries to model changes in different income sources using micro-simulations. The following section will be implementing this so-called dynamic decomposition of income inequality.

Following Azevedo et al. (2013), the micro-simulations used in his approach model counterfactuals by changing one factor at a time in order to decompose the contribution of the effect of measured changes in the different income sources. An additional strength to these dynamic decompositions is that it facilitates the modeling of changes in income per capita and, therefore, a focus on changes in the denominator allows us to examine and separate out the impact of changes in household demographics.

Following the notation of Azevedo et al. (2013), household income per capita can be represented as the sum of incomes of all household members over the number of household members n.

$$Y_{pc} = \frac{Y_h}{n} = \frac{1}{n}\sum_{i=1}^{n} y_i, \tag{4}$$

where y_i is the income of individual i and Y_h is the total household income. Equation (4) can be rewritten assuming that only persons aged 15 years and above are able to contribute to household income. Then, in fact, household income per capita will depend on the number of adults in the household or n_A such that

$$Y_{pc} = \frac{n_A}{n}\left(\frac{1}{n_A}\sum_{i\in A}^{n} y_i\right), \tag{5}$$

where $\frac{n_A}{n}$ represents the share of adults in the household. The expression in parentheses is the income per adult which can be written as the sum of income from different income sources. Assume for simplicity that income per adult can be divided into two sub categories, labour income and income from non-labour sources or y_i^L and y_i^{NL} respectively (Azevedo et al., 2013). In the context of this paper, income from non-labour sources may include income from social grants, pensions and other government sources, remittances or investment income. Regarding labour income, it is important to note that not all adults in the household will be employed, instead only the share $\frac{n_0}{n_A}$ will earn income from labour markets with n_0 being the number of employed adults. Then, equation (5) transforms into

$$Y_{pc} = \frac{n_A}{n}\left(\frac{1}{n_A}\sum_{i\in A}^{n} y_i^L + \frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}\right) \tag{6}$$

$$= \frac{n_A}{n}\left[\frac{n_0}{n_A}\left(\frac{1}{n_0}\sum_{i\in A}^{n} y_i^L\right) + \frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}\right]. \tag{7}$$

The distribution of household per capita income $F(\cdot)$ depends on the different components outlined in equation (7) and in turn, inequality measures depend on the cumulative density function $F(\cdot)$ and as such, can be written as a function of the components discussed above.

Azevedo et al. (2013) show that micro simulations can be used to estimate the contribution of each component to the observed changes in the inequality measures by changing each component one at a time. With this in mind, assume that ϑ is a measure of inequality and as such a function of the cumulative density function $F(\cdot)$ and the components outlined above. Then

$$\vartheta = \Phi(F(Y_{pc}(n, \frac{n_A}{n}, \frac{n_0}{n_A}, \underbrace{\frac{1}{n_0}\sum_{i\in A}^{n} y_i^L}_{y_{P0}^L}, \underbrace{\frac{1}{n_A}\sum_{i\in A}^{n} y_i^{NL}}_{y_{PA}^{NL}}))), \tag{8}$$

with y_{P0}^L representing labour market incomes and y_{PA}^{NL} being the non-labour income including government grants, remittances and investment income. In order to estimate the contribution of each component to the observed changes in the inequality between period 1 and period 2, Azevedo et al. (2013) substitute the period 1 level of the respective income source into the counterfactual distribution of period 2. To give an illustration for the case of the study at hand, assume there is a change in the share of adults in a household between 1993 and 2008. Following Azevedo et al. (2013), the counterfactuals will be created by ordering households according to their household income per capita and then averaging the values of each component in equation (8) by quantiles. In order to compute $\hat{\vartheta}$, the 1993 value of $\frac{n_0}{n_A}$ will be substituted into the distribution of income $f(\cdot)$ by quantiles observed in 2008:

$$\hat{\vartheta} = \Phi(F(Y_{pc}(n, \frac{n_A}{n}, \frac{\hat{n_0}}{n_A}, y_{P0}^L, y_{PA}^{NL}))). \tag{9}$$

Then, $\vartheta - \hat{\vartheta}$ is the estimated contribution of the share of adults that earn labour market income in 2008. In the same manner in which $\frac{\hat{n_0}}{n_A}$ was substituted, each of the other components of interest can be substituted into the distribution of income per capita in 2008 following the rank-preserving exercise and their contribution to changes in inequality can be estimated. For example, when decomposing the impact of labour market incomes, the 2008 labour market income will be substituted with the average labour market income in 1993 for each quantile. The effect of labour market income on inequality is then measured by comparing the level of inequality of the simulated data with actual levels of inequality observed in 2008.

