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Drivers of inequality in South Africa

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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. However, 20 years after the democratization of South Africa, levels of inequality remain stubbornly high. The focused contribution of this paper is to examine the role of income from different sources driving these high levels of inequality, and which ones cause changes over time. We use data from the 1993 Project for Statistics on Living Standards and Development as well as from the National Income Dynamics Study from 2008 and 2014 to assess the role of different income sources in overall inequality and compare snapshots of the level and texture of inequality across time. We start with the static exercise of explaining the role of income sources in driving income inequality at each of the three points in time. With this static picture as a base, we go on to the dynamic exercise of explaining the role of changing income sources in changes in income inequality over time. The static exercise is an update on work that has been done often before. The dynamic exercise is a fresh contribution. We find that over the past 20 years, labour income has been the major contributor to overall inequality but became less dis-equalizing in later periods. A more nuanced decomposition technique within the dynamic decomposition allows us to separate out the effect of changes in household demographics from changes in income sources. Stripping these demographic effects out of the income sources is important. Now, different income sources decrease inequality between 2008 and 2014 in particular, and over the entire post-apartheid period in general.

Keywords: income distribution, inequality drivers, labour markets, South Africa
JEL classification: D31, I32, J30

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1 Introduction

Levels of inequality have remained high in the recent history of South Africa and analysing the drivers of these income inequalities is 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. 2010, 2012). Decompositions of inequality by income source allow us to determine which source(s) lead to the overall high levels of inequality and provide a foundation for how to address inequalities in those income sources in particular.

This paper starts by updating existing static inequality decomposition work using the National Income Dynamics Study (NIDS) data from 2014/2015. We compare the 1993 Project for Statistics on Living Standards and Development (PSLSD) data, the 2008 NIDS data, and the most contemporary picture in detail. The static decomposition methods utilized in the existing literature are useful, but only loosely indicative of drivers of inequality. This paper complements current research by applying micro-simulations as outlined by Azevedo et al. (2013) that allows for an assessment of how changes in income sources and relevant demographic factors have influenced changes in inequality over time.

Our results show a small drop in overall inequality between 1993 and 2014, despite an increase between 1993 and 2008. The Gini coefficient increased between 1993 and 2008 from 0.68 to 0.69, and dropped to 0.66 in 2014. The decrease between 2008 and 2014 seems to be driven largely by a decrease arising from inequality in income from labour market sources. As has been found in previous research, our static decomposition analysis shows a strong correlation between labour market incomes and total household income, and reports a decrease in inequality within this income source. It remains by the far the dominant driver of inequality though. 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 the dynamic decomposition method allowed us not only to evaluate the effect of changes in different income sources on the overall Gini coefficient, but also to account for changes in household composition. While the effects of the increasing share of adults in the household are small, they seem to be driving inequality slightly upwards. The share of employed adults, however, decreased inequality between 1993 and 2008. The effort to separate out these demographic effects is important as they directly account for a small but important share of the change in inequality, and removing their influence changes the impacts of the income sources quite notably. The strongest driver was found to be labour income, which increased the Gini coefficient by 0.045 points or 6.6 per cent between 1993 and 2008, and led to a 0.047 or 6.7 per cent decrease in the Gini coefficient between 2008 and 2014. However, the inequality-increasing forces of labour income between 1993 and 2008 was 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 Section 2 we review the NIDS data in detail and compare the characteristics of NIDS with the PSLSD data. We continue in Section 3.1 by outlining and applying the so-called static decomposition method by Lerman and Yitzhaki (1985), 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 frames from 1993 to 2008 and 2008 to 2014/2015 respectively in Section 3.2. Finally, Section 4 concludes by summarizing the main results and drawing out some of the implications for policies with respect to the high levels of inequality South Africa continues to face.

