

Southern Africa Labour and Development Research Unit

Patterns of persistence: Intergenerational mobility and education in South Africa

by
Arden Finn, Murray Leibbrandt
and
Vimal Ranchhod



SALDRU Working Paper
Number 175



N.i.D.S.
NATIONAL INCOME DYNAMICS STUDY

NIDS Discussion Paper
2016/2

About the Author(s) and Acknowledgments

Arden Finn: fnnard001@myuct.ac.za, Doctoral student and researcher at the Southern Africa Labour and Development Research Unit, University of Cape Town.

Murray Leibbrandt: murray.leibbrandt@uct.ac.za, Professor of economics and director of SALDRU at the University of Cape Town.

Vimal Ranchhod: vimal.ranchhod@uct.ac.za, Associate professor in SALDRU at the University of Cape Town.

Acknowledgements:

Funding for this research from the Department of Planning, Monitoring and Evaluation is gratefully acknowledged.

Arden Finn acknowledges the National Research Foundation for financial support for his doctoral work through the Chair in Poverty and Inequality Research. Murray Leibbrandt acknowledges the Research Chairs Initiative of the Department of Science and Technology and National Research Foundation for funding his work as the Chair in Poverty and Inequality Research. Vimal Ranchhod acknowledges support from the Research Chairs Initiative of the Department of Science and Technology and the National Research Foundation.

Recommended citation

Finn, A., Leibbrandt, M., Ranchhod, V. (2016). Patterns of persistence: Intergenerational mobility and education in South Africa. Cape Town: SALDRU, University of Cape Town. SALDRU Working Paper Number 175/ NIDS Discussion Paper 2016/2.

ISBN: 978-1-928281-36-8

© Southern Africa Labour and Development Research Unit, UCT, 2016

Working Papers can be downloaded in Adobe Acrobat format from www.saldru.uct.ac.za.

Printed copies of Working Papers are available for R25.00 each plus vat and postage charges.

Orders may be directed to:

The Senior Administrative Officer, SALDRU, University of Cape Town, Private Bag, Rondebosch, 7701,
Tel: (021) 650 5698, Fax: (021) 650 5697, Email: tania.hendricks@uct.ac.za



Patterns of Persistence: Intergenerational Mobility and Education in South Africa

Arden Finn, Murray Leibbrandt and Vimal Ranchhod

Saldru Working Paper 175

NIDS Discussion Paper 2016/2

University of Cape Town, August 2016

Abstract

How should the correlation between the earnings of parents and children in South Africa be calculated in the presence of high unemployment, and what is the role of education in determining this relationship? We use the first four waves of the National Income Dynamics Study (NIDS) for 2008 to 2014/15, and the 1993 Project for Statistics on Living Standards and Development (PSLSD) to investigate the shape of the association between parental and child earnings across the earnings distribution, and find that the correlation is strongest at the ends of the distribution. We correct for possible biases that arise from co-resident parent-child pairs, and from selection into labour market participation in South Africa's high-unemployment society. We find that correcting for selection into employment increases the intergenerational elasticity of earnings by approximately 10 per cent. We unpack the role of education in determining the association of intergenerational earnings and find that the impact is strongest at the bottom of the earnings distribution, and that education accounts for approximately 40 per cent of the total intergenerational earnings elasticity.

Introduction

South Africa has long been highlighted as a country with some of the highest cross-sectional inequality in the world. Studies of why the level of disparity in economic outcomes has remained consistently high have touched on many areas, but it is only the recent emergence of high quality longitudinal data that has allowed researchers to begin to unpack the role of intergenerational persistence of income and earnings in shaping longer run trends. The dynamic relationship between the earnings of parents and the earnings of their offspring shapes the unfolding series of snapshot estimates of inequality that have been calculated for the country. Understanding the mechanisms behind these dynamics is therefore an important part of understanding why inequality in South Africa has remained so high.

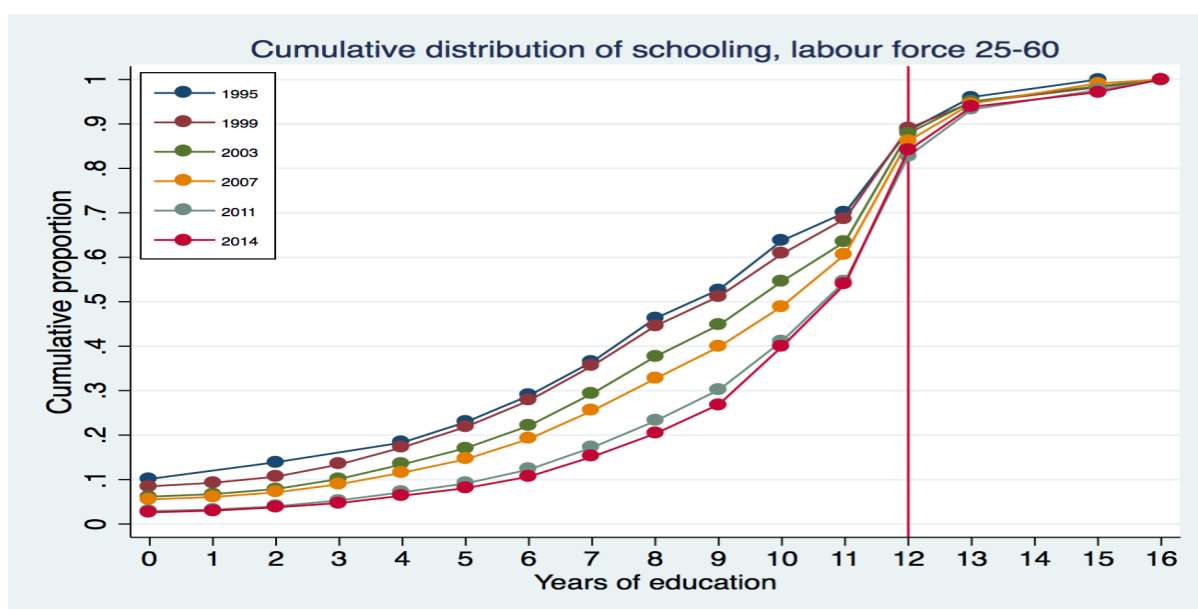
The degree of persistence of intergenerational earnings is often closely linked to the question of the equality of opportunity present in society. Recently, Corak (2013) has led the cross-country research into this relationship and has produced what has become popularly known as the ‘Great Gatsby curve’. This curve shows a strikingly positive relationship between the persistence of earnings from parents to children, and the level of inequality in a country. The implication is that the closer the correlation between parental and child earnings, the higher the level of inequality in society. The corollary is that equality of opportunity is lower in societies with high persistence between the earnings of parents and those of their children compared to societies with relatively lower levels of persistence. Piraino (2015) has undertaken the most comprehensive work in this area using South African data, and has calculated the intergenerational earnings elasticity and an inequality of opportunity index for the country. He finds that the level of persistence between the earnings of fathers and sons is very high and is comparable to other developing countries with high levels of income inequality. He locates South Africa along the ‘Great Gatsby curve’ as a country with both a high level of intergenerational persistence and a high level of economic inequality.

In this paper we aim to deepen the understanding of intergenerational earnings dynamics in South Africa by focusing on the roles of education and selection into employment in determining the relationship between the earnings of parents and the earnings of their children. This is largely motivated by three stylised facts that have emerged from the post-apartheid South African literature on education and economic inequality. First, there has been an increase in the general level of educational attainment, along with a reduction in the inequality of education levels. Second, the last two decades have seen an increase in the returns to matric and post-matric education relative to other education categories. Third, the levels of cross-sectional economic inequality and unemployment have been very high and persistent in South Africa’s democratic era.

Stylised fact 1: Increased educational attainment

There has been a sharp decrease in the inequality of educational attainment in the country, and this has come about because of a general increase in the number of years of schooling completed by South Africans. The coefficient of variation of education for working-age South Africans fell from 0.5 in 1994 to just over 0.3 in 2011 (Lam et al., 2015). The increase in educational attainment for working-age South Africans is confirmed in figure 1 which is reproduced from Lam et al. (2015), with the addition of data from 2014. Improvements in the average level of education are evident in the cumulative distribution functions (CDFs) from 1995 to 2014, with the increase being driven by higher proportions of the labour force completing primary school. In 1995 more than half the labour force had dropped out of school by grade 9. By 2014 this proportion was below 30%. Though the increase in educational attainment is impressive, a figure of CDFs remains agnostic as to the quality of that education.

Figure 1: The increasingly educated South African labour force



Source: 1995 to 2011 based on Figure 1 in Lam et al. (2015) using the Post Apartheid Labour Market Series (PALMS) dataset. 2014 calculated using the Labour Market Dynamics in South Africa (LMDSA) 2014 dataset.

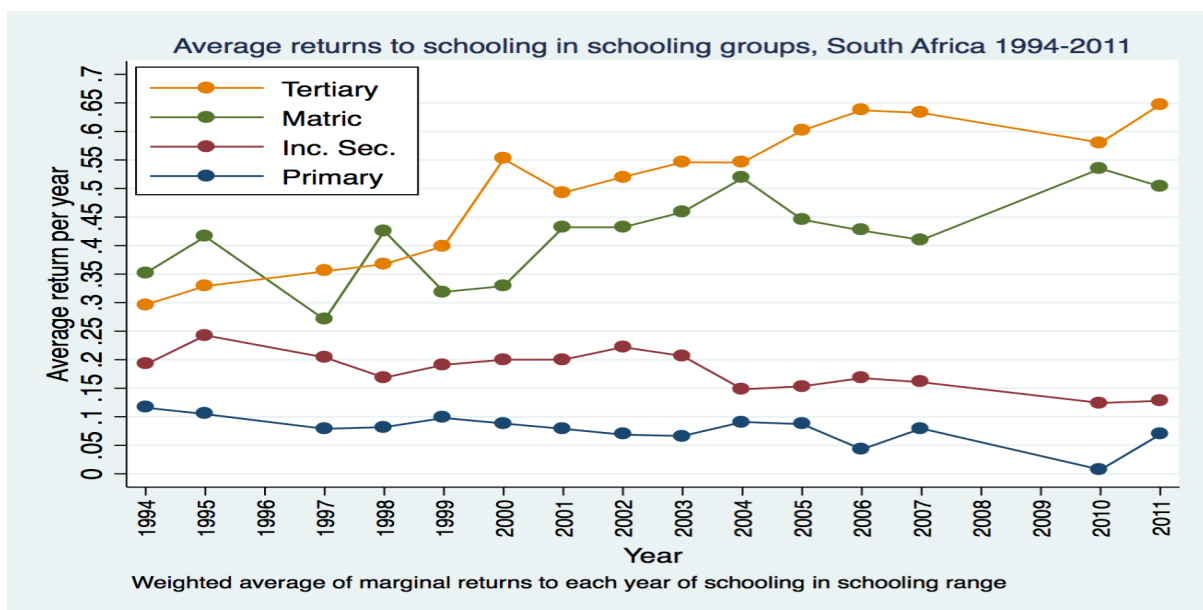
Stylised fact 2: Changing patterns in the returns to schooling

Although the average level of education of the South African labour force has increased, this may not have been matched by a proportional increase in earnings. Keswell and Poswell (2004) and Branson and Leibbrandt (2013) among others have found that the country displays a strongly convex returns to education function, even once experience and educational quality are controlled for. Figure 2 below is adapted from Lam et al. (2015)¹ and plots the average re-

¹Lam et al. (2015) plot only three categories – primary, incomplete secondary, and matic and above.

turns to schooling for four schooling groups from 1994 to 2011. The figure shows that there has been an increase in the returns to matric and post-matric education relative to the incomplete secondary and primary schooling categories. The increase in the returns to matric and above occur at the same time as a relative decrease in the returns to both of the other categories. The full benefits from a more educated labour force are therefore not translated into a proportional increase in earnings unless a worker has completed high school and continues into postsecondary education. This resonates with concerns about the persistent nature of inequality, as Corak (2013) notes that relatively higher returns to tertiary education often go hand-in-hand with high and sticky cross-sectional inequality.

