Income Convergence in South Africa: Fact or Measurement Error?[1]

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Abstract

This paper asks whether income mobility in South Africa over the last decade has indeed been as impressive as currently thought. Using new national panel data (NIDS), substantial measurement error in reported income data is found, which is further corroborated by a provincial income data panel (KIDS). By employing an instrumental variables approach using two different instruments, measurement error can be quantified. Specifically, self-reported income in the survey data is shown to suffer from mean-reverting measurement bias, leading to sizable overestimations of income convergence in both panel data sets. The preferred estimates indicate that previously published income dynamics may have been largely overestimated by as much as 77% for the national NIDS panel and 39% for the provincial KIDS panel. Overall, income mobility appears much smaller than previously thought, while chronic poverty remains substantial and transitory poverty is still very limited in South Africa.

JEL Classifications: C81, I32, O15

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1. Introduction

The measurement of income dynamics lies at the heart of development economics and is of great concern to researches and policy makers alike. The collection of panel data in many developing countries has allowed tremendous progress in this regard. While progress in poverty alleviation and income mobility is important, it remains unclear just how much these dynamics are affected by measurement error. The standard measure of income mobility is the slope coefficient from a regression of current period earnings on lagged earnings. It is well known that the collection of income and consumption data in household surveys is often very imprecise. In the presence of classical measurement error this will cause an attenuation bias towards zero in the estimated slope coefficient, overstating the degree of mobility. The results are what is being referred to as convergence towards the mean (Fields et al. 2003, Antman and Mckenzie, 2005). This paper aims to identify the effect of measurement error when estimating income dynamics.

Twenty years after the end of the apartheid era, South Africa is still characterized by extremely high inequality. Even more, the overall Gini coefficient for South Africa increased from 0.67 in 1993 to 0.70 in 2008. During apartheid the high overall level of inequality was driven by inequality between races. Today there is rising inequality within the racial groups (e.g. the Gini coefficient for the black population increased from 0.55 in 1993 to 0.62 in 2008) (Leibbrandt et al. 2011). Despite the positive indication that wealth and poverty are being distributed less along racial lines today and that a new affluent black elite and middle class have come into being, there seems to be another part of the black population that is falling behind in relative terms, e.g. Adato et al. (2006) show that there is an asset level below which households are trapped in poverty. These findings are in sharp contrast to other literature on South Africa that has found high mobility and convergence to the mean (Fields et al. 2003a and 2003b, Finn and Leibbrandt 2013).

This paper aims to address this apparent contradiction by estimating the effect of measurement error in two prominent datasets from South Africa. The two panels are the National Income Dynamics Survey (NIDS) covering the period 2008-2012, and the smaller KwaZulu-Natal Income Dynamics Study (KIDS) covering the period of 1993-2004 for only one province. Using the KIDS data, Fields et al. (2003a and 2003b) and Woolard and Klasen (2005) previously found strong signs of income convergence. However, the authors also highlighted the problem of measurement error that could bias their results.

This paper is adding to a growing body of literature on income measurement by enhancing the linear dynamic panel model by allowing for the potential existence of measurement error. Specifically, an instrumental variable approach is used which controls for measurement error by instrumenting the initial income variable. The present paper tests two different instruments, lagged income and household wealth. The use of instruments is particularly valuable to the analysis of income convergence because it allows an estimation of both (i) the direction and (ii) the size of the measurement error.

The initial income variable is shown to be endogenous, which implies that measurement error is indeed a problem in the data and that standard linear panel models do not provide consistent estimates. The results suggest that estimates that do not control for measurement error may suffer from substantial bias. Between a third and half of the naïve estimates of income convergence is found to be a result of measurement error. The magnitude of these findings suggests that the degree of income mobility is overestimated in South Africa. The results are robust to different choices of instrumental variables and holds for both the provincial and national South African panel surveys.

The remainder of this paper is structured as follows: Section 2 provides an overview of the literature. Section 3 briefly discusses the data followed by an outline of the empirical strategy, including a discussion of possible robustness checks. Section 4 presents the results. Section 5 offers some concluding remarks.