2 Descriptive statistics

The data sets we use in this paper stem from the 1993 PSLSD and the 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 included 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 data set 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 administered to 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. Even though NIDS is a panel data set, in this paper we make use of the base wave (2008) and the fourth wave (2014/2015) of NIDS data as cross-sections of South Africa at that time. This analysis is facilitated by the fact that each wave of NIDS data is released with a series of cross-sectional weights that weight the data from that wave to totals from the relevant population estimates for that year.[1]

In order to compare changes over time, this paper will use the 1993 PSLSD data (see SALDRU 2012) and compare it to NIDS data collected in 2008 (see SALDRU 2015), as well as the data collected in 2014/2015 (see SALDRU 2014–2015). Leibbrandt et al. (2012) compare and contrast the PSLSD and NIDS instruments in much detail and conclude that the data on income sources are largely comparable, with the exception of information collected on agricultural income and imputed rent. We therefore exclude these two income sources from our analysis, across the board. Agricultural income is cash or income in kind from selling or consuming produce from home production. Even in the NIDS household questionnaire, in which a full module is devoted to such production, consumption, and sales, it amounts to a very small income component. Imputed rent is potentially more important. However, there really are irreconcilable differences between the methodologies of the PSLSD and NIDS in this regard. For simplicity, we will refer to 2014 incomes from here on as all numbers will be represented in 2014 prices.[2]

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 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 of a significant increase in total household income per capita and, as such, income from all income

[1] See Wittenberg (2009) for the details of the derivation of these cross-sectional weights.

[2] The authors use the monthly updated statistical release of the consumer price index by Statistics South Africa for this conversion.

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 0.68 to 0.66 between 1993 and 2014, despite an increase of the Gini coefficient to 0.69 in 2008.

Table 1: Income components in per capita terms

Variable	1993	2008	2014
Total household (HH) income			
Mean of HH income	1,328.17	2,062.68	2,398.57
Gini of HH income	0.68	0.69	0.66
Labour income			
Mean of labour income	1,078.18	1,659.86	1,971.98
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 government grants	86.17	161.31	187.34
Share in total HH income	3.4%	15.6%	16.4%
Proportion of HHs receiving government 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%
Proportion of HHs receiving investment income	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 data.

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 per cent in 1993 to 64 per cent of all households in 2008 and 73 per cent 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, many 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 increased, as did the proportion of households receiving this type of income. The proportion of households receiving some form of government support rose significantly from 23.5 per cent in 1993 to 56.3 per cent in 2008, and as far as 68 per cent in 2014. Income from government grants has 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 were receiving grant income by 2014. Therefore, grant income plays a much larger role in total household income, with its share having risen from only 6 per cent in 1993 to 16.4 per cent 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 per cent of households received income in the form of inter-household transfers in cash and in kind. This proportion dropped to a low of 14 per cent in 2008. In 2014, 38 per cent of households received this form of income. There are fewer 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 per cent to 6.1 per cent in total household income.

Lastly, we observe a strong increase in the proportion of households receiving income from investment sources between 1993 and 2014. While previously only 3.5 per cent of households reported income from investment, 23 per cent reported this type of income in 2014. Investment income remains highly unequal over the observed time period, with a Gini coefficient close to 1 in all three years. The fact that the share of investment in total household income has decreased would indicate that other income components, namely labour income and government grants, have grown more strongly than investment income and play a more important role in the income composition of the households.

Table 1 discussed the development of income per capita 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 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 are constituted largely of adults, rather idiosyncratically defined as persons aged 15 years and older. This threshold has been chosen since it represents the age at which young people could potentially leave school and start working in South Africa. Although both numbers fall in absolute terms, the share of adults in the household increase 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 1993–2014. Due to the decrease in overall household size, however, this implies that a share of 37 per cent was employed in the household in 1993 compared to a share of 46 per cent 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 in this variable.

Table 2: Household composition from 1993 to 2014

Variable	1993	2008	2014
HH 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*

Note: Standard errors are in italics.

Source: authors' calculations using PSLSD and NIDS weighted data.