Figure 2: Returns to schooling by schooling category



Source: Based on Figure 1 in Lam et al. (2015) using the Post Apartheid Labour Market Series (PALMS) dataset.

Stylised fact 3: Stubbornly high economic inequality

Although there is some debate as to the precise level of economic inequality in South Africa, there is no doubt that it has been consistently high in the post-apartheid period. The Gini coefficient for labour market earnings in South Africa has averaged around 0.55 (Finn, 2015), while the Gini coefficient for total household income per capita has been at 0.66 or above since 1993 (Leibbrandt et al., 2010; Yu, 2010). Part of the blame for the stickiness of inequality in South Africa comes from the dynamics of how educational attainment and labour market earnings of parents feeds through to the educational attainment and earnings of children. Uncovering part of this dynamic relationship is an important part of understanding inequality in contemporary South Africa, and is the main contribution of this study.

The structure of this paper is as follows. Section I discusses the relationship between intergenerational mobility and inequality, and outlines the theoretical framework that will be used to measure and decompose the intergenerational earnings elasticity. Section II describes the data and estimation procedures used in our study, and presents some descriptive statistics. In section III we report the results from a number of different estimations of the intergenerational earnings elasticity, and this is followed by an analysis of the role of education in determining and shaping this elasticity. The final section provides some concluding remarks.

I Theoretical background

There has recently been something of a shift in the focus of the inequality literature, with studies of inequality of opportunity becoming more prevalent relative to studies of the inequality of outcomes. A key feature of these works is the attempt to distinguish between inequality that arises because of inherited circumstances and inequality that arises due to the application of effort. The former, which is often subsumed in the idea of inequality of opportunity, is usually seen as less ethically justifiable than the latter. If variables that are beyond a person's control, such as parental education, race or sex, do not have any bearing on their realized economic outcome, then one may say that there is equality of opportunity because differences in economic outcomes are driven by the effort expended by each individual, and by luck. However, as noted by Atkinson (2015) the distinction between inequality of opportunity and inequality of outcomes is not a clear one in either a single generational or inter-generational sense. The reason for this is the fact that 'today's ex-post outcomes shape tomorrow's ex-ante playing field' (p. 11). There is no reason to think that equal opportunities will lead to equal outcomes in a dynamic sense. Even if it were possible for an entire generation to start off with identical opportunities, the unequal ex-post distribution of economic outcomes would mean that the next generation would face ex-ante inequality.² If the starting point for each generation is highly unequal, and the transmission of economic outcomes from parents to children is largely deterministic, then this has clear implications for the persistence of inequality in society. Therefore South Africa's, low level of *intergenerational* mobility has dynamic consequences for the production of *intragenerational* inequality, and understanding this relationship is important from a policy and ethical perspective.

The focus on labour market earnings is warranted because of the important role that wages play in determining the extent of cross-sectional inequality in South Africa (Leibbrandt et al., 2010). A better understanding of wage inequality goes a long way to assist an understanding of household income inequality, and understanding intergenerational earnings mobility goes a long way to explaining why inequality has been so persistent in South Africa.

The reason for focusing on education as a transmission mechanism is because education is

²This presumes that the state is non-interventionist in equalizing ex-ante opportunities.

widely cited as being the key factor in reducing cross-sectional inequality, but an equalization of education may not lead to lower inequality, as we have witnessed over the last twenty years in South Africa. The impact of equalizing education, therefore, cannot be seen in isolation. It must be understood together with the labour market outcomes associated with education. These include the probability of finding a job and the shape of the returns to education function itself.

Another dynamic to note is that credit constraints may be significant barriers to both the quantity and quality of education a child receives, and this can contribute to a pattern of inequality that is self-reinforcing. Furthermore, the higher the correlation of economic outcomes between parents and children, the longer it takes for a society to reach the equilibrium social status of each generation (Checchi, 1997).

A seminal theoretical paper by Becker and Tomes (1979) sets about trying to explain the dynamics of educational attainment from generation to generation. One of the central motivations of this paper is to unify the analysis of cross-sectional inequality (inequality within a generation) and intergenerational inequality. The persistence of income from one generation to the next is determined by a mix of factors including the level of endowments of an individual, the inheritability of various characteristics, the propensity of each generation to invest, and luck.

The Becker and Tomes (1979) framework has inspired a large body of economic theory on the transmission of economic advantage between generations that is distinct from the sociology literature which preceded it by several decades. Empirical applications inspired by these models soon followed and, as noted in Chusseau et al. (2013), one of the defining features of this literature is the attempt to separate out the roles of ‘effort’ and ‘luck’ in determining social mobility, and this is generally done by isolating the influence of different channels that determine educational attainment and labour market returns.

Lefranc and Trannoy (2005) present a simplified version of the Becker and Tomes model. Let us assume that the transmission of income or earnings from parent to child is determined by the individual endowment of human capital, and by the innate ability of the child. The Becker and Tomes model is built on the assumption that the child’s utility enters the parent’s utility function, and that the child’s level of human capital is chosen by the parent as a result of the optimal allocation of permanent income. The relationship between the child’s permanent income (denoted by c) and the parent’s permanent income (denoted by p) is given by the following equation:

$$Y^c = \phi Y^p + \theta a^c \quad (1)$$

In this equation the parameter ϕ represents the extent of the causal relationship between the permanent income of the parent and the permanent income of the child. As noted by Lefranc and Trannoy (2005), the source of this correlation maps to the positive relationship between the father’s earnings and the investment in the child’s human capital. The constraint on this

investment is the amount of financial resources available to the family. This is something that may be particularly important in South Africa, as credit constraints have been shown to be a barrier to post-secondary enrollment (Lam et al., 2013). In addition, the constraint may bind before post-secondary enrollment by limiting parents' ability to send their children to a better school that may require a higher level of expenditure.

The second term on the right hand side captures the determinants of the child's permanent income that are related to the child's that 'money can't buy'. These include things like IQ, social networks, or preferences (Lefranc and Trannoy, 2005). Becker and Tomes (1979) differentiate this effect from the previous effect by noting that its influence on the intergenerational transmission of income comes from earnings determinants that are independent of parental investment decisions.

Separating out the two different types of transmission mechanisms that arise from the Becker and Tomes model would yield interesting policy implications. If the dominant mechanism determining intergenerational earnings transmission is parental investment in education, then overcoming credit constraints would lead to a smaller correlation between the earnings of successive generations, and therefore more economic mobility. If, however, the dominant mechanism is individual ability, then increasing social mobility may be more difficult.

Much of the research that is motivated by this theoretical model does not make a distinction between the two mechanisms explaining intergenerational earnings. In general, a simple regression of son's permanent income³ (or earnings) on father's permanent income (or earnings) is the preferred approach, given the data's inability to convincingly isolate the 'ability' mechanism. Combining both mechanisms into a single coefficient will lead to an upward bias in the estimate of the elasticity of intergenerational earnings (Lefranc and Trannoy, 2005). In this paper we estimate the intergenerational elasticity of earnings using a reduced form version of this model, in line with most of the international literature. In doing so we attempt to overcome the bias that may arise from co-resident selection, and the bias that may arise from selection into a job in a society with a very high unemployment rate.

The canonical estimation of intergenerational mobility comes from a simple regression of the logarithm of child's (usually son's) permanent income on the logarithm of parent's (usually father's) permanent income.

$$Y_i^c = \alpha + \beta Y_i^p + \varepsilon_i \quad (2)$$

β is generally referred to as the intergenerational elasticity of earnings (IGE), when labour market returns are the focus, and is the most commonly used measure of the persistence of earnings between generations. As β is a measure of persistence, $(1 - \beta)$ may be thought of as a measure of intergenerational mobility. As β approaches zero, society approaches a situation

³Most of the studies in the international literature focus on the correlation of earnings between fathers and sons because of the added complication of accounting for female labour market participation decisions.

of perfect intergenerational mobility in which the earnings of the parent do not determine the earnings of the child. Conversely, as β approaches 1, the earnings of the parent increasingly determine the earnings of the child, and intergenerational mobility goes to zero. Though the interpretation of the intergenerational elasticity in this model cannot be interpreted in a purely structural sense, it is nonetheless a widely used and useful descriptive measure of how persistent earnings are between generations.

Another descriptive statistic that has been used widely in the literature is the intergenerational earnings correlation, ρ . As shown in Jäntti and Jenkins (2013) the relationship between the β measure of intergenerational earnings elasticity and the Pearson product moment correlation is given by the following:

$$\rho = \beta \frac{\sigma_{y_p}}{\sigma_{y_c}}$$

where σ_{y_p} and σ_{y_c} are the standard deviations of log earnings in the child's generation and the parent's generation respectively. This measure also highlights the link between intergenerational mobility and inequality, as the numerator and denominator on the right hand side are the log variance inequality indices for the parent's and child's generations respectively.

The intergenerational elasticity measure has been preferred to the intergenerational correlation in much of the literature for a number of reasons. First, as noted in Lefranc and Trannoy (2005), the elasticity may be measured independent of calculating the inequalities in each generation. Second, intergenerational elasticity is perhaps a more intuitively appealing concept to economists than the intergenerational correlation. Consider a policy shift that reduces the deviation from the mean of all income in the child's generation by the same factor. The effect of this policy should see a decrease in the persistence of intergenerational income (that is, an increase in intergenerational mobility). Indeed, the intergenerational elasticity would decrease under this policy, but the intergenerational correlation would not. The intergenerational correlation would remain unchanged, and the increased mobility would not be reflected. Third, the intergenerational elasticity is not biased if there is measurement error in the variable reflecting child's earnings (the dependent variable in the regression), unlike the correlation (Black and Devereux, 2011). Finally, as Jäntti and Jenkins (2013) point out, researchers may want to compare their estimates of intergenerational mobility to those of other studies, and the popularity of the measure ensures its continued use independent of any theoretical concerns.

Many studies have calculated the intergenerational elasticity in the last five to ten years. Reviews and international comparisons can be found, among others, in Blanden (2009), Brunori et al. (2013), Corak (2013) and Hertz et al. (2007), which provide tables of the intergenerational elasticities for a number of countries. The international evidence lends support to the 'Great Gatsby Curve', which suggests that countries with higher levels of inequality have lower levels of intergenerational mobility. Countries with low levels of cross-sectional inequality - in particular Scandinavian countries - have a higher degree of intergenerational mobility (a lower

intergenerational elasticity) than those with a higher degree of inequality such as the United States, the United Kingdom, and Italy (Corak, 2013). The Scandinavian countries have intergenerational elasticities that are below 0.2, while for countries with higher levels of inequality the elasticity is around 0.5.