Azevedo et al. (2013) refine the method introduced by Barros et al. (2006) by computing what they call a "cumulative counterfactual distribution". By adding one variable at a time, the impacts of a change in each of the variables of interest and their interactions can be estimated as the difference between those cumulative counterfactuals (Azevedo et al., 2013).

One technical issue that has to be addressed in the simulation is the fact that the cumulative counterfactuals estimated differ depending on the order in which the different variables are added. In other words, the path that is used for the estimation of the cumulative effects matters. This problem is called path-dependence (Azevedo et al., 2013). In order to overcome this caveat, Azevedo et al. (2013) suggest calculating the Shapley-Shorrocks estimate of each component. The Shapley-Shorrocks estimate calculates the decomposition across all possible paths before averaging the results.[6] Since there are eight variables of interest, this aggregates to $40,320$ possible paths, i.e. the result of 8 *factorial*. The estimates of the Shapeley-Shorrocks values are reported in the tables below.

While this prevents the analysis from suffering from this major shortcoming, one caveat remains. The counterfactuals calculated in this manner are the result of a statistical exercise rather than actual economic equilibria, in which it is assumed that one component can be changed at a time, keeping all other factors constant. However, an increase in any income source would generally lead to an adjustment in economic behaviour. Households tend to substitute a loss in one income source with an increase in another and, vice versa, an increase in one income source may cause a decrease in efforts to obtain income from another source. Nevertheless, since the Shapeley-Shorrocks values calculate the averages of this substituting exercise, they represent the closest possible approximation. Therefore, we proceed to calculate these simulated counterfactuals using the 1993 PSLSD and NIDS 2008 and 2014 data sets.

The decompositions are done in two steps, first from 1993 to 2008, then from 2008 to 2014. The dynamic decomposition will be broken into these two steps since the results of the static decomposition exercises showed that there was an increase in inequality between 1993 and 2008, whereas the static decomposition reported a decrease between 2008 and 2014. In the dynamic decomposition, we would like to assess what drove the increase and later decrease of inequality over these periods of time.[7]

[6] For details of this cumulative path method, see Box 2 from Azevedo et al. (2013) in Appendix B.

[7] The results of the dynamic decomposition from 1993 to 2014 are reported in Appendix B.

Table 4: Dynamic Decomposition - 1993 to 2008

Effect	**Gini**	**%-Change**
Labour Income	0.029	4.3%
Government Grants	-0.063	-9.3%
Remittances	0.018	2.6%
Investment	-0.002	-0.3%

Note: Own Calculations using PSLSD and NIDS weighted
Number of paths = 40320
Number of factors = 8

Before we can proceed and compare the PSLSD and NIDS data sets in this dynamic decomposition, it is necessary to undertake a rank-preserving exercise as discussed above. Following Azevedo et al. (2013), households will be ranked by income per capita and divided into quantiles. For each of those quantiles, the average of each component in equation (8) in the first period, say 1993, will be assigned to each household in the same quantile in the second period, say 2008. This will be done for households ranked according to their household income per capita, however, it is possible to order households by the different income components instead. This may offer some insights into the effects of changes in that particular component on overall inequality. For components that are highly correlated with overall inequality, this change in the ranking order will result in small differences. However, when this is not the case, re-ranking according to different income sources allows us to differentiate shifts in the overall income distributions from developments within the distribution of the particular income source.

Table 5: Dynamic Decomposition - 2008 to 2014

Effect	**Gini**	**%-Change**
Labour Income	-0.021	-3.0%
Government Grants	-0.012	-1.7%
Remittances	-0.012	-1.7%
Investment	-0.006	-0.9%

Note: Own Calculations using NIDS W1 and W4 weighted
Number of paths = 40320
Number of factors = 8

To sum up, Tables 6 and 7 will provide the results of the simulations following different rankings. The decomposition in Tables 4 and 5 ranks households according to overall per capita income. It reports the estimation without taking account of changes in demography. It is therefore implicitly attributing these demographic to changes in the per capita values of the different income sources. As such, the results in Tables 4 and 5 serve as benchmarks for further analysis.