The discussion of the variables in this section has shown that the PSLSD and the NIDS data sets offer detailed information on income components and household demographics as a platform 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 analysing the effects of different income sources on overall income inequality, and then by extending these results using micro-simulations that allow a dynamic analysis of 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 (1985) and Stark et al. (1986) for a static decomposition of the Gini coefficient.[3] 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, by taking the derivative with respect to a small percentage change in income from a particular source, Stark et al. (1986) analysed 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 analyse the methodology of this static approach before comparing the decomposition of 1993 income source data to data from 2008 and 2014.

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.[4] R_k represents the so-called Gini correlation of component k with total household income. It shows similar characteristics to the Pearson's and Spearman's correlation coefficients.

As such, equation (1) 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 equation (2) by G_0 yields

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

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

[4] The decomposition and the methodology are discussed in more detail in Hundenborn et al. (2016).

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.

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, $S_K \cdot R_k \cdot G_k$, are reported as the (absolute) contribution in Column 4. The results in Table 3 show that income from labour market sources is the biggest contributor to household income inequality. In 1993, labour income contributed 84.4 per cent of overall inequality. This inequality share increased to 87.2 per cent in 2008 and 90.2 per cent in 2014, as can be seen in Column 5 of Table 3. The Gini coefficient of labour income was 0.73 in 1993, 0.76 in 2008, and 0.73 in 2014. Labour income is also the most strongly correlated of all income sources with total income. The Gini correlation, or R_k is close to 1 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 of total income. While the Gini of labour income decreased by 0.03 between 2008 and 2014, the relative contribution increased by 3 per cent. As labour income is the largest contributor to overall income inequality, the drop in the Gini of this income source explains partially why overall income inequality in per capita terms has decreased.

The second largest contributor to inequality is investment income. This is despite the fact that between 1993 and 2014, the relative contribution of investment income to overall income inequality decreased from 11.7 per cent in 1993 to 10.1 per cent in 2008 and 9.2 per cent 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, with values reported close to 1. 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. In 2014, that share was 76.7 per cent of households. In previous years it was significantly higher at 95 per cent in 2008 and 96 per cent of households reporting no income from investment in 1993.

Table 3: Static decomposition of the Gini index by income sources

	Income share	Gini correlation	Gini index	Contribution	Percentage contribution	Elasticity
	S_k	R_k	G_k	$S_k \cdot R_k \cdot G_k$	$\frac{S_k \cdot R_k \cdot G_k}{G}$	$\frac{\partial G/\partial e}{G_0}$
			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			
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			
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	–

Standard errors are in italics.

Decomposition follows Stark et al.'s approach (1986).

Source: authors' calculations using NIDS and PSLSD weighted data.

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 per cent 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 of 0.064 in 2014. While the dis-equalizing effect of investment income 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 dis-equalizing effect in response to a 1 per cent change in investment income. In 2008, a marginal increase in investment income would lead to an increase of the Gini of 0.016 and in 2014, the Gini would increase by 0.015.

The equalizing forces of government grants and remittances offset to some degree the effects discussed so far. 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) lower the overall Gini coefficient. Government grants report relatively high Gini coefficients of 0.92 in 1993, 0.77 in 2008, and 0.76 in 2014. The large drop in the Gini of government grants is most likely due 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 a negative correlation of income from government grants for the post-apartheid years. It is this negative correlation that 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 per cent) and in 2014 by 0.007 points (1 per cent). The elasticity reported in the last column of Table 3 shows that a 1 per cent 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 per cent and increased to 3 per cent in 2008, only to decrease again to 1.6 per cent in 2014. Over the same period of time, the share of remittances in total household income has remained fairly stable at between 3.1 per cent and 3.8 per cent of total household income. The correlation of remittance income with total income, R_k, increased between 1993 and 2008 and decreased between 2008 and 2014. Overall, the 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 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 shows that remittances have potential to lower the Gini coefficient. A 1 per cent 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 examination 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. For example, if the arrival of a state old-age pension pushes a household up the income distribution, the decomposition is only able to reflect the situation after the arrival of the pension. The elasticities are an attempt to correct for this weakness. However, as they are driven by taking the partial derivative of the Gini with respect to each income source, they can only simulate a small or marginal change in income from one source, holding all other sources constant. This becomes problematic as an increase in labour market income, for example, might lead to a disqualification from receiving government grants. The elasticities reported on labour market income cannot account for these consequences. Therefore, even though the static decomposition clearly identifies the considerable contribution of labour market income to overall income inequality, it fails in assessing the role of changes, particularly in income sources that are relatively small compared to the large share of income from the labour market. The estimated elasticities are limited in simulating the influence of income sources that changed quite markedly over the post-apartheid period on the overall income distribution. Thus, we proceed to a more contemporary approach that uses micro-simulations that connect the cross-sectional data from each year to assess the effect of changes in one income source on overall inequality.