Intensive data requirements have precluded the calculation of intergenerational elasticities for developing countries until recently. Piraino (2015) notes that these developing countries tend to have less intergenerational mobility than their OECD counterparts, and calculates an intergenerational elasticity that is between 0.57 and 0.67 for South Africa, depending on the variables used in the imputation of father's earnings. In other examples, Hnatovska et al. (2013) calculate an elasticity of around 0.5 for India, while Ferreira and Veloso (2006) find an elasticity of about 0.58 in Brazil. Grawe (2004) calculates an elasticity of 0.54 in Malaysia and 0.67 for Peru, while Bevis and Barrett (2015) calculate separate elasticities for sons and daughters, but find an average of about 0.5 in the rural Philippines. Recent data from urban China put the elasticity at around 0.6 (Gong et al., 2012), though the authors find that intergenerational persistence is far stronger for sons than it is for daughters.

The research on intergenerational income mobility in South Africa is relatively sparse, with the first example being Hertz (2001) who uses data on co-resident fathers and sons in the KwaZulu Natal Income Dynamics Study (KIDS) to calculate a range of intergenerational elasticities. A problem facing any analysis of this kind is the fact that the co-residency requirement may introduce selection bias into the estimation – the wages and characteristics of sons who co-reside with their fathers may be different to the wages and characteristics of those who do not.

A number of studies address this concern by making use of a two sample two stage least square (TSTSLS) estimation in which the earnings of the fathers are imputed using a nationally representative dataset from a previous time period. Piraino (2015) adopts this method and locates South Africa's position on the 'Great Gatsby Curve', adding further evidence to the pattern of high-inequality societies having low intergenerational mobility. He also links the literature on intergenerational mobility to that focusing on the inequality of opportunity, and finds that South Africa's inequality of opportunity index is high by international standards. We use Piraino's approach as a benchmark in our calculation of the intergenerational income elasticity, and build on this to highlight the role of education in shaping the earnings dynamics from generation to generation.

II Data and estimation procedure

Calculating the intergenerational elasticity of earnings and extracting the contribution of education to this elasticity requires data that are not often present in a single dataset. The ideal dataset would be a long panel that allows the researcher to calculate permanent income for both parents and children, whether they co-reside or not.

Given that this kind of comprehensive dataset is not yet available in South Africa, in this study we make use of two different datasets that allow us to calculate the earnings of two generations. Earnings for the second (younger) generation are calculated using the first four waves of the National Income Dynamics Study (NIDS) which were collected in 2008, 2010/2011, 2012 and 2014/2015, respectively. NIDS contains comprehensive information about the labour market activities and earnings of adults in the sample. Monthly earnings are calculated by combining reported income from all jobs, self-employment activities, profit shares, and bonuses.

One option available to researchers who want to calculate the earnings of the parental generation is to focus on families in which children co-reside with parents. Indeed, this is the approach adopted by Hertz (2001) using data from KwaZulu Natal. There are at least two significant problems with this approach. First, the subsample of co-resident parents and children may be relatively small. Second, selection bias may be introduced by restricting the analysis to those children who earn wages and still live with their parents. Co-resident children may have observed and unobserved characteristics that are systematically different from those who do not live with their parents, and this will bias our estimates of the intergenerational earnings elasticity.

The adult questionnaire in NIDS asks respondents a series of questions about their parents who are either non-resident or deceased.⁴ These include the age, education, and occupation of the parent. Thus, even if a parent is not interviewed directly, we are able to impute the earnings of the parent for a given set of characteristics. Following Piraino (2015) we use nationally representative data from 1993, the Project for Statistics on Living Standards and Development (PSLSD) to generate an earnings variable for the parental generation in NIDS. This Two Sample Two Stage Least Squares (TSTSLS) approach is explained in detail below, but in summary the following takes place. First an earnings regression is run on the PSLSD 1993 data in order to capture the determinants of wages in the parental generation. The dependent variable is the log of wages, and the independent variables are education categories, race, occupational categories and province of residence. These independent variables are chosen because they are the same as those reported by children about their parents in the NIDS dataset. Earnings for parents in NIDS are then imputed by using the estimated coefficients from the wage regressions in the 1993 data, along with parental characteristics from the NIDS data. The approach was introduced by Klevmarken (1982) and is sometimes thought of as a ‘cold deck’ linear regression imputation because an auxiliary sample is used to impute the missing variable of interest in the main sample.

Drawing on the exposition in Cervini-Plá (2013) and Lefranc and Trannoy (2005), we estimate the TSTSLS variant of the intergenerational earnings elasticity in the following way.⁵ In NIDS - what we call our main sample - we have information about Y^c , but not about Y^p . NIDS

⁴Co-resident parents are interviewed directly.

⁵The TSTSLS method for calculating the intergenerational income elasticity first appeared in Björklund and Jäntti (1997).

also contains sociodemographic information about parents contained in the vector of characteristics Z . The auxiliary sample, the PSLSD 1993, contains a wage variable for parental earnings, Y^p , as well as the same vector of characteristics Z .

Let us begin by denoting the log of parental earnings at time t , Y_{it}^p as:

$$Y_{it}^p = Y_i^p + u_{it}^p \quad (3)$$

where the error term captures transitory shocks as well as measurement error in parental earnings. We assume that the log of earnings in the child's generation is related to the log of permanent earnings in the same way, and that the errors from the parental and child generations are not correlated. For the vector of characteristics Z_i^p (in our case education, occupation, race, and province of residence), we assume that current parental income can be written as:

$$Y_{it}^p = Z_i^p \gamma + v_i^p + u_{it}^p \quad (4)$$

in which the time invariant error is uncorrelated with the set of characteristics. Our first problem is that Y_{it}^p is not available in our main sample I , in this case NIDS. However, in the PSLSD 1993, sample J , we have the same nationally representative population as in NIDS and we are able to extract an estimate of γ , $\hat{\gamma}$ which is obtained through estimating parental earnings in the auxiliary sample J :

$$Y_{jt}^p = Z_j^p \gamma + v_j^p + u_{jt}^p \quad (5)$$

in which $j \in J$. This is then used to form a prediction of parental earnings in the main sample, and in turn estimate β in the following way:

$$Y_{it}^c = \alpha + \beta(Z_i^p \hat{\gamma}) + \eta_{it} \quad (6)$$

Björklund and Jäntti (1997) note that if the characteristics in Z are also determinants of the child's income, then the intergenerational earnings elasticity will be biased upwards. That is, if the parental level of education and occupational category both have a positive impact on the child's earnings, then the elasticity may be biased upward. In this light, many calculations of the intergenerational elasticity using the TSTSLS method can be thought of as an upper bound for the measure of income persistence between generations (Piraino, 2015). At this point it is useful to echo Blanden (2015) who stresses that the intention is not necessarily to extract the causal effect of parental income on child income. Rather, the intention is to generate a measure of persistence of earnings across generations in a similar vein to how the Gini coefficient measures inequality in a cross-section.⁶

⁶Blanden (2015) draws the inequality-mobility connection succinctly in saying, 'The Gini coefficient provides a summary measure of cross-sectional inequality, but it does not provide any information about its source. The intergenerational elasticity measure performs a similar function for intergenerational inequality.'

In this study we estimate the intergenerational earnings elasticity using equation 6. Bootstrapped standard errors from 500 repeated processes are reported in which separate samples of parents and children are drawn. We also adjust for the fact that we observe both parents and children at different stages of their age-earning profiles using the method outlined in Bratberg et al. (2007). This is done separately for parents and children by regressing earnings on age and age squared, and then using the sum of the constant term and the residual from that regression as the measure of earnings. The age range for the younger generation is from 20 to 44 years old,⁷ while for the parental generation in the PSLSD 1993 dataset, we focus on adult earners between 30 and 59 years of age.

In general the focus will be on the relationship between the earnings of fathers and sons, and mothers and sons. This is in line with most of the international literature which avoids parent-daughter estimations due to the added complication of adjusting the elasticity to account for female labour market participation decisions.⁸ In this paper we acknowledge the difficulty of correcting for the bias that may arise from this process, and report both father-son and mother-son elasticities for the most part. We also evaluate how sensitive our measures of intergenerational mobility are in a high-unemployment labour market, and report the selection-adjusted measures for both fathers and mothers.⁹

We restrict our analysis to those sample members who appear in all four waves of NIDS.¹⁰ In theory we would like to get a measure that is as close to permanent income as possible. Averaging earnings across four waves for the second generation will get us closer to this than using single points in a cross-section. We are unable to estimate a similar averaged measure for the parental generation, and instead use the single imputed earnings point, as described above.¹¹ Another reason for choosing to focus on the balanced panel members is the fact that we are able to correct for selective attrition by using panel weights. Attrition rates between each of the waves of NIDS varied widely by racial group and by socio-economic characteristics (de Villiers et al., 2013). White respondents were more likely to drop out between waves than any of the other racial groups, as were those who were relatively wealthier. We construct attrition-corrected longitudinal weights in the same way as Finn and Leibbrandt (2013). This involves modeling attrition by running a series of unfolding probit models from wave 1 to wave 2, from

⁷The age interval refers to the age of the respondent in the first wave of NIDS.

⁸The parental sample is drawn from data from 1993, just before a surge in female labour force participation rates in South Africa. Female labour force participation rates have changed substantially in the post-1993 period (Casale and Posel, 2002). Much of the international literature in fact excludes mother's earnings altogether. We choose to contrast the intergenerational elasticity relative to both father's and mother's earnings as the high father absenteeism rate in South Africa may mean that recalled information about mothers in the sample is more reliable. In practice our sample sizes for mothers are relatively smaller, and the qualitative findings are similar whether fathers or mothers are used.

⁹These are corrected using Heckman's two-step approach, and are reported in section III.

¹⁰Piraino (2015) pools the data across three waves and uses observations that appear once, twice or thrice in the data. Like Piraino (2015) we also use average earnings in cases where respondents report earnings in multiple waves of NIDS.

¹¹Using snapshots of parental earnings when estimating the intergenerational elasticity biases the elasticity downwards because of the presence of measurement error (for example see Solon (1992)).

wave 2 to wave 3, and from wave 3 to wave 4. The wave 2 longitudinal weight is constructed by multiplying the wave 1 post-stratified weight by the inverse of the conditional probability of re-interview in wave 2. The same process is applied between wave 2 and wave 3, and between wave 3 and wave 4. The final longitudinal weight is applied to all respondents who were successfully interviewed in all four waves of NIDS. Our sample size is always larger than 1 200, and so we are not overly concerned about power issues given our decision to focus on the balanced panel members. All subsequent analysis in this paper makes use of this weighting structure.

Table 1 presents some descriptive statistics for the balanced panel members that form part of our analysis. The sample is restricted to those males between the ages of 20 and 44 who report their earnings and who have non-missing information about their parents.

The mean age in wave 4 of the 1 785 respondents in our analysis sample is 35. About 85.5% of those in the sample are African, and the proportion of White and Coloured respondents is similar. The second panel of the table presents the proportion of respondents and their parents in different education categories. Consistent with the pattern in figure 1, there is a significant increase in the level of education attainment from parents to children in the sample. Over 40% of respondents reported having parents who had no education, while the corresponding figure for respondents themselves was under 3%. The bulk of the shift in education attainment was to matric and postsecondary education. 43% of respondents in the balanced panel reported having attained at least a matric. The corresponding proportions for the fathers and mothers of these respondents are 12.4% and 11.7% respectively.