The estimation in Table 4 shows that between 1993 and 2008, changes in labour income had an increasing effect on the Gini which is similar to the results found in the static decomposition. In the observed time period, changes in labour income increased the Gini by 0.029 points or 4.3% of the original Gini. Changes in incomes from non-labour sources, on the other hand, mostly had an equalizing effect, lowering the overall Gini coefficient. The strongest effect is from government grants. Changes in government grants lowered the Gini by 0.063 points (9.3%). This reflects the substantial roll out of social grants and, in particular, the Child Support Grant that is documented in Leibbrandt et al. (2010). Changes in income from investment also had an overall negative effect on the Gini of 0.002 points or 0.3%. This is most likely due to the fact that the share of income from investment sources fell sharply in the period observed while the proportion of households receiving this type of income increased. Income from remittances increased the Gini by 0.018 points which translates into a 2.6% change from the 1993 Gini coefficient. If we recall Table 1 that reported on descriptive statistics of the different income sources, we see that the share of remittances in total income as well as the share of households receiving income from this source decreased between 1993 and 2008. This can help explain how remittances contributed to an increase in inequality between 1993 and 2008.

Turning now to the 2008 to 2014 period, from the static decomposition we know that between 2008 and 2014 the overall Gini coefficient decrease from 0.69 to 0.655. The dynamic decomposition using NIDS 2008 and 2014 data shows that all income components contributed to this fall in overall inequality. Again, we used a rank preserving and demography preserving exercise to compare households in 2008 with 2014. Results are reported in Table 5. The strongest contributor to the decline in overall inequality was income from labour market sources. Changes in income from labour markets resulted in a decrease in the Gini of 0.021 or 3%. This supports the results of the static decomposition which showed that the Gini within labour market income had fallen but the contribution to the overall Gini had increased. As such, a decrease in inequality from labour market income may have driven the overall decrease in inequality. However, labour market income was not the only contributor to a decrease in total household income inequality. Changes in incomes from government grants as well as remittances each resulted in a decrease in the Gini of 1.7%. Furthermore, changes in investment income decreased the Gini coefficient by another 0.9%.

The approach developed by Azevedo et al. (2013) allows us to differentiate the changes in inequality not only according to different income sources but also by household demographics. In Table 2, we presented a basic description of household demographics at each of the three points in time. To recapitulate, household size decreased between 1993 and 2014 from an average of 4.4 persons in a household to only 3.2 on average. At the same time, the share of adults as well as the share of employed household members increased. In 1993, 73.4% of the household were 15 or above compared to 95.4% in 2014 and the share of employed had increased from 37% to 46%. Tables 6 and 7 go on to factor in these changes in household decomposition into the dynamic decompositions. The tables also allow for a re-ranking of income sources.

It can be seen from Table 6 that between 1993 and 2008 the change in the share of adults in the household increased the Gini coefficient by 0.002 units (0.3%). The share

Table 6: Dynamic Decompositions - 1993 to 2008
Including Household Composition and Different Ranking Variables

Variable	Gini	%-Change
Share of Adults in HH	0.002	0.3%
Share of Employed in HH	-0.025	-3.7%
One over Employed	0.02	2.9%
One over Adtuls	0.007	1.0%
Labour Income		
Ranked by Total HH Income	0.045	6.6%
Ranked by Labour Income	0.05	7.3%
Government Grants		
Ranked by Total HH Income	-0.041	-6.0%
Ranked by Government Grants	-0.044	-6.5%
Remittances		
Ranked by Total HH Income	0.005	0.7%
Ranked by Remittances	0.003	0.4%
Investment		
Ranked by Total HH Income	-0.016	-2.3%
Ranked by Investment	-0.02	-2.9%

Note: Own Calculations using NIDS and PSLSD weighted.
Number of paths = 40320
Number of factors = 8

of employed adults on the other hand decreased the Gini by a significant 3.7% or 0.025 points. From Table 2, we know that both these variables had increased slightly between 1993 and 2008. However, even a slight increase in the share of employed indicates a decrease in the overall levels of inequality. We move on to discuss how changes in the different income sources affected changes in the Gini coefficient keeping changes in the household composition in mind.