3.2 Micro-simulations

In this subsection we introduce an approach used by Barros et al. (2006) and Azevedo et al. (2013) that models changes in different income sources using micro-simulations. Following Azevedo et al. (2013), these micro-simulations 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 on the aggregate change in inequality. An additional strength of these dynamic decompositions is that 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 incomes 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 includes 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 each of the different components outlined in equation (7), and in turn, inequality measures depend on the cumulative density function $F(\cdot)$. Through this framework, inequality in any period is linked to each income component as well as three key demographic indicators: household size, the share of adults in the household, and the share of employed adults in the household.

That said, there are no easy analytic solutions linking equation (7) through $F(\cdot)$ to a contribution to inequality driven by each income component and each demographic source. Rather, if equation (7) holds as an identity in each time period and in each of our cross-sectional surveys, 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 incomes, 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 quantile 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 change in the share of adults that earn labour market income between 1993 and 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 changes in 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.

The method introduced by Barros et al. (2006) is refined by Azevedo et al. (2013) 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. Since there are eight variables of interest, this aggregates to $40,320$ possible paths; that is, the result of *8 factorial*. The estimates of the Shapley–Shorrocks values are reported in the tables that follow.

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 Shapley–Shorrocks values calculate the averages of this substitution 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 dynamic decomposition will be broken into 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, the decrease of inequality over these periods of time.[5]

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 are 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. It is possible and interesting also to rank-order households by the different income components instead. This offers 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 shifts within the distribution of the particular income source.

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 demographics 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 Tables 6 and 7, which will provide the results of the simulations following different rankings while also accounting for household composition. So, for example, if there have been changes across the quantiles of the distribution in which households are accessing labour market income or in the targeting of social grants, this will be reflected in these income component re-rankings. This is very useful information in understanding changing income inequality.

Table 4: Dynamic decompositions of per capita income sources, 1993–2008

Effect	Gini	Percentage change
Labour income	0.029	4.3%
Government grants	–0.063	–9.3%
Remittances	0.018	2.6%
Investment	–0.002	–0.3%

Number of paths = 40n320
Number of factors = 8
Source: authors' calculations using PSLSD and NIDS weighted data.

Starting with the 1993–2008 period, we know that the overall Gini coefficient barely moved from the very high 0.681 to 0.69. Thus, this is the change that we are explaining. The fact that there is only a very slight increase to be explained does not nullify the exercise. Indeed, it heightens the usefulness of the exercise as it is likely to reveal much change in the income distribution that nets out to almost the

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

same aggregate picture. The estimation in Table 4 shows that between 1993 and 2008, changes in labour income contributed to the observed increase in the Gini over this period, 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 per cent 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 equalizing effect is from government grants. Changes in government grants lowered the Gini by 0.063 points (9.3 per cent). This reflects the substantial roll-out of social grants and, in particular, the Child Support Grant that is documented by 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 per cent. 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 per cent 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.

Table 5: Dynamic decompositions of per capita income sources, 2008–2014

Effect	Gini	Percentage change
Labour Income	–0.021	–3.0%
Government Grants	–0.012	–1.7%
Remittances	–0.012	–1.7%
Investment	–0.006	–0.9%

Number of paths = 40,320
Number of factors = 8
Source: authors' calculations using NIDS 2008 and 2014 weighted data.