In the final panel of the table we present the proportion of respondents, fathers and mothers in different occupational categories. These are based on the South African Standard Classification of Occupations (SASCO) conventions and are adjusted so as to overlap directly with the occupational categories present in the PSLSD 1993 data. These categories can be thought of as loose proxies for occupational skill level, and mirror those used by Keswell et al. (2013) in their study of intergenerational occupational mobility in South Africa. The categories are rather broad and in reality each category probably covers a wide range of skill levels itself, but they are reported here as they form part of the imputation for parental earnings in the first stage of the TSTSLS estimation. The occupational distributions for fathers and sons look relatively similar, though there are a higher proportion of sons in clerk/sales categories, and a lower proportion in operator/semi-skilled jobs than their fathers. Almost 60% of the mothers of our balanced panel respondents were employed in elementary occupations - nearly three times the proportion of sons. Interestingly, 13.2% of mothers were employed in the highest skill category (professional/technical/manager), and the corresponding percentage for sons was lower at 8%.

Table 1: Summary statistics of the balanced panel

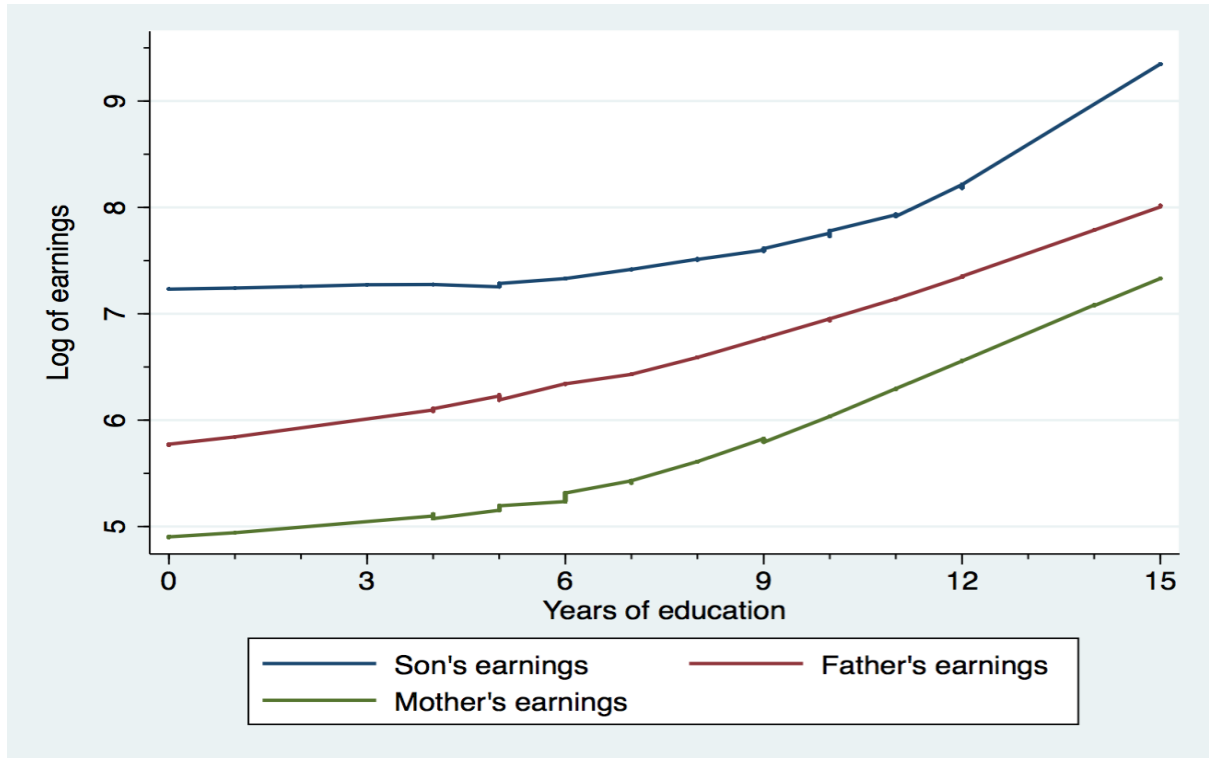
Age (mean in wave 4)	35.41			
Race				
African	85.53			
Coloured	6.49			
Asian/Indian	2.23			
White	5.75			
Education	Son	Father	Mother	
None	2.86	46.50	40.39	
Primary	13.32	18.54	24.17	
Incomplete secondary	40.97	22.62	23.78	
Matric	21.90	8.22	6.95	
Postsecondary	20.95	4.13	4.71	
Occupation	Son	Father	Mother	
Elementary	21.46	23.62	59.51	
Craft/trade	23.90	23.67	5.33	
Clerk/sales	22.59	14.17	16.75	
Operator/semi-skilled	23.96	29.33	5.21	
Professional/manager	8.08	9.20	13.20	
N	1 785			

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Five different earnings variables were created for parents, and these correspond to five different imputation equations in the first stage of estimation. They use the following variables to impute parental earnings respectively: Education; education and race; education, race and occupation; education, race and province; education, race, occupation and province. Figure 8 in the appendix shows kernel densities of the log of earnings of fathers and mothers that were generated by the fifth imputation process.

These earnings are mapped against years of education and are shown in the education-earnings profiles in figure 3. The real earnings of respondents in our balanced panel lie above those of their parents at every education level, and the same is true for father's earnings relative to mother's earnings. The convexity of the education-earnings profile of sons is evident, with a generally flat profile until the completion of secondary education, after which there are relatively higher returns to each year of postsecondary education.

Figure 3: Education-earnings profiles for the balanced panel and parents

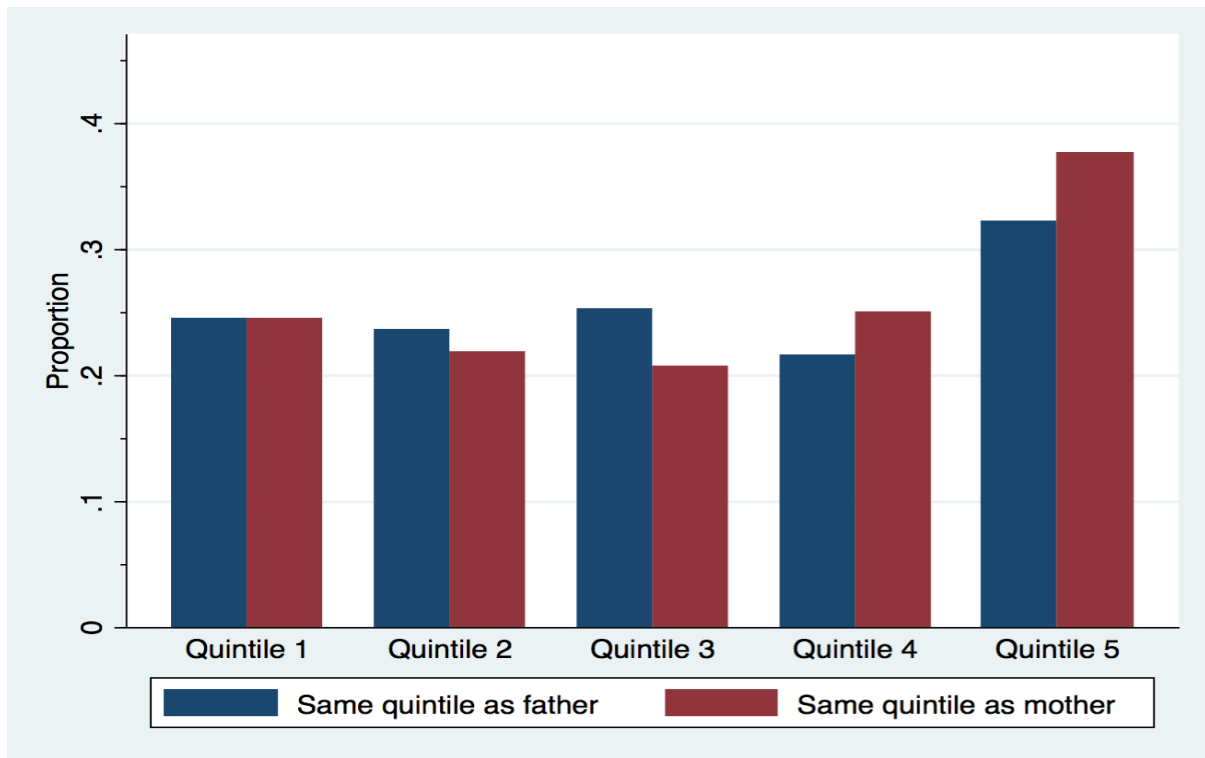


Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

We now turn our attention to the relative positions of parents and children in the distribution of earnings. Figure 4 below plots the probability that a son will be in the same earnings quintile as his parents.¹² Around one quarter of sons whose parents were in the bottom 20% of the earnings distribution are themselves in the bottom quintile. This proportion decreases to just under 20% for the middle quintile. Interestingly, sons whose fathers were in the 3rd earnings quintile are as likely to be in the bottom quintile or the top quintile themselves. There was relatively more downward mobility for sons whose parents were in the middle of the earnings distribution. Unsurprisingly, the highest probability of parent and child quintile matching is at the top of the earnings distribution. This top quintile shows a difference of about 5.5 percentage points between father and mothers, with child quintile matches of 32.3% and 37.7% respectively.

¹²The full transition matrices are presented in table 6 in the appendix.

Figure 4: Unconditional probability of a son being in the same earnings quintile as his parents



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

The general increase in educational attainment, as described in the first stylised fact in the introduction, is clear if we examine an educational transition matrix for parents and their children in the balanced panel. Table 2 shows the proportion of children in each education category, conditional on their parents being in a certain category. This reflects similar findings in Keswell et al. (2013) who use only the first wave of NIDS. The patterns for son's educational outcomes are similar whether we condition on the father's or the mother's highest attained level of education. Over a quarter of sons who had either a father or a mother with no education managed to complete at least a matric. There was very little downward educational mobility for sons whose parents had either a primary or an incomplete secondary education. The sample sizes for father and mothers with matric or postsecondary education are rather small, so the relatively large downward mobility for both of these categories should be interpreted with this in mind. It is important to note that though the increase in the general level of educational attainment has been large (particularly for the lower education categories) this presentation abstracts away from the quality of that increased education, though this is clearly an important part of understanding South Africa's labour market returns (Louw et al., 2007).

Table 2: Education transition matrices for parents and sons

		Son's education					
Father's education	None	None	Primary	Inc. Sec.	Matric	Postsec.	
	None	5.9	20.3	41.1	19.3	13.3	100
	Primary	0.3	9.8	49.8	18.5	21.5	100
	Inc. Sec.	0.0	7.5	41.1	28.0	23.5	100
	Matric	0.0	3.7	32.2	24.7	39.4	100
	Postsec.	0.0	0.3	21.6	26.6	51.5	100

		Son's education					
Mother's education	None	None	Primary	Inc. Sec.	Matric	Postsec.	
	None	7.3	20.3	41.9	18.5	11.9	100
	Primary	0.7	15.1	43.1	19.7	21.3	100
	Inc. Sec.	0.4	3.7	44.1	24.0	27.8	100
	Matric	0.0	1.0	42.7	29.4	26.9	100
	Postsec.	0.0	4.2	11.7	22.1	62.0	100

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Having shown that the increase in the level of education attained from generation to generation went hand in hand with an education-earnings profile that became more convex, we turn now to the estimation of the intergenerational earnings elasticity.