Accounting directly for these demographic variables changes the contributions of the income sources markedly. Now, the changes in labour income worsen inequality and are driving the increase in the Gini coefficient by 6.6% or 0.045 points between 1993 and 2008. The result of the simulations after ranking the distribution by labour market incomes shows an even stronger effect at 7.3% or 0.05 points. It seems that the earlier finding that labour changes in labour incomes were equalizing was driven by the favourable demographic change in the share of the employed in households rather than by changes in the distribution of labour income itself. The fact that this effect is stronger when ranked by labour income indicates that the distribution within this income remained highly unequal between 1993 and 2008 and that labour income remains a driver of inequality, even after household demographics are accounted for.

Government grants have a strongly equalizing effect when ranked by household income and more so when ranked by grant income. The impact of income from social grants increases from 6% to 6.5% depending on the ranking variable. The fact that the equalizing effect of government grants are stronger when ranked by grants implies that the targeting of grants was effective in addressing households at the bottom of the income distribution. Compared to the baseline results of Table 4, the effect of government grants is lower once demographic changes are separated out. This highlights the necessity to account for these demographic variables.

Changes in remittances increased inequality, both when ranked by total household income as well as ranked by remittance income. The effect is small at 0.7% in the first case and decreases to 0.4% in the latter. Remittances probably have such a small effect on the Gini due to the fact that they play only a minor role in overall household income. The results of the static decomposition in Table 3 showed that remittances only contributed between 0.5% and 3% to total inequality and their shares in income were at about 3%. When we asses the effect of remittances and rank by remittance income, we find that the effect is smaller than when ranked by total household income. This indicates that the distribution of remittances is slightly more equal than the distribution overall household income. It supports the findings of the static decomposition that highlighted the equalizing potential of remittances even though they were contributing positively to overall inequality.

Finally, changes in income from investment sources had a small but equalizing effect on changes in the Gini for the different rankings. When ranked by total income, this effect is at 2.3%. When assessing the effect of changes in the distribution of investment income, the effect is at 2.9%. These effects are much larger than the 0.3% estimated in the benchmark case which highlights the importance of separating out the role of changes in household composition.

Overall, it would seem that increased efforts by the post-Apartheid state in addressing poverty and inequality through government grants have largely offset inequality increasing effects of labour market income. Government grants reduced inequality significantly but not enough so that overall inequality increased between 1993 and 2008, driven predominantly by changes in inequality from labour market incomes. Table 7 will now analyse the drivers of changes in inequality between 2008 and 2014.

We start with demographic changes. Both the share of adults as well as the share of employed adults in a household had an increasing effect on inequality between 2008 and 2014. The effects are significant at about 1% of the 2008 Gini in both cases. This is interesting as both shares have increased between 2008 and 2014 (see Table 1). The share had increased previously, however, between 1993 and 2008 the share of employed had led to a decrease in the Gini. In order to harmonize these results, we move on to analyzing the effects of changes in the different income sources.

Once these demographic variables are accounted for, income from all sources contributed to the decline in overall inequality. The strongest driver in the fall of the Gini coefficient is income from labour market sources. The effect is at -0.046 points of the Gini or -6.7%. This large change is the same when ranked by total household income as when ranked by labour income. This supports the very strong correlation found between labour income and total household income per capita in the static decomposition. In Table 1 we reported that the share of labour income dropped between 2008 and 2014 while the

Table 7: Dynamic Decompositions - 2008 to 2014
Including Household Composition and Different Ranking Variables

Variable	**Gini**	**%-Change**
Share of Adults in HH	0.006	0.9%
Share of Employed in HH	0.007	1.0%
One over Employed	-0.003	-0.4%
One over Adtuls	0.004	0.6%
Labour Income		
Ranked by Total HH Income	-0.046	-6.7%
Ranked by Labour Income	-0.046	-6.7%
Government Grants		
Ranked by Total HH Income	-0.006	-0.9%
Ranked by Government Grants	-0.008	-1.2%
Remittances		
Ranked by Total HH Income	-0.004	-0.6%
Ranked by Remittances	-0.006	-0.9%
Investment		
Ranked by Total HH Income	-0.011	-1.6%
Ranked by Investment	-0.002	-0.3%

Note: Own Calculations using NIDS W1 and W4 weighted.
Number of paths = 40320
Number of factors = 8

proportion of households receiving this type of income increased from 64.4% to 72.6%. This sharp increase in the reach of this type of income may help explain the decrease in inequality. The increased diversity in income sources and stronger impact of equalizing income sources may have further strengthened this effect. At the same time, the Gini coefficient within labour incomes decreased from 0.76 to 0.73 in 2014, implying that the increased proportion of households receiving this income also report a slightly more equal distribution of this income than in 2008. The interaction of these effects contributed to the fall in inequality between 2008 and 2014.