2. Theory and Literature Review

This section provides a review of the empirical literature on the effect of measurement error and poverty dynamics with a focus on South Africa. The problem of potential measurement error in the existing income panel data has been well recognized in the literature concerned with poverty dynamics in South Africa (see Agüero et al. 2007, Fields et al. 2003a and 2003b, and Woolard and Klasen 2005). However, an absence of adequate remedies in these datasets did not allow a detailed analysis of or avoidance of any bias stemming from these.

2.1 Income Measurement in South Africa

Woolard and Klasen (2005) in particular emphasized the risk of obtaining biased estimates of income dynamics when the data erroneously cause income regressions to convert towards the mean. The bias makes results appear as if large numbers of poor households benefited from income mobility. This is in fact a result found by much of the existing literature, which suggests that income mobility in developing countries is higher than in industrialized countries, especially at the poor end of the income distribution (Woolard and Klasen 2005, p.869). Thus, to obtain a valid picture of income mobility, potential measurement error needs to be taken into account, a challenge which most of the existing literature has highlighted. Fields et al. (2003a) stress that income measurement errors can be of serious concern in developing countries. As Agüero et al. (2007) point out, the problem occurs when income or expenditure are measured with errors, i.e. the observed data are "noisy". This means that panel data will incorrectly show households with stable incomes changing their position along the income distribution. While the effect on incomes in the middle of the distribution will be somewhat random, incomes at the tails of the distribution will be predominantly biased towards the mean. In other words, income measurement errors in panel data tend to make poor households look better off, and rich households worse off. In other words "[…] measurement error in initial income contributes to an apparent negative correlation between base-year income and subsequent income change" (Fields et al., 2003a, 87).

Following a methodology introduced by Glewwe (2005) to expose measurement errors, Agüero et al. (2007) note that measurement error could account for up to 60% of previously found income mobility between 1993 and 1998, using KIDS data. Similarly, Woolard and Klasen (2005) observe large differences in welfare trends when comparing income and expenditure measures. These discrepancies indicate that measurement error may indeed play an important role when analysing income dynamics in South Africa. Despite these indications, Fields et al. (2003a and 2003b) conclude that even though measurement error may bias income predictions, true income has likely converged in South Africa and that their main findings are robust to measurement error.

This paper contributes to the existing literature by using the recently expanded national NIDS panel dataset for South Africa to re-assess income dynamics and to quantify the likely bias caused by measurement error. While some of the existing literature has analysed South African income mobility using NIDS data[3], this paper is the first to explore the possible impact of measurement error on existing results.

[3] See for example Finn et al., 2013 or Finn and Leibbrandt, 2013.

2.2 Problems in measuring income mobility

In most of the literature from industrialized countries, income mobility of individuals rather than households is analyzed. Most commonly, income dynamics are estimated using the variance component model proposed by Lillard and Willis (1978).[4] The model includes a standard income function and an error structure allowing for individual random effect and first order autocorrelation of a transitory component. It does not include any lagged dependent variable. Other models assume unobserved heterogeneity to be time-invariant and include first differences. Under such setting the permanent component of income inequality cannot be identified.[5] Very few existing articles address the measurement error issue (Baulch and Hoddinott 2000). An exception is the work by Pischke (1995), who uses administrative data to quantify the effect of measurement error in self-reported income data.[6]

In contrast, literature from developing countries tend to estimate income mobility using measures derived from household income, such as per capita household income.[7] When defining income mobility as $\Delta Y_{i,t} \equiv Y_2 - Y_1$ to determine how initial income influences income change, most researchers use income models of the following form:

$$\Delta Y_{i,t} \equiv Y_2 - Y_1 = \alpha + \beta_1 Y_{i,t-1} + \beta_2 Z_{i,} + \beta_3 X_{i,t-1} + \beta_4 X_{i,t} + \varepsilon_{i,t} \qquad (1)$$

These models are straightforward to interpret and provide a measure of convergence. When $\beta_1<0$, incomes are exhibiting conditional convergence, while when $\beta_1>0$, conditional divergence takes place. Empirically, the existing literature from developing countries has mostly found that $\beta_1<0$, which implies that incomes converge to the conditional mean (e.g. Fields et al., 2003a, Woolard and Klasen 2005, Fields and Puerta, 2010). However, when income Y_1 of the base year is measured with error, such error is present on both sides of the regression equation (1), which will produce a downward-bias (attenuation) and inconsistent parameter estimates of the true effect. As previous research has pointed out, the convergence found in existing studies could be the result of measurement error rather than a closing of the income gap (Fields, 2008). To address measurement error in the absence of administrative data, several studies use predicted income to replace Y_1 on the

[4] The model is also referred to as autocorrelated individual component model.