III The intergenerational elasticity of earnings

Table 3 below presents the estimates of the intergenerational earnings elasticity between sons in the balanced panel and their fathers and mothers. Bootstrapped standard errors are presented along with the coefficients for each of the five columns, and all data are weighted using the attrition-corrected panel weights. Each numbered column represents a different imputation process for calculating parental earnings, and follows a similar sequence to Piraino (2015). In the first column the only variable used to predict parental earnings using the main and auxiliary datasets is the education of the parent. The number of variables used in the imputation process increases until column five, in which education, race, occupation, and province of residence in 1994 are used. In this table we have maintained the same sample for each estimation of the intergenerational earnings elasticity in order to ensure the comparability of our estimates. If we did not apply this restriction then differences in sample sizes would arise based on the availability of parental information in the NIDS dataset.¹³ Table 7 in the appendix shows that the unrestricted results are in line with the results in table 3. For the remainder of this paper we will restrict ourselves to the sumsamples of sons who report all imputation variables for their

¹³For example, more sons provide information about parental education than parental occupation.

parents - 1 389 fathers and 1 258 mothers, respectively. Though these sample sizes are slightly smaller than those in Table 7 in the appendix, they are nonetheless large enough to give us some confidence in the power of our calculations.

The elasticity relative to father's earnings ranges from 0.613 in the first column (education) to 0.678 in the third column (education and race). The elasticity is 0.659 if the province of residence of the father is added to education and race as an explanatory variable in the imputation equation. The fullest imputation, shown in column 5, reflects an elasticity of 0.627. Where comparable, these numbers are generally slightly lower than those reported in Piraino (2015), though it must be restated that the two studies use different sample members in their calculations and make different assumptions about weighting the data.

The degree of persistence relative to mother's earnings is also high, but differs in certain areas from the persistence relative to father's earnings. Imputing mother's earnings using only education generates an estimated elasticity that is about 4% higher than the corresponding figure for father's earnings. This differs slightly from Piraino (2015)'s calculations which find that the elasticity relative to mother's earnings is always lower than the elasticity relative to father's earnings. In fact, we find that the elasticity relative to mother's earnings is higher for all imputation procedures except for when education, race and occupation are used jointly. The difference is reinforced if earnings are imputed using all four of the available variables - from 0.627 for fathers to 0.650 for mothers.

Table 3: Intergenerational earnings elasticities for different imputation procedures

	Variables used to construct parental earnings				
	1 Education	2 Education, race	3 Education, race, occupation	4 Education, race, province	5 Education, race, occupation, province
Father's earnings					
Elasticity	0.613 (0.159)	0.678 (0.186)	0.674 (0.188)	0.659 (0.187)	0.627 (0.187)
N	1,389	1,389	1,389	1,389	1,389
Mother's earnings					
Elasticity	0.639 (0.184)	0.693 (0.176)	0.592 (0.168)	0.754 (0.184)	0.650 (0.170)
N	1,258	1,258	1,258	1,258	1,258

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel. Bootstrapped standard errors in parentheses.

Accounting for selection into employment

The matter of selection bias is something that always underlies estimates of intergenerational mobility. Indeed, the possible bias arising from not modeling female labour force participation decisions is a major reason for why daughters' earnings are usually not reported in these kinds of studies. Another bias already mentioned is the selection bias that may arise from restricting the analysis to children who co-reside with their parents. This is dealt with in this paper by the use of the TSTSLS estimator. There is, however, another selection issue that is often ignored in the international literature that we may want to consider, and that is selection bias arising from who finds a job and who does not. We only observe the earnings of those who are employed, and it may be that both labour market participation decisions and finding employment are not random. This is a particularly pertinent issue in South Africa, given that unemployment rates are high in general, and are very high for youth in particular (Ranchhod and Finn, forthcoming). The structure of the South African labour market and the relatively high demand for high-skilled workers means that it is possible that we calculate a biased elasticity when we do not take selection into employment into account. It is possible that those potential workers with parents whose earnings were low are less likely to find employment themselves. In a counterfactual world in which we observe earnings for all our respondents (rather than only for those who are employed), we may find that correcting for selection matters in the measurement of the correlation between parental and child earnings. However, applying the correction only to sons ignores the fact that the pseudo-parents in the 1993 dataset faced similarly high unemployment rates, and that the coefficients extracted from the first stage imputation may be biased as well. We are therefore faced with an estimating equation that requires two corrections – one in the first stage when the parental earnings variable is imputed, and one in the second stage when the intergenerational earnings elasticity is calculated.

We correct for possible selection bias into employment for both parents and children by using a two-stage Heckman model that was proposed for modeling selection into employment by Vella (1998) and has been used in the intergenerational mobility literature by Ermisch et al. (2006) among others.

In the first stage we use a probit to model whether a respondent is employed (and therefore earning a wage) or not. Variables included in this selection equation but not in the outcome equation are a dummy for the presence of dependent children in the household, marital status, age, and parental earnings. The first two of these variables are included so that the model is identified by exclusion restrictions, rather than by the non-linearity of the first stage.¹⁴ We generate the correction term (the inverse Mills ratio) which can be thought of as capturing the 'surprise' of observing an individual who is employed and earning. In other words, the residuals from the first stage are captured by the inverse Mills ratio. For example, a respondent who has a job but also has a low level of education will have a larger residual, and therefore a

¹⁴Full results are available from the authors.

higher inverse Mills ratio, than a respondent with postsecondary employment who is employed. Our results can therefore be thought of in somewhat clumsy terms as being derived from a two sample, two stage, twice corrected least squares (TSTSTCLS) estimator.

Correcting for selection into employment yields elasticities that are higher than the ‘naïve’ estimation for son’s earnings relative to fathers and mothers. Employment selection biases our uncorrected elasticity downwards for fathers – the corrected elasticity is 0.678 compared to an uncorrected elasticity of 0.627. For mothers the bias is in the same direction and of an even greater magnitude – a corrected elasticity of 0.718 compared to an uncorrected elasticity of 0.650. The full results of this double correction are presented in Table 4 below. This is our preferred set of results in general, with the elasticities in column 5 being the preferred point estimate in particular. Once again we restrict ourselves to the subsample of sons who report full information on parental background. The unrestricted sample estimates can be found in Table 8 in the appendix.

Table 4: Intergenerational earnings elasticities for different imputation procedures with a double Heckman correction

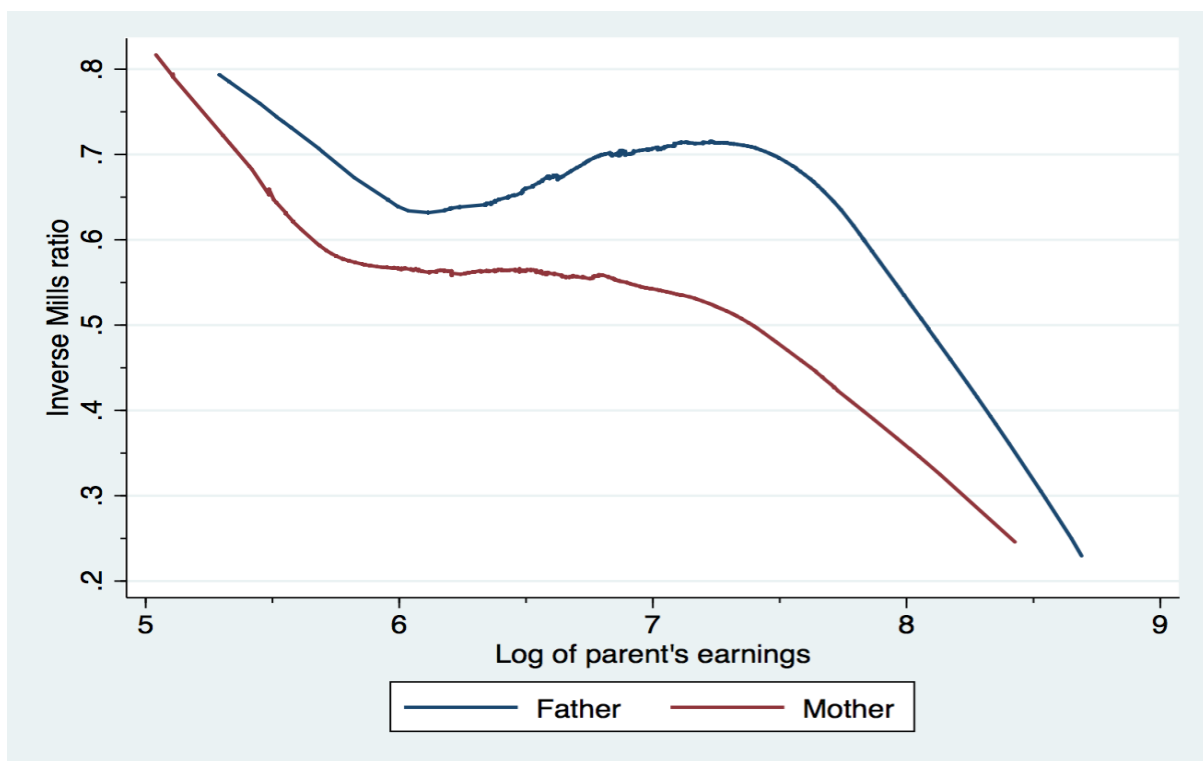
	Variables used to construct parental earnings				
	1 Education	2 Education, race	3 Education, race, occupation	4 Education, race, province	5 Education, race, occupation, province
Father’s earnings					
Elasticity	0.612 (0.214)	0.718 (0.234)	0.697 (0.220)	0.723 (0.204)	0.678 (0.215)
N	1,389	1,389	1,389	1,389	1,389
Mother’s earnings					
Elasticity	0.659 (0.225)	0.739 (0.247)	0.650 (0.221)	0.825 (0.214)	0.718 (0.220)
N	1,258	1,258	1,258	1,258	1,258

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel. Bootstrapped standard errors in parentheses.

We can investigate our intuition that children with low-earning parents are less likely to find a job themselves by plotting the inverse Mills ratio over the range of parental income. In figure 5 the inverse Mills ratios are presented for fathers and mothers over their respective earnings ranges. The higher the line, the more ‘surprised’ we are to see an individual in a wage-earning job, given parental earnings. The figure accords with our intuition in that the ratio decreases as we move rightward across the parental earnings distributions. Those with parents who earned relatively higher salaries are more likely to be employed than those with parents who earned at

the lower end of the distribution. The inverse mills ratio for the log of mother's earnings drops sharply, then flattens out, and then drops again as we move rightward along the distribution. The pattern for fathers is slightly different as the ratio first drops, then rises, and then drops off sharply. This suggests that the 'surprise' at seeing a son in employment, conditional on his father's earnings, does not decrease monotonically across the distribution of earnings.