Both income from government grants and remittances have small effects when ranked by total household income. For government grants, the effects on changes in the Gini are slightly larger when ranked by grant income. Changes in government grants reduce the Gini by 0.9% when ranked by total household income and 1.2% when ranked by government grants. It is important to note that between 1993 and 2008 government grants played a strong role in decreasing inequality but inequality within labour market income was a much stronger force at increasing levels of inequality. Between 2008 and 2014, these roles have changed in the way that while government grants are still reducing inequality, it is income from labour market sources that dominates the decrease in the overall Gini coefficient. Here we are assessing the further redistributive effect after 2008 and it seems that government grants are still playing the strongly equalizing role that they were by 2008 but that this has not become that much more equalizing between 2008 and 2014.

Remittances have a much smaller effect and changes in income from this sources lead to a 0.6% decrease in the overall Gini when ranked by total household income. This effect is slightly stronger when ranked by remittance income at 0.9%. This supports the potential to decrease inequality that we discussed in the static decomposition. However, the static decomposition reported that remittances are currently contributing to inequality. The dynamics decompositions shows that when the effects of household composition variables are netted out, remittances decrease inequality between 2008 and 2014.

Finally, income from investment sources has a decreasing effect on the Gini as well. Interestingly, the effect is lower when ranked by investment income at only 0.3%. Ranked by total household income, changes in investment result in a 1.6% change in the Gini. The fact that the changes in the Gini are smaller when ranked by investment income may indicate that the distribution of income from this source is still rather unequal and only small changes occurred between 2008 and 2014.

In Appendix B, Tables 8 and 9 report the aggregate trends from a broad-period decomposition that applies the different methods of Azevedo et al. (2013) to compare changes between 1993 and 2014. In this long-term comparison we find that the effect of government grants on changes in the Gini is very strong (-10.6%) in the baseline decomposition. Table 8 which does not account for household demographics finds that changes in labour income contributed 1.0% to the overall changes in inequality measured by the Gini and that remittances contributed 0.7%. Investment income decreased the Gini coefficient by 0.01 units or 1.5% between 1993 and 2014. Once we account for household composition variables, these effects change slightly.

The results reported in Table 9 show that the share of adults in a household contribute to a 1.3% change in the Gini coefficient between 1993 and 2014, this is equivalent to 0.009 units. The share of employed adults in a household lead to a 2.9% decrease over the same time period. However, it is important to note that the separated decomposition of Table 6 and Table 7 reported that the share of employed had a decreasing effect of close to 4% only between 1993 and 2008, whereas between 2008 and 2014 changes in the share of employed contributed to a 1% increase in the Gini.

Table 9 also reports that over the period of 1993 to 2014 changes in labour income contributed to a 0.6% decrease in the Gini when ranked by total household income. When this is ranked by labour income, however, the effect reverses and it reports an increase in the Gini by 0.6%. The fact that the change in the Gini is negative when ranked by total household income and positive when ranked by labour income would indicate a slightly more unequal distribution within labour market income. It fails to decompose the inequality increasing effect of labour income that we found between 1993 and 2008 and the inequality reducing effect between 2008 and 2014.

Furthermore, between 1993 and 2014, changes in government grants reduced the Gini by 6.3%, 7% when ranked by grant income. This is in line with the inequality reducing effects we found previously and seems to be the aggregate of the effects we found between 1993 and 2008 and between 2008 and 2014 respectively. The effect of remittances over the entire time period netted out to zero when ranked by total household income and a small -0.3% when ranked by remittance income. While this appears to be the aggregate of the separate effects found in Tables 6 and 7, this overall analysis fails to uncover the inequality increasing effects of remittances between 1993 and 2008 that were offset by the inequality decreasing effect of changes in this income source between 2008 and 2014.