Turning now to the 2008–2014 period, from the static decomposition we know that between 2008 and 2014 the overall Gini coefficient decreased from 0.69 to 0.66. The dynamic decomposition using NIDS 2008 and 2014 data shows that all income components contributed to this fall in overall inequality, using 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 labour market income resulted in a decrease in the Gini of 0.021 or 3 per cent. 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 per cent. Furthermore, changes in investment income decreased the Gini coefficient by another 0.9 per cent.

These dynamic decompositions are very interesting as they shed light on the drivers of the changes in inequality that were not surfaced in the static decompositions. For example, the static decompositions gave social grants only a muted role, whereas the dynamic decompositions showed that the roll-out of social grants played a major equalizing role in both periods, whether or not aggregate inequality went up or down. But, as we showed earlier in discussing the theory of these dynamic decompositions, in all decompositions of per capita income to this point we have joined the previous literature in conflating income changes and demographic changes. However, the approach developed by Azevedo et al. (2013) allows us to differentiate the changes in inequality not only according to changes in different income sources but also according to changes in 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 per cent of household members were 15 or older compared to 95.4 per cent in 2014, and the share of employed had increased from 37 per cent to 46 per cent. Tables 6 and 7 go on to factor in these changes in household demographics into the dynamic decompositions. The tables also allow for a re-ranking of income sources.

Table 6: Dynamic decompositions: 1993–2008 including household composition and different ranking variables

Variable	Gini	Percentage 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 adults	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%

Number of paths = 40,320
Number of factors = 8
Source: authors' calculations using NIDS and PSLSD weighted data.

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 per cent). The share of employed adults, on the other hand, decreased the Gini by a significant 3.7 per cent or 0.025 points. From Table 2, we know that both of 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 when the effect of changes in the household composition are separated out.

It turns out that accounting directly for the changes in demographic variables affects the estimated contributions of the changes in income sources markedly. Now, the changes in labour income worsen inequality and are driving the increase in the Gini coefficient by 6.6 per cent 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 per cent 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 source worsened between 1993 and 2008, and that labour income remains a driver of inequality, especially after household demographics are accounted for.

Changes in government grants have a strongly equalizing effect when ranked by household income, and more so when ranked by grant income. The impact of changes in income from social grants increases from 6 per cent to 6.5 per cent, depending on the ranking variable. The fact that the equalizing effects of government grants are stronger when ranked by grants implies that changes in 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 and when ranked by remittance income. The effect is small at 0.7 per cent in the first case and decreases to 0.4 per cent in the latter. Remittances probably have such a small effect on changes of the Gini coefficient 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 per cent and 3 per cent to total inequality and their shares in income were about 3 per cent. When we assess 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 of 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. Compared to a change of 2.6 per cent in the benchmark case, the change in remittances only contribute to a 0.7 per cent change in inequality when the effect of demographic variables is separated out. This implies that in the benchmark case, inequality changes actually attributed to the change in demographic household variables were implicitly accounted for by income sources.

Finally, changes in income from investment sources had a small equalizing effect on changes in the Gini for the different rankings. When ranked by total income, this effect is at 2.3 per cent. When assessing the effect of changes in the distribution of investment income, the effect is at 2.9 per cent. These effects are much larger than the 0.3 per cent estimated in the benchmark. This shows that when changes in demographics are not accounted for, the true impact of changes in investment income are overestimated.

Overall, it would seem that increased efforts by the post-apartheid state to address 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 notable at about 1 per cent 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.

Table 7: Dynamic decompositions: 2008–2014 including household composition and different ranking variables

Variable	Gini	Percentage 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 adults	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%

Number of paths = 40,320

Number of factors = 8

Source: authors' calculations using NIDS 2008 and 2014 weighted data.