Figure 5: Inverse Mills ratio over the distribution of parental earnings



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

The intergenerational elasticities that we report are high by international standards, but focusing on a single number may hide underlying patterns. The heteroskedasticity present in the sample¹⁵ means that quantile regression analysis is a potentially useful tool in evaluating the joint distribution of parental and child earnings. To this end we run quantile regressions from the 5th to the 95th percentile, increasing in intervals of 5. As described in Buchinsky (1998), we estimate the coefficient vector β as the solution to the following:

$$\min_{\beta(\theta)} \left\{ \sum_{i: y_i \geq x_i \beta(\theta)} \theta |y_i - x_i \beta(\theta)| + \sum_{i: y_i < x_i \beta(\theta)} (1 - \theta) |y_i - x_i \beta(\theta)| \right\}$$

where y_i is son's earnings, x_i is the earnings of either the father or the mother, and θ is the quantile being estimated.

¹⁵The White test for heteroskedasticity rejects the null of constant variance for all specifications of the regression.

Quantile regression analyses of intergenerational mobility in low-inequality countries have found that the correlation between parental and child income falls over the distribution of earnings. For example, Bratberg et al. (2007) use Norwegian data and find a monotonic decline in the intergenerational elasticity for men, and a decreasing but non-monotonic fall for women in Norway from the 5th to the 95th percentile, showing that earnings persistence is far higher at the bottom of the earnings distribution than at the top.

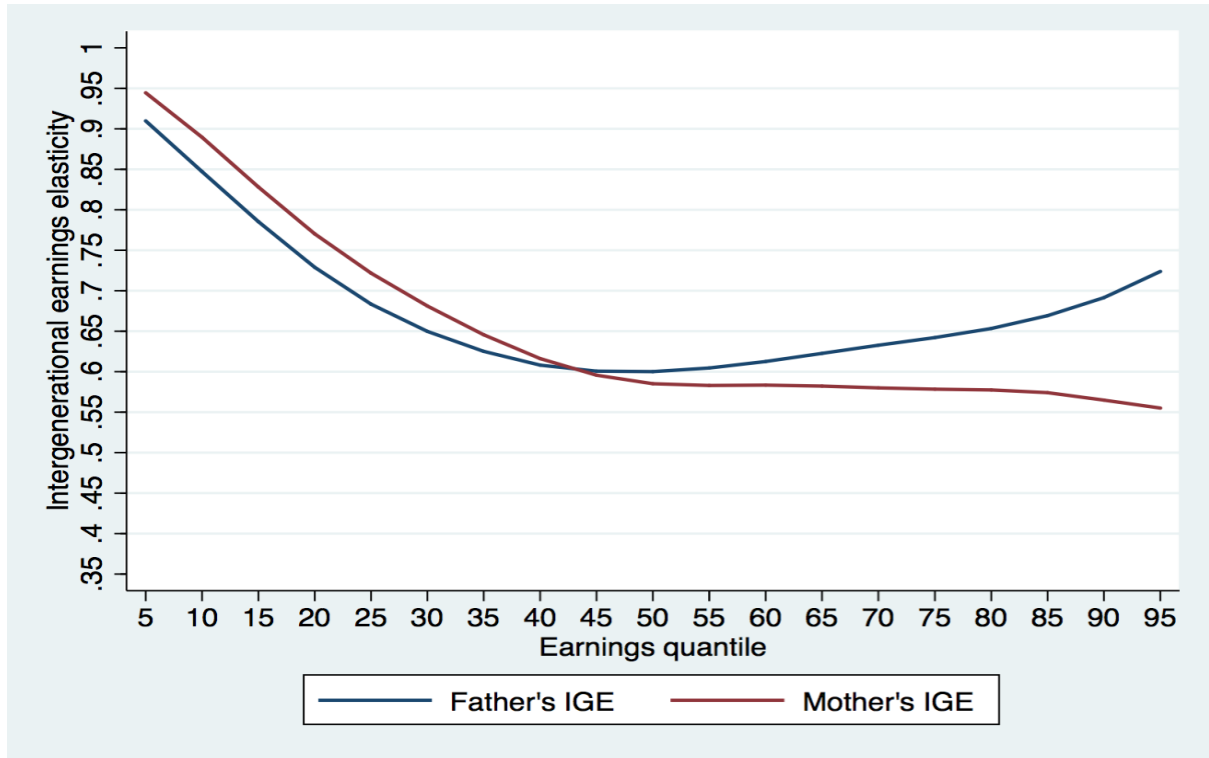
Studies using data from the US consistently find that persistence is highest at the bottom of the earnings distribution, but disagree as to what happens to the correlation as earnings increase. Eide and Showalter (1999), using a rather small sample of American father and son pairs, find a decreasing pattern with a slight upturn at the very top of the earnings distribution. A relatively higher correlation between parental and child earnings at the bottom of the child's earning distribution in the US is also found by Lee et al. (2009). A slightly different pattern emerges in a recent paper by Palomino et al. (2014) who use a much larger sample of US data and find what they refer to as a 'U' shape, indicating that persistence is highest at the bottom of the earnings distribution, but that there is an upturn at the top of the distribution as well.¹⁶ It is likely that high-inequality societies produce a U-shaped relationship between the intergenerational elasticity and earnings. High cross-sectional inequality is stable over time if there is high persistence between both low-earning parents and their children, as well as high-earning parents and their children. Given how high and persistent inequality in South Africa has been over the last two decades, we might expect to see a turning point in the elasticity-earnings relationship.

Figure 6, below, plots the intergenerational earnings elasticities for South Africa between the 5th and 95th percentiles of the earnings distribution. It is clear that relying only on the conditional mean hides a great deal about the pattern of persistence in the country. The intergenerational elasticity is highest at the bottom of the distribution, and this accords with the international evidence for both developed and developing countries. What is different about the South African case is the fact that the persistence is so high in this part of the distribution - over 0.9 for both mothers and fathers at the lowest end. This shows that the low-earning sons have a far higher correlation with their parents' wages than high-earning sons do with theirs. There is an interesting difference in the shapes of parental elasticities. The strength of the association between son's earnings and mother's earnings decreases monotonically as we move rightwards across the distribution of earnings. For father's earnings, however, a turning point is reached at around the 40th percentile, after which there is an increase to about 0.73 at the top of the distribution.¹⁷

¹⁶The Palomino et al. (2014) paper finds that the turning point occurs around the 70th percentile.

¹⁷Quantile graphs for all the different imputed versions of father's and mother's earnings are available from the authors on request.

Figure 6: Intergenerational earnings elasticity over earnings quantiles



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

IV The role of education in shaping intergenerational mobility

We build on the previous section by investigating the role that education plays in shaping intergenerational mobility in South Africa. The ideal set of data for getting precise estimates of various transmission mechanisms would include child's ability, parent's ability and school quality. Although we are able to make use of a rich dataset, we do not have all of these variables available and so we must find more indirect ways of getting at the relationship between education and intergenerational mobility.

One way of doing this is to follow Palomino et al. (2014) by measuring the strength of the association between child's education and the intergenerational elasticity of earnings by quantiles by including the child's level of education as an additional regressor in the canonical regression in equation 2. We can think about the effect that including child's education would have on the elasticity in the same way that we think about omitted variables in OLS regressions. Retaining the representation of parental earnings as Y_{it}^p and using Edu_i^c as the variable indicating child's education¹⁸ (which is omitted from equation 2), we can represent the

¹⁸Though there are a few exceptions in the data, the level of education attained by each child is time-invariant across the four waves. Those respondents whose education status changes are generally those who move from matric to postsecondary. For sons whose education changes over the four waves we use the level of education

elasticity as:

$$plim\hat{\beta}^{OLS} = \beta + \frac{cov(Y_{it}^p, Edu_i^c)}{\sigma_{Y_{it}^p}^2}$$

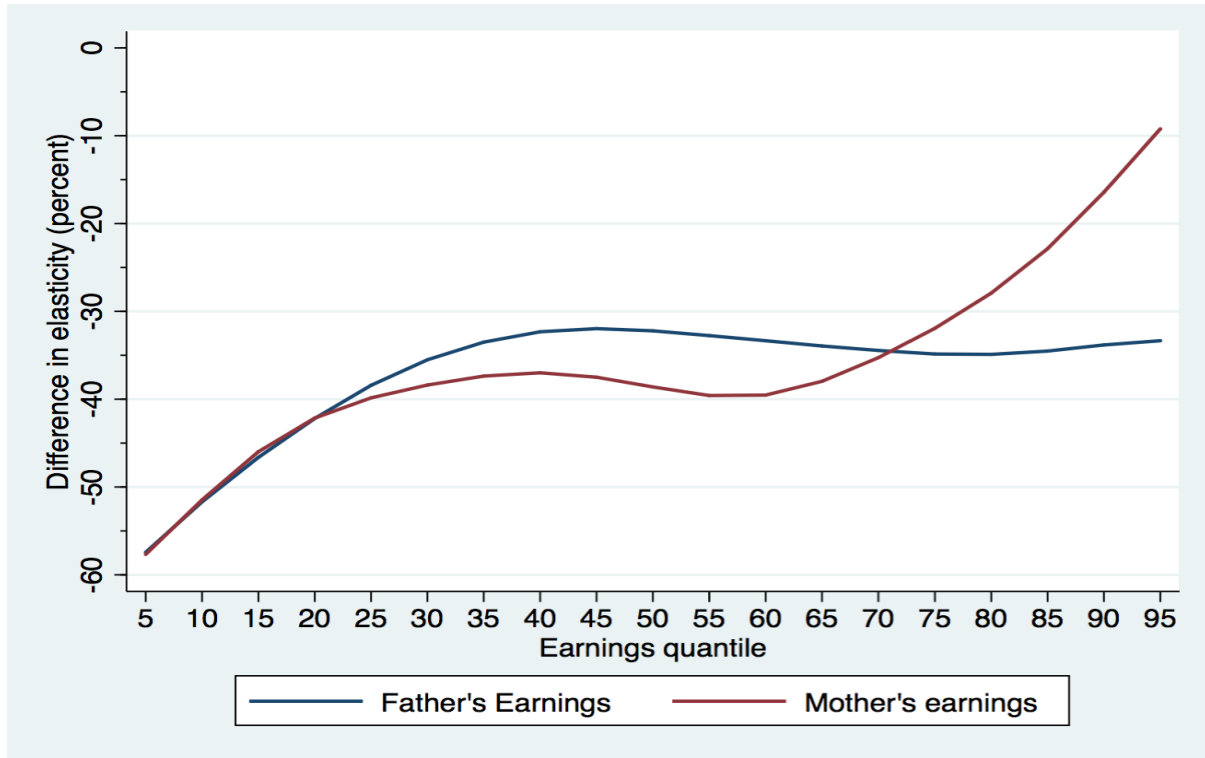
This equation can be used to interpret what happens to the intergenerational elasticity when we add a control for child's education into the estimating equation. If there is a strong positive correlation between parental earnings and child's education, then the elasticity as estimated in equation 2 will be higher if education is not controlled for. On the other hand, if there is a zero correlation between parental earnings and the child's education then there will be no change in the estimated elasticity once a control for education is included. This is true even in the presence of the relationship between education and earnings for the child.