Finally, investment was found to have a decreasing effect of 4.6% when ranked by total household income and reports a slightly smaller effect of 2.3% when ranked by investment income. It should have become clear that while the decomposition between 1993 and 2014 generally reports the aggregated trends in inequality over the observed time period, it fails to account for changes in the effects of the different income source on the increase and then decrease of overall inequality measured by the Gini coefficient uncovered by the separate decompositions.

The above decompositions of changes in inequality between 1993 and 2008 as well as 2008 and 2014 respectively, show that government grants are strong drivers in the reduction of overall income inequality. Furthermore, changes in labour market income have strong effects on overall inequality measured by the Gini coefficient. Between 1993 and 2008, it was income from labour markets that drove the increase in inequality and between 2008 and 2014, income from this source contributed strongly to a decrease in the Gini. The equalizing role of government grants has long been established in the literature (see Leibbrandt et al., 2012, and Leibbrandt et al., 2010) and as such, the ambivalent effect of changes in the labour income are left to be explored in more detail in future research.

4 Conclusion

This paper has applied different decomposition methods in order to ascertain drivers of inequality in South Africa over the post-apartheid period. A static decomposition by income sources highlighted the dominance of contributions in labour market income. Using data from the Project for Statistics on Living Standards and Development from 1993 as well as from the National Income Dynamics Study from 2008 and 2014, labour market income has been shown to be the largest contributor to the high levels of inequality in South Africa. Furthermore, we have shown that while inequality was rising from 0.68 in 1993 to about 0.7 in 2008, it has been declining in recent years to a Gini coefficient of 0.655 by 2014. According to the decompositions performed in this paper, households benefit significantly from income from government grants, however, labour income as well as investment income strongly contribute to overall inequality.

The different methods of decomposing inequality according to income sources have shown that income from labour markets is a strong driver behind high inequality levels in South Africa. The static decomposition method following Stark et al. (1986) suggested that labour market income contributes between 84% and 90% to the overall Gini coefficients between 1993 and 2014, proceeded by large contributions of investment income to inequality. We also find that between 2008 and 2014, labour market incomes remain highly correlated with overall inequality. The dynamic decomposition has shown that between 1993 and 2008 it was income from labour markets that dominated the increase in inequality and that changes in inequality within labour market income contributed strongly to the decrease on inequality between 2008 and 2014.

The dynamic approach following Azevedo et al. (2013) implements a series of counterfactual simulations to identify the direct effect of a change in a particular income source on the total income inequality. The results of the different ranking exercises within the dynamic decomposition showed that changes in the targeting and extensions to the system of government grants largely offset the inequality increasing effects of labour income between 1993 and 2008. The static decomposition method was unable to differentiate between the effects of labour income and government grants in that way. The role of government grants changed hugely between 1993 and 2008. Poverty-alleviating policies that resulted in an increase in government grants limited the increase in inequality over this period immensely. Even between 2008 and 2014, government grants played a significant role in reducing inequality and different ranking methods show that targeting of social policies was successful in addressing those households at the bottom of the income distribution.

Furthermore, the dynamic approach has shown that investment income played a much smaller yet inequality reducing role, particularly between 1993 and 2008. The static decomposition failed to detect these lowering effects of investment income on inequality. Additionally, the results of the static decomposition suggested that while remittances have the potential to lower inequality, as shown by negative elasticities, they are contributing positively to inequality. However, the dynamic approach using micro simulations paints a different picture. Once we account for demographic changes, remittances led to increases in the Gini between 1998 and 2008 but helped decrease inequality between 2008 and 2014. Aggregated across both time periods, however, the effects of remittances were close to zero.

The more nuanced analysis using micro-simulations allowed us to account for changes in household demographics as well as changes in income sources. Changes in the share of employed adults had a dis-equalizing effect between 1993 and 2008 but an equalizing effect between 2008 and 2014, whereas changes in the number of adults in a household led to an increase in the Gini in both periods. The effects of both these variables would be overlooked in the decomposition method by Stark et al. (1986). Particularly between 2008 and 2014 we find that it is the household composition variables that drive inequality upwards, whereas all income sources report an equalizing effect. This highlights the improvement in information by using the method of Azevedo et al. (2013).