We move on to analysing 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 –0.046 points of the Gini or –6.7 per cent. This large change is the same when ranked by total household income as when ranked by labour income. This highlights the very strong correlation found between labour income and total household income. In Table 1 we reported that the share of labour income dropped between 2008 and 2014 while the proportion of households receiving this type of income increased from 64.4 per cent to 72.6 per cent. This sharp increase in the reach of this type of income may help to explain the decrease in inequality. But one would expect that allowing for the influence of employed adults would already have picked up this demographic effect. Indeed, there is a direct labour income effect too, as the Gini coefficient within labour incomes decreased from 0.76 to 0.73 in 2014, implying a direct, non-demographic income effect through more equal distribution of this income than in 2008. The interaction of these direct and demographic labour market income 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 per cent when ranked by total household income and 1.2 per cent 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 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 equalizing role that they were by 2008 but that this has not become that much more equalizing between 2008 and 2014. This makes some sense because the massive roll-out of the Child Support Grant occurred in the earlier period and then stabilized in the later period.

Remittances have a much smaller effect. Changes in income from this source lead to a 0.6 per cent decrease in the overall Gini when ranked by total household income. This effect is slightly stronger when ranked by remittance income at 0.9 per cent. This supports the potential to decrease inequality that we discussed in the static decomposition. However, the static decomposition reported that remittances were contributing to inequality in 2014. The dynamic decompositions show 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 per cent. Ranked by total household income, changes in investment result in a 1.6 per cent 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 is clustered at the top of the income distribution. This has not changed very much between 2008 and 2014.

Given that the 1993–2008–2014 story is somewhat different in the two sub-periods, we end this section by looking to confirm this general picture across the whole period. In the Appendix, Table A1 reports the aggregate trends from a broad-period decomposition that applies the methods of Azevedo et al. (2013) to compare changes between 1993 and 2014. In this long-term comparison, Table A1 shows that the share of adults in a household contribute to a 1.3 per cent increase in the Gini coefficient between 1993 and 2014; this is equivalent to 0.009 units. The share of employed adults in a household leads to a 2.9 per cent decrease over the same time period. However, it is important to note that the decomposition of Tables 6 and 7, in which the effects of changes in household demographics were accounted for separately, reported that the share of employed had a decreasing effect of close to 4 per cent only between 1993 and 2008, whereas between 2008 and 2014 changes in the share of employed contributed to a 1 per cent increase in the Gini. Thus, 2.9 per cent is an awkward average across a strongly decreasing earlier period and a slightly increasing later period.

Table A1 also reports that over the period 1993–2014, changes in labour income contributed to a 0.6 per cent 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 per cent. The fact that the change in the Gini is negative when ranked by total household income and positive when ranked by labour income is important in indicating that those accessing labour incomes were higher up the total household income distribution in the later period. Because this overall decomposition reports the net changes, it falls short in showing the inequality-increasing effect of labour income between 1993 and 2008 or the inequality-reducing effect between 2008 and 2014. These movements in inequality have important policy implications. Therefore, it is highly beneficial to carry out a step-by-step analysis rather than looking at the overall time period.

Furthermore, between 1993 and 2014, changes in government grants reduced the Gini by 6.3 per cent, or 7 per cent when ranked by grant income. This is in line with the inequality-reducing effects we found previously and reflects an aggregate of similar-sized effects 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 per cent 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 ignores 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 per cent when ranked by total household income and reports a slightly smaller effect of 2.3 per cent 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 cannot 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 dynamic decomposition method is a novel approach in the South African context. Using micro-simulations, 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. The equalizing role of government grants has long been established in the literature (see Leibbrandt et al. 2010, 2012); however, the results of our dynamic decomposition prove the powerful effect of correctly targeting these grants. Furthermore, the above analysis revealed that 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. These ambivalent effects of changes in income from the labour market have previously been overlooked when using static decomposition methods.

4 Conclusion

This paper has applied different income source decomposition methods in order to ascertain drivers of inequality in South Africa over the post-apartheid period. Previous analysis of inequality in South Africa has relied heavily on this type of static decomposition by income source (see Leibbrandt et al. 2009 or Leibbrandt et al. 2012). The context on which the decomposition work is shedding light is a slight increase in income inequality from 1993 to 2008 and then a bigger decrease in inequality between 2008 and 2014. Using data from the PSLSD from 1993, as well as from the NIDS from 2008 and 2014, labour market income has been shown to be the largest contributor to the high levels of inequality in South Africa. According to the decompositions performed in this paper, households benefit significantly from income from government grants, whereas labour income as well as investment income contribute strongly to overall inequality.