Including child's education in the estimation of the intergenerational elasticity of earnings reduces the elasticity at the mean by 41% and 39% relative to father's and mother's earnings respectively. The relationship between education and the intergenerational elasticity changes along the distribution of earnings, however, and this is shown in figure 7 below. The estimation procedure underlying the figure is the same as it was for figure 6. Intergenerational elasticities are estimated for parental earnings from the 5th to the 95th percentile. The vertical axis shows the percentage difference in the intergenerational elasticity for a regression that includes child's education versus one that does not. The larger the negative difference between the elasticities in a particular quantile, the higher the positive correlation between education and parental earnings in that quantile.

The relationship between educational attainment and parental earnings follows a different shape over the distribution of child's earnings depending on whether we look at mother's earnings or father's earnings. Including the child's education as an additional control has the largest negative effect at the bottom of the distribution for both parents - reducing the coefficient by close to 50%. For mothers this effect is generally decreasing as we move up the earnings quantiles, and is almost negligible at the top of the distribution. There is a low correlation between mother's earnings and child's education at the top end of the distribution, and this corresponds to the part of the earnings distribution with the lowest level of intergenerational elasticity. One of the insights of this figure is that the further up the earnings distribution we travel, the less important educational attainment is in explaining the level of mobility between parental and child earnings. For fathers the pattern is slightly different. The correlation between child's education and parent's earnings is strongest at the bottom of the distribution, and the strength of this relationship decreases steadily until the 35th percentile of earnings. Thereafter it remains relatively flat, with roughly the same correlations at the 35th and 95th percentiles.

reported in the fourth wave.

Figure 7: Difference in intergenerational elasticity when controlling for education, over parental earnings quantiles



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Another way of extracting the role of education in determining intergenerational mobility is to decompose the intergenerational elasticity into a component that is due to education and a component that is due to parental earnings. Blanden and Macmillan (2014), referencing an earlier model by Blanden et al. (2007),¹⁹ break the estimation of the intergenerational elasticity into two stages. This allows us to look at the relationship between parental characteristics, child characteristics, and the labour market returns to these characteristics when the child is working.

In the first stage we regress the child's level of educational attainment on the log of parental income. In the second stage we regress the child's income on his education and parental income - this is the same estimating equation underlying the previous figure. The two equations are:

$$edu_i^c = \hat{\alpha}_2 + \gamma Y_i^p + \hat{e}_i \quad (7)$$

and

$$Y_i^c = \hat{\alpha}_2 + \hat{\rho} edu_i^c + \hat{\delta} Y_i^p + \hat{u}_i \quad (8)$$

Taken together, these two equations decompose the intergenerational elasticity into the con-

¹⁹Originally this was done in order to separate out the relative importance of cognitive versus non-cognitive skills in the association of parental and child earnings.

tribution of education inequality ($\hat{\gamma}$), the contribution of the returns to education ($\hat{\rho}$), and the influence of parental income on child's income (controlling for child's education). Blanden et al. (2007) show how the intergenerational elasticity can be written as:

$$\hat{\beta} = \hat{\gamma}\hat{\rho} + \hat{\delta} \quad (9)$$

According to this formulation the relative contribution of education variables²⁰ to the overall intergenerational elasticity at the mean is close to 40% for father's earnings and 43% for mother's earnings.

In our final decomposition we turn to the question of the intergenerational transmission of occupational skill, and how this shapes the intergenerational earnings elasticity. We follow Keswell et al. (2013)²¹ and use the occupational codes in the NIDS dataset as proxies for the skill level of each respondent and his parents.

The original decomposition of the intergenerational elasticity of earnings into education and skill components comes from the sociology literature (Bowles and Gintis, 2002), and was quickly adopted in the economics literature (two recent examples are Lefranc and Trannoy (2005) and Cervini-Plá (2013)). We adopt Lefranc and Trannoy's notation in explaining this decomposition. It is important to note that this is not to be interpreted as a 'causal' decomposition in the traditional sense, but rather as an attempt to extract the relative importance in the correlations between parental and child education versus occupation in generating the intergenerational earnings elasticity.

Let us assume that for $g = c, p$, parental and child income may be expressed as:

$$Y_i^g = Edu_i^g \gamma_e^g + Skill_i^g \gamma_s^g + \nu_i^g \quad (10)$$

The TSTSLS estimate of β derived from this relationship is:

$$\beta = \frac{cov(Y_i^c, Edu_i^p \gamma_e^p + Skill_i^p \gamma_s^p)}{V(Edu_i^p \gamma_e^p + Skill_i^p \gamma_s^p)} \quad (11)$$

We expand β using equation 11 so that:

$$\begin{aligned} \beta &= \frac{1}{V(Edu_i^p \gamma_e^p + Skill_i^p \gamma_s^p)} \\ &\times [\gamma_e^c cov(Edu_i^c, Edu_i^p) \gamma_e^p + \gamma_s^c cov(Skill_i^c, Edu_i^p) \gamma_e^p \\ &+ \gamma_e^c cov(Edu_i^c, Skill_i^p) \gamma_s^p + \gamma_s^c cov(Skill_i^c, Skill_i^p) \gamma_s^p \\ &+ cov(\nu_i^c, Edu_i^p) \gamma_e^p + cov(\nu_i^c, Skill_i^p) \gamma_s^p] \end{aligned} \quad (12)$$

²⁰We do not separate out educational attainment and returns to education at this stage.

²¹The authors link educational opportunity to the distribution of steady state occupations in South Africa using the first wave of NIDS data.

β has been decomposed into six terms comprising the covariances of the child and parental education and occupational skill, and the covariance of the child's earnings residual and parental education and skill. These are multiplied by the relevant coefficients from equation 10.

In table 5 each row represents the relative contribution of each term in the decomposition to the overall intergenerational earnings elasticity. The relationship between father's education and son's education accounts for almost 40% of the intergenerational elasticity. The corresponding share for the mother-son elasticity is slightly lower at 34%. The intergenerational correlation of occupational skill is less important in determining β than the intergenerational correlation of education - 7% for fathers and sons, and 9% for mothers and sons. These contribute less than the 'cross' correlation of parental education and the child's occupational skill, and parental skill and child's education. It therefore appears that the joint impact of parental education on son's education and occupational position is far larger than the impact of parental occupational skill through the same channels. This is in contrast to studies in OECD countries by Cervini-Plá (2013), Lefranc and Trannoy (2005) and Österbacka (2001) who find that parental social position, rather than parental education, is the most important determinant of intergenerational mobility.

Table 5: Relative contributions to intergenerational elasticity - education versus skills

Fathers and sons	
Edu. father, edu. son	38.29
Skill father, skill son	7.01
Edu. father, skill son	16.61
Skill father, edu. son	4.40
Edu. father, resid. son	29.28
Skill father, resid. son	4.41
Mothers and sons	
Edu. mother, edu. son	34.22
Skill mother, skill son	8.94
Edu. mother, skill son	7.91
Skill mother, edu. son	3.51
Edu. mother, resid. son	36.24
Skill mother, resid. son	9.16

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

V Conclusion

One of the social questions that sparked this study is why earnings inequality in South Africa has remained so high from one generation to the next in the face of increasing educational

attainment. The dynamics of intergenerational earnings imply that the higher the intergenerational elasticity, the longer it will take for a convergence in earnings in society to take place. As a first step to uncovering some of the underlying intergenerational patterns we followed the methodology outlined in Piraino (2015) and calculated the intergenerational earnings elasticity for a balanced panel of South African males. We corrected for two kinds of bias in the estimation of the intergenerational elasticity. The first - co-resident selection - was mitigated through the use of a TSTSLS estimator. The second - selection into employment in a high-unemployment society - was corrected through the use of a Heckman two-step procedure.

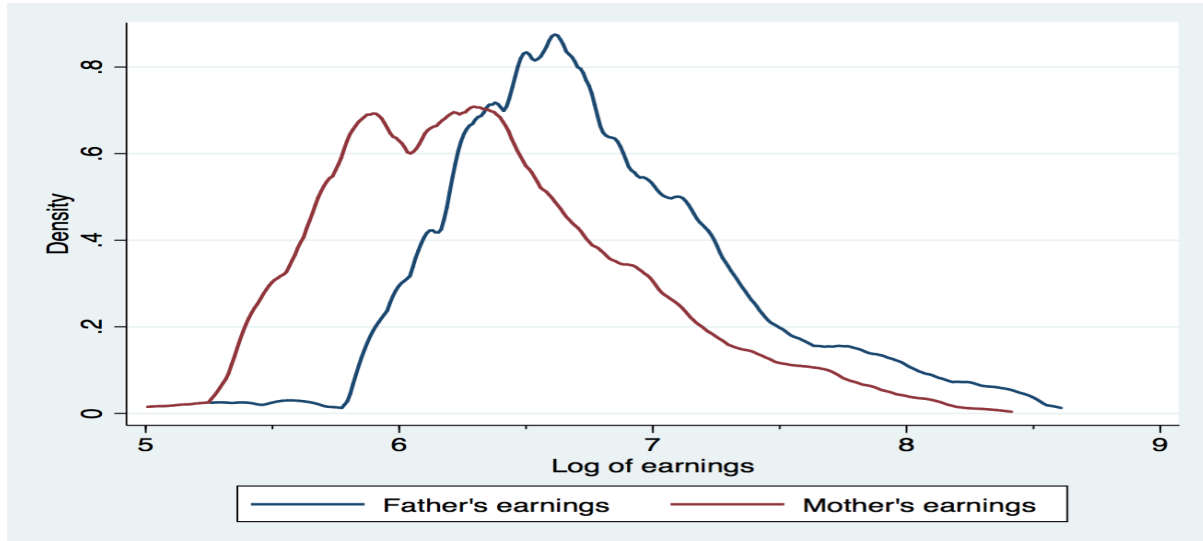
We found that although the intergenerational elasticity of earnings is very high (implying low mobility) it varies markedly over the distribution of earnings. The degree of association between parental and child earnings changes along the distribution of earnings. It is highest at the bottom of the distribution and then falls until the middle of the distribution. For mothers this trend continues, and the association is weakest at the top of the distribution. For fathers, however, there is a turning point, and the correlation rises until reaching approximately 0.73 for the 95th percentile.

We then tried to reconcile the high association between parental and child earnings with the rise in educational attainment in the country over the last two decades. Other studies have found that although schooling attainment has increased in South Africa, the returns to education remain convex. This implies that even if the younger generation is more educated than the older generation, there will not necessarily be a proportional increase in earnings. We found that the correlation between education and the intergenerational persistence of earnings is highest at the bottom of the earnings distribution, and that the pattern of this correlation over the first half of the distribution is the same whether father's or mother's earnings are the focus. Thereafter the correlation between education and mother's earnings decreases steadily, while the correlation between education and father's earnings remains roughly the same. Finally, we made use of two different decompositions of the intergenerational earnings elasticity, and found that education accounts for around 40% of the elasticity, and that education plays a greater role in understanding earnings persistence than does occupational skill.

One issue that we did not touch upon is the quality of education in South Africa. This refers to both the average quality and the variance in quality across educational institutions. Though there has been steady growth in the access to education in South Africa, it is debatable whether there has been a concomitant rise in the quality of that education. Given the richness of the NIDS dataset and the possibility of linking respondents to administrative data, uncovering the roles of the education quality versus quantity in shaping intergenerational earnings and persistent inequality is something that may be possible in the future.

Appendices

Figure 8: Kernel densities for imputed parental earnings (specification 5)



Source: Own calculations from the first four waves of NIDS and the PSLSD. Attrition-corrected panel weights applied to members of the balanced panel.