All in all, this paper analyzed the development of inequality over the past 20 years using household survey data, showing that inequality has started to fall in South Africa. However, the static and dynamic analysis in this paper highlight the need for further improvement especially with regards to the high level of inequality within the distribution of labour market income which seems to be driving the overall high levels of inequality. The dynamic analysis shows a greater impact on inequality of social grants than the static decomposition. This makes sense given the massive increase in social grants over the post-apartheid period. Nonetheless, extensive dependency on government grants will not be sustainable in tackling prevailing levels of inequality further. Therefore, the key to lowering income inequality in the long-term remains in labour market policies that are inclusive of those at the bottom of the income distribution through employment and earnings.

The dominant role of labour market income both in the increase of inequality between 1993 and 2008 as well as the decrease in recent years has been established in this paper. As such, the effect of changes in labour market income may be analyzed with more detail in future research. Furthermore, as survey data tend to miss or under-report the top end of the income distribution, we hope to be able to utilize income tax records from the South African Revenue Service. This would allow us to combine these data with surveys to get a more comprehensive picture of the income distribution and the pre-tax and post-tax distributions of income.

A Extended Methodology

Assume that households derive income y_K from different income components K. Total household income is then given by the sum of income from all income components K. This can be formalized as $y_0 = \sum_{k=1}^{K} y_k$. Following Stark et al. (1986), the Gini coefficient for total household income y_0 is then given by

$$G_0 = \frac{2Cov\left[y_0, F(y_0)\right]}{\mu_0}, \tag{10}$$

where G_0 represents the Gini coefficient of all household incomes and μ_0 denotes the mean of household incomes. $F(y_0)$ in equation (10) denotes the cumulative distribution function of overall household income y_0. Given the property that $y_0 = \sum_{k=1}^{K} y_k$, equation (10) can be rewritten as

$$G_0 = \frac{2\sum_{k=1}^{K} Cov\left[y_k, F(y_0)\right]}{\mu_0}, \tag{11}$$

where $Cov\left[y_k, F(y_0)\right]$ is the covariance between income source k and the cumulative distribution of income, $F(y_0)$. It is necessary to utilize the properties of the covariance in this way in order to arrive at the next step of the decomposition of the overall Gini G_0. As such, let $S_k = \frac{y_k}{y_0}$ denote the share of income from component k in total household income y_0 and let G_k denote the corresponding Gini coefficient measuring the level of inequality within income component k. Using S_k and G_k, equation (11) can be rewritten following the steps outlined below.

$$G_0 = \underbrace{\frac{2\sum_{k=1}^{K} Cov\left[y_k, F(y_0)\right]}{\mu_0 \cdot y_0}}_{\text{Relative Gini}} \cdot \frac{Cov(y_k, F_k)}{Cov(y_k, F_k)} \cdot \frac{y_k}{y_k}.$$

Equation (11) has been multiplied with $\frac{Cov(y_k,F_k)}{Cov(y_k,F_k)}$ and $\frac{y_k}{y_k}$ to obtain equation (1) discussed above. Each of the components of equation (1) can be rewritten as follows.

$$\begin{aligned} G_0 &= \sum_{k=1}^{K} R_k \cdot G_k \cdot S_k \\ &= \sum_{k=1}^{K} \frac{Cov\left[y_k, F(y_0)\right]}{Cov\left[y_k, F(y_k)\right]} \cdot \frac{2Cov\left[y_k, F(y_k)\right]}{\mu_k} \cdot \frac{y_k}{y_0}, \end{aligned} \tag{12}$$

To repeat, S_k and G_k are the share and the Gini coefficient of income component k respectively. R_k represents the so-called Gini correlation of component k with total household income. This correlation is given by

$$R_k = \frac{Cov\left[y_k, F(y_0)\right]}{Cov\left[y_k, F(y_k)\right]}.$$

Note that in order to dervive equation (1) we need to take into account that $\mu_0 \cdot y_k = \mu_k y_0$ since $\sum \frac{\sum y_k}{N} \cdot y_k = \frac{\sum y_k}{N} \cdot \sum y_k$ with $\mu_k = \frac{\sum y_k}{N}$ and $\sum y_k = y_0$.