The static decomposition method following Stark et al. (1986) suggested that labour market income contributes between 84 per cent and 90 per cent 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. However, the static decomposition falls short in explaining how changes in the different income sources affect changes in observed levels of inequality. This makes a significant difference, especially when assessing the effect of incomes that have a smaller share in overall household income, such as government grants.

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. These counterfactual methods are much less common in South Africa, even though an understanding of changes in inequality is crucial. Thus, the application of these changes is our core contribution in this paper. Using these methods, we have shown that although government grants only make up 3–16 per cent of overall household income, these incomes have significantly contributed to reducing inequality. The results of 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 expansion of government grants limited the increase in inequality driven by changes in labour market incomes over this period. Even between 2008 and 2014, government grants played a significant role in reducing inequality, and different ranking methods show that targeting of social policies continued to successfully address households at the bottom of the income distribution. In addition to the successful implementation of government grants, the dynamic decomposition has shown that changes in inequality within labour market income contributed strongly to the decrease of inequality between 2008 and 2014 once changes in household composition were separated out. This is not because labour market income became equalizing, but rather because it became less dis-equalizing. The nuances of the effects of the different income sources are largely overlooked when relying on the static decomposition approach.

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. 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 refined 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 of 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 importance of separating out income changes from demographic changes as both have changed substantially over the post-apartheid period. There is improved information in using the method of Azevedo et al. (2013).

Overall, the novel decomposition methods using micro-simulations applied in this paper allowed us to identify the role of changes in different income sources on this reduction in ways we have not been able to before.

Our improved analytical methods have surfaced some important points about the policies that are needed to overcome 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. It is affirming to know that these grants are serving as a platform in the lower tail of the income distribution and that they have pushed this lower tail rightwards over time. In a benefit-incidence exercise, Maboshe and Woolard (2018) strongly confirm the fact that these social grants are well targeted and strongly equalizing. Collectively, these grants represent a very large and expensive fiscal intervention and our analysis is clear that they cannot be expected to play further inequality-reducing roles unless they are further augmented with additional prongs, such as some form of coverage of the working-age population. It is hard to see how such a prong could be put in place without clear re-prioritization of the budget. Even if an ambitious addition to social grants of this sort is put in place, our analysis has identified that the changes in inequality within labour market income remains the pivotal driver of overall changes in inequality. Therefore, the key to lowering income inequality in a long-run, dynamic process of sustained inequality reduction remains a labour market issue and requires a set of labour market policies that are inclusive of those at the bottom of the income distribution through employment and earnings. As such, changes in labour market income must be analysed in more detail. A step in this direction is found the work of Finn and Leibbrandt (2018), which reviews recent research on the post-apartheid earnings distribution and then, in very much the same spirit as this paper, conducts new empirical analysis on changes in earnings inequality over the post-apartheid period. Earnings inequality has increased since 2008. Thus, recent dynamics in the labour market are not encouraging in that they do not complement the dampened role of household labour market income that we have reported in this study.

The analysis of earnings makes use of the labour force surveys consolidated into the Post-Apartheid Labour Market Series data set, whereas our analysis in this paper makes use of the panel data of the NIDS. One possible reconciliation of the earnings inequality trends and our analysis at the household level in this paper is that the NIDS data are missing or under-reporting the top end of the income distribution. Certainly, it is clear that this top end is more prone to panel attrition than the middle and lower sections of the NIDS distribution of income. Indeed, utilizing income tax records from the South African Revenue Service, Hundenborn et al. (2018) find strong evidence that the top end of the NIDS distribution is truncated. If the Gini coefficient is measured using a merged distribution of NIDS data and tax data for the top end, then it is substantially higher. This is not good news and suggests that our promising findings of the less dis-equalizing roles of labour and investment incomes post-2008 need to be treated with caution. Thus, social grants are still pushing against very dis-equalizing forces stemming from market income.