Table 6: Earnings transition matrices

		Son quintiles						
		1	2	3	4	5		
Father	quintiles	1	24.5	27.6	18.8	17.2	11.9	100
		2	25.1	23.7	19.5	23.0	8.6	100
		3	22.5	18.1	25.3	12.9	21.3	100
		4	18.3	18.2	17.1	21.6	24.8	100
		5	9.7	11.8	19.4	26.8	32.3	100
		Son quintiles						
		1	2	3	4	5		
Mother	quintiles	1	24.6	25.1	22.6	16.9	10.9	100
		2	23.5	21.9	16.8	16.4	21.4	100
		3	20.6	21.6	20.8	18.8	18.2	100
		4	16.2	14.3	27.4	25.1	17.0	100
		5	6.9	12.9	14.9	27.6	37.7	100

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Table 7: Intergenerational earnings elasticities for different imputation procedures for different subsamples

Variables used to construct parental earnings					
	1	2	3	4	5
	Education	Education, race	Education, race, occupation	Education, race, province	Education, race, occupation, province
Father's earnings					
Elasticity	0.634 (0.166)	0.706 (0.204)	0.682 (0.205)	0.680 (0.194)	0.627 (0.187)
N	1,782	1,782	1,397	1,774	1,389
Mother's earnings					
Elasticity	0.615 (0.197)	0.689 (0.185)	0.601 (0.158)	0.723 (0.181)	0.650 (0.170)
N	1,698	1,698	1,266	1,690	1,258

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel. Bootstrapped standard errors in parentheses.

Table 8: Intergenerational earnings elasticities for different imputation procedures with a double Heckman correction for different subsamples

Variables used to construct parental earnings					
	1	2	3	4	5
	Education	Education, race	Education, race, occupation	Education, race, province	Education, race, occupation, province
Father's earnings					
Elasticity	0.641 (0.242)	0.750 (0.241)	0.704 (0.217)	0.742 (0.234)	0.678 (0.215)
N	1,782	1,782	1,397	1,774	1,389
Mother's earnings					
Elasticity	0.681 (0.250)	0.767 (0.261)	0.660 (0.215)	0.838 (0.218)	0.718 (0.220)
N	1,698	1,698	1,266	1,690	1,258

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel. Bootstrapped standard errors in parentheses.

References

- Atkinson, A. (2015), *Inequality: What can be done?*, Harvard University Press.
- Becker, G. and Tomes, N. (1979), 'An equilibrium theory of the distribution of income and intergenerational mobility', *Journal of Political Economy* **87**(6), 1153–1189.
- Bevis, L. and Barrett, C. (2015), 'Decomposing intergenerational income elasticity: The gender-differentiated contribution of capital transmission in rural Philippines', *World Development* **74**, 233–252.
- Björklund, A. and Jäntti, M. (1997), 'Intergenerational income mobility in Sweden compared to the United States', *American Economic Review* **87**(4), 1009–1018.
- Black, S. and Devereux, P. (2011), Recent developments in intergenerational mobility, in O. Ashenfelter and D. Card, eds, 'Handbook of Labor Economics', Vol. 4B, Elsevier, chapter 16, pp. 1487–1541.
- Blanden, J. (2009), How much can we learn from international comparisons of intergenerational mobility?, CEE Discussion Paper 111, Centre for the Economics of Education.
- Blanden, J. (2015), 'Intergenerational income persistence', *IZA World of Labor* 2015 **176**.
- Blanden, J., Gregg, P. and Macmillan, L. (2007), 'Accounting for intergenerational income persistence: Noncognitive skills, ability and education', *The Economic Journal* **117**(519), C43–C60.
- Blanden, J. and Macmillan, L. (2014), Education and intergenerational mobility: Help or hindrance?, DoQSS Working Paper 14-01, Department of Quantitative Social Science, Institute of Education, University of London.
- Bowles, S. and Gintis, H. (2002), 'The inheritance of inequality', *Journal of Economic Perspectives* **16**(3), 3–30.
- Branson, N. and Leibbrandt, M. (2013), Education quality and labour market outcomes in South Africa, OECD Working Papers 1021, OECD Economics Department.
- Bratberg, E., Nilsen, Ø. and Vaage, K. (2007), 'Trends in intergenerational mobility across offspring's earnings distribution in Norway', *Industrial Relations* **46**(1), 112–129.
- Brunori, P., Ferreira, F. and Peragine, V. (2013), Inequality of opportunity, income inequality, and economic mobility: Some international comparisons, in E. Paus, ed., 'Getting development right: Structural transformation, inclusion, and sustainability in the post-crisis era', Palgrave Macmillan, chapter 5, pp. 85–115.

- Buchinsky, M. (1998), 'Recent advances in quantile regression models: A practical guideline for empirical research', *The Journal of Human Resources* **33**(1), 88–126.
- Casale, D. and Posel, D. (2002), 'The continued feminisation of the labour force in South Africa', *South African Journal of Economics* **70**(1), 156–184.
- Cervini-Plá, M. (2013), 'Exploring the sources of earnings transmission in Spain', *Review of Public Economics* **204**(1), 45–66.
- Checchi, D. (1997), 'Education and intergenerational mobility in occupations: A comparative study', *American Journal of Economics and Sociology* **56**(3), 331–351.
- Chusseau, N., Hellier, J. and Ben-Halima, B. (2013), Education, intergenerational mobility and inequality, in J. Hellier and N. Chusseau, eds, 'Growing income inequalities', Palgrave Macmillan, chapter 8, pp. 227–273.
- Corak, M. (2013), Income inequality, equality of opportunity, and intergenerational mobility, IZA Discussion Paper 7520, Institute for the Study of Labor.
- de Villiers, L., Brown, M., Woolard, I. and Leibbrandt, M. (2013), National Income Dynamics Study Wave 3 user manual, Technical report, Southern Africa Labour and Development Research Unit.
- Eide, E. and Showalter, M. (1999), 'Factors affecting the transmission of earnings across generations: A quantile regression approach', *The Journal of Human Resources* **34**(2), 253–267.
- Ermisch, J., Francesconi, M. and Siedler, T. (2006), 'Intergenerational mobility and marital sorting', *The Economic Journal* **116**(513), 659–679.
- Ferreira, S. and Veloso, F. (2006), 'Intergenerational mobility of wages in Brazil', *Brazilian Review of Econometrics* **26**(2), 181–211.
- Finn, A. (2015), A national minimum wage in the context of the South African labour market, SALDRU Working Papers 153, Southern Africa Labour and Development Research Unit, University of Cape Town.
- Finn, A. and Leibbrandt, M. (2013), Mobility and inequality in the first three waves of NIDS, SALDRU Working Papers 120, Southern Africa Labour and Development Research Unit, University of Cape Town.
- Gong, H., Leigh, A. and Meng, X. (2012), 'Intergenerational income mobility in urban China', *Review of Income and Wealth* **58**(3), 481–503.
- Grawe, N. (2004), Intergenerational mobility for whom? The experience of high- and low-earning sons in international perspective, in M. Corak, ed., 'Generational Income Mobility in North America and Europe', Cambridge University Press, chapter 4, pp. 58–89.

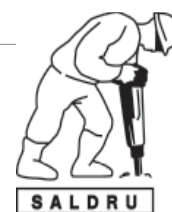
- Hertz, T. (2001), Education, inequality and economic mobility in South Africa, PhD thesis, University of Massachusetts.
- Hertz, T., Jayasundera, T., Piraino, P., Selcuk, S., Smith, N. and Verashchagina, A. (2007), ‘The inheritance of educational inequality: International comparisons and fifty-year trends’, *The B.E. Journal of Economic Analysis and Policy* **7**(2), 1–46.
- Hnatovska, V., Lahiri, A. and Paul, S. (2013), ‘Breaking the caste barrier: Intergenerational mobility in India’, *Journal of Human Resources* **48**(2), 435–473.
- Jäntti, M. and Jenkins, S. (2013), Income mobility, IZA Discussion Paper 7730, Institute for the Study of Labor.
- Keswell, M., Girdwood, S. and Leibbrandt, M. (2013), ‘Educational inheritance and the distribution of occupations: Evidence from South Africa’, *Review of Income and Wealth* **59**, S111–S137.
- Keswell, M. and Poswell, L. (2004), ‘Returns to education in South Africa: A retrospective sensitivity analysis of the available evidence’, *South African Journal of Economics* **72**(4), 834–860.
- Klevmarcken, N. A. (1982), ‘Missing variables and two-stage least-squares estimation from more than one dataset’, *1981 Proceedings of the American Statistical Association, Business and Economic Statistics Section* pp. 156–161.
- Lam, D., Ardington, C., Branson, N. and Leibbrandt, M. (2013), Credit constraints and the racial gap in post-secondary education in South Africa, NBER Working Paper 19607, National Bureau of Economic Research.
- Lam, D., Finn, A. and Leibbrandt, M. (2015), Schooling inequality, returns to schooling, and earnings inequality: Evidence from Brazil and South Africa, WIDER Working Paper 2015/050, United Nations University World Institute for Development Economics Research.
- Lee, S., Linton, O. and Whang, Y.-J. (2009), ‘Testing for stochastic monotonicity’, *Econometrica* **77**(2), 585–602.
- Lefranc, A. and Trannoy, A. (2005), ‘Intergenerational earnings mobility in France: Is France more mobile than the US?’, *Annales d’Economie et Statistique* **78**, 57–77.
- Leibbrandt, M., Woolard, I., Finn, A. and Argent, J. (2010), Trends in South African income distribution and poverty since the fall of apartheid, OECD Social, Employment and Migration Working Papers 101, OECD Publishing.

- Louw, M., van der Berg, S. and Yu, D. (2007), 'Convergence of a kind: Educational attainment and intergenerational social mobility in South Africa', *South African Journal of Economics* **75**(3), 548–571.
- Österbacka, E. (2001), 'Family background and economic status in Finland', *Scandinavian Journal of Economics* **103**(3), 467–484.
- Palomino, J., Marrero, G. and Rodriguez, J. (2014), One size doesn't fit all: A quantile analysis of intergenerational income mobility in the US (1980-2010), ECINEQ Working Paper 349, Society for the Study of Economic Inequality.
- Piraino, P. (2015), 'Intergenerational earnings and inequality of opportunity in South Africa', *World Development* **67**, 396–405.
- Ranchhod, V. and Finn, A. (forthcoming), 'Estimating the short run effects of South Africa's employment tax incentive on youth employment probabilities using a difference-in-differences approach', *South African Journal of Economics* .
- Solon, G. (1992), 'Intergenerational income mobility in the United States', *American Economic Review* **82**(3), 393–408.
- Vella, F. (1998), 'Estimating models with sample selection bias: A survey', *The Journal of Human Resources* **33**(1), 127–169.
- Yu, D. (2010), Poverty and inequality trends in South Africa using different survey data, Stellenbosch Economic Working Papers 04/10, Stellenbosch University.

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.



www.saldru.uct.ac.za

Level 3, School of Economics Building, Middle Campus, University of Cape Town
Private Bag, Rondebosch 7701, Cape Town, South Africa

Tel: +27 (0)21 650 5696

Fax: +27 (0) 21 650 5797

Web: www.saldru.uct.ac.za