B Additional Figures and Tables

Figure 1: Box 2 in Azevedo et al. (2013)

Box 2. Proposed Methodology along One possible path	
1. $\vartheta_0 = \Phi\left(F\left(Y_{pc}\left(\frac{n_A}{n}, \frac{n_o}{n_A}, y_{PO}^{L}, y_{PA}^{NL}\right)\right)\right)$	Initial inequality rate
2. $\widehat{\vartheta_1} = \Phi\left(F\left(Y_{pc}\left(\frac{\widehat{n_A}}{n}, \frac{n_o}{n_A}, y_{PO}^{L}, y_{PA}^{NL}\right)\right)\right)$	Contribution of share of household adults is $\widehat{\vartheta_1} - \vartheta_0$
3. $\hat{\vartheta}_2 = \Phi\left(F\left(Y_{pc}\left(\frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, y_{PO}^{L}, y_{PA}^{NL}\right)\right)\right)$	Contribution of the share of occupied adults is $\widehat{\vartheta_2} - \widehat{\vartheta_1}$
4. $\hat{\vartheta}_3 = \Phi\left(F\left(Y_{pc}\left(\frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, y_{PO}^{L}, y_{PA}^{\widehat{Pens}}, y_{PA}^{Trans}, y_{PA}^{Cap}, y_{PA}^{Oth\ NL}\right)\right)\right)$	Contribution of pensions is $\widehat{\vartheta_3} - \widehat{\vartheta_2}$
5. $\hat{\vartheta}_4 = \Phi\left(F\left(Y_{pc}\left(\frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, y_{PO}^{L}, y_{PA}^{\widehat{Pens}}, y_{PA}^{\widehat{Trans}}, y_{PA}^{Cap}, y_{PA}^{Oth\ NL}\right)\right)\right)$	Contribution of transfers is $\widehat{\vartheta_4} - \widehat{\vartheta_3}$
6. $\hat{\vartheta}_5 = \Phi\left(F\left(Y_{pc}\left(\frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, y_{PO}^{L}, y_{PA}^{\widehat{Pens}}, y_{PA}^{\widehat{Trans}}, y_{PA}^{\widehat{Cap}}, y_{PA}^{Oth\ NL}\right)\right)\right)$	Contribution of capital income is $\widehat{\vartheta_5} - \widehat{\vartheta_4}$
7. $\hat{\vartheta}_6 = \Phi\left(F\left(Y_{pc}\left(\frac{\widehat{n_A}}{n}, \frac{\widehat{n_o}}{n_A}, y_{PO}^{L}, y_{PA}^{\widehat{Pens}}, y_{PA}^{\widehat{Trans}}, y_{PA}^{\widehat{Cap}}, y_{PA}^{\widehat{Oth\ NL}}\right)\right)\right)$	Contribution of other non-labor income is $\widehat{\vartheta_6} - \widehat{\vartheta_5}$
8. $\vartheta_F = \Phi\left(F\left(Y_{pc}\left(\frac{n_A}{n}, \frac{n_o}{n_A}, y_{PO}^{L}, y_{PA}^{NL}\right)\right)\right)$	Final inequality rate. Contribution of labor income is $\widehat{\vartheta_F} - \widehat{\vartheta_3}$

Table 8: Dynamic Decomposition - 1993 to 2014

Effect	**Gini**	**%-Change**
Labour Income	0.007	1.0%
Government Grants	-0.072	-10.6%
Remittances	0.005	0.7%
Investment	-0.01	-1.5%

Note: Own Calculations using PSLSD and NIDS weighted
Number of paths = 40320
Number of factors = 8

Table 9: Dynamic Decompositions - 1993 to 2014
Including Household Composition and Different Ranking Variables

Variable	**Gini**	**%-Change**
Share of Adults in HH	0.009	1.3%
Share of Employed in HH	-0.02	-2.9%
One over Employed	0.023	3.4%
One over Adults	0.013	1.9%
Labour Income		
Ranked by Total HH Income	-0.004	-0.6%
Ranked by Labour Income	0.004	0.6%
Government Grants		
Ranked by Total HH Income	-0.043	-6.3%
Ranked by Government Grants	-0.048	-7.0%
Remittances		
Ranked by Total HH Income	0	0.0%
Ranked by Remittances	-0.002	-0.3%
Investment		
Ranked by Total HH Income	-0.031	-4.6%
Ranked by Investment	-0.016	-2.3%

Note: Own Calculations using NIDS and PSLSD weighted.
Number of paths = 40320
Number of factors = 8

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Data Sources

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southern africa labour and development research unit

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

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

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