References

Azevedo J., G. Inchauste, and V. Sanfelice (2013). 'Decomposing the Recent Inequality Decline in Latin America'. Technical Report. Washington, DC: World Bank.

Barros, R.P.D., M.D. Carvalho, S. Franco, and R. Mendonça (2006). 'Uma análise das principais causas da queda recente na desigualdade de renda Brasileira'. Technical Report 1203. Brasilia: Instituto de Pesquisa Economica Aplicada (IPEA).

Finn, A., and M. Leibbrandt (2018). 'The Evolution and Determination of Earnings Inequality in Post-Apartheid South Africa'. UNU WIDER Working Paper 83/2018. Helsinki: UNU-WIDER.

Hundenborn, J., I. Woolard, and M. Leibbrandt (2016). 'Drivers of Inequality in South Africa'. Technical Report 194. Cape Town: Southern Africa Labour and Development Research Unit.

Hundenborn, J., I. Woolard, and J. Jellema (2018). 'The Effect of Top Incomes on Inequality in South Africa'. UNU WIDER Working Paper 90/2018. Helsinki: UNU-WIDER.

Leibbrandt, M., C. Woolard, and I. Woolard (2009). *Poverty and Inequality Dynamics in South Africa: Post-Apartheid Developments in the Light of the Long-Run Legacy*. Oxford: Oxford University Press.

Leibbrandt, M., I. Woolard, A. Finn, and J. Argent (2010). 'Trends in South African Income Distribution and Poverty Since the Fall of Apartheid'. OECD Social, Employment and Migration Working Paper 101. Paris: OECD.

Leibbrandt M., A. Finn, and I. Woolard (2012). 'Describing and Decomposing Post-Apartheid Income Inequality in South Africa'. *Development Southern Africa*, 29: 19–34.

Lerman, R.I., and S. Yitzhak (1985). 'Income Inequality Effects by Income Source: A New Approach and Applications to the United States'. *The Review of Economics and Statistics*, 67: 151–56.

Maboshe, M., and I. Woolard (2018). 'Revisiting the Impact of Direct Taxes and Transfers on Poverty and Inequality in South Africa'. UNU-WIDER Working Paper 79/2018. Helsinki: UNU-WIDER.

NIDS (2013). 'Wave 3 Overview'. Technical Report. Pretoria: National Planning Commission.

SALDRU (1994) 'South Africans Rich and Poor: Baseline Household Statistics. Project for Statistics on Living Standards'. Technical Report. Cape Town: Southern Africa Labour and Development Research Unit.

Shorrocks A.F. (1982). 'Inequality Decomposition by Factor Components'. *Econometrica: Journal of the Econometric Society*, 50: 193–211.

Stark, O., J.E. Taylor, and S. Yitzhaki (1986). 'Remittances and Inequality'. *The Economic Journal*, 96(383): 722–40.

Wittenberg, M. (2009). 'Weights: Report on NIDS Wave 1'. Technical Report. Cape Town: National Income Dynamics Study.

Data sources

SALDRU (2012). Project for Statistics on Living Standards and Development: PSLSD (dataset). Version 2.0. Cape Town: Southern Africa Labour and Development Research Unit (producer).

SALDRU (2015). National Income Dynamics Study 2008, Wave 1 (dataset). Version 6.0. Cape Town: Southern Africa Labour and Development Research Unit (producer).

SALDRU (2015). National Income Dynamics Study 2014–2015, Wave 4 (dataset). Version 1.0. Cape Town: Southern Africa Labour and Development Research Unit (producer).

Appendix

Table A1: Dynamic decompositions: 1993–2014 including household composition and different ranking variables

Variable	Gini	Percentage 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%

Number of paths = 40,320

Number of factors = 8

Source: authors' calculations using NIDS and PSLSD weighted data.