[5] McCurdy (1982) uses this approach and tries to improve the model using time series processes and taking first differences.

[6] Pischke (1995) analyses the Panel Study of Income Dynamics Validation Study (PSIDVS). Similarly, Gottschalk and Huynh (2006) and Dragoset and Fields (2006) use tax records from the Detailed Earnings Record (DER).

[7] See Baulch and Hoddinott (2000) for a literature review on economic mobility and poverty dynamics.

right hand side of the equation (1), where the prediction is based on household or individual characteristics such as age, education, sector of occupation and dwelling characteristics (e.g. Fields et al., 2003a, Fields et al., 2010).

A very nascent literature has also shown the existence of nonlinear relationships between current and lagged income. Lokshin and Ravallion (2004) study poverty traps and report nonlinear income dynamics for Hungary and Russia. However, their analysis does not control for potential measurement error. Antman and McKenzie (2007a&2007b) investigate the nonlinear relationship between current and lagged income and allow for unobserved heterogeneity and measurement error by using a pseudo-panel approach. This method assumes that the mean of measurement error across cohorts converges to zero as the number of individuals within a cohort increases. The authors show that with larger sample size this approach yields consistent estimates, although the magnitude of existing measurement errors cannot be quantified.[8]

Most similar to this paper is the work by Newhouse (2005), who estimates income dynamics in Indonesia and addresses non-random income measurement error and unobserved household heterogeneity by using several instruments, including rainfall, assets and consumption.

In conclusion, very few studies explicitly control for measurement error and estimate the size and direction of the effect. The analysis below aims to shed additional light on this.

Lastly, for most developing countries administrative income data, such as tax records or other official income statements, remain largely unavailable or incomplete. Such data would provide an alternative to self-reported survey data for estimating income convergence, even though such data would come with its own caveats.

3. Data and Analysis

3.1 South African Panel Data

[8] Their studies correct for bias even from non-classical measurement error but, like Lokshin and Ravallion (2004)'s study, find no evidence for the existence of a poverty trap.

To measure poverty dynamics while controlling for unobservable heterogeneity, household panel data is needed. The two panel studies used in this paper are the National Income Dynamics Survey (NIDS) and the KwaZulu-Natal Income Dynamics Study (KIDS).

The main rationale for using NIDS is its coverage of the entire country. After the release of the new 2012 data set, NIDS now contains a three wave panel spanning a time period of four years. NIDS is quite large, including 26,776 completed individual interviews in 2008 (wave 1), 28,519 individual observations for 2010 (wave 2) and 32,571 successful interviews in 2012 (wave3). As with all panel studies, there is some attrition between the different waves. Yet, in comparison to the second wave, wave 3 has negative attrition rates (see De Villiers et al. 2013). That means that out of 26 776 core household members, 22 058 have been observed again in wave two and 22 375 in wave three. Attrition among the richest decile is 41.59% and is especially common among the white population (50.31%), which is more than three times higher than attrition among black Africans (13.39%).[9] As richer households drop out at a higher rate, an analysis with the resulting unbalanced sample would incorrectly indicate income convergence towards the mean. To take account of this, we only use the balanced sample and specific panel weights are generated to deal with the drop outs. The balanced sample of individuals that appears in all three waves consists of 18826 individual observations.[10]

In addition, KIDS has the advantage of being a three-wave panel dataset spanning the first decade of South Africa's democracy. However, KIDS only covers the province of KwaZulu-Natal and is limited to the main ethnic group of so-called black (about 80% of the population) and Indian households, thereby excluding households with coloured or white heads.[11] Nevertheless, KIDS is the most used panel dataset in South Africa and has covered 841 households through all three survey waves, starting just before the end of apartheid. Overall attrition is reasonable with 1132 households (83.6%) having been successfully re-interviewed for the second wave in 1998 (Adato et al., 2006, 249). For the third wave in 2004, some 74% of the households contacted in 1998 were re-interviewed.[12] Attrition becomes a problem and might lead to sample bias if the households that drop out of the sample have different characteristics than those that remain. Because of this and additional limitations of the original sampling, some researchers have been concerned that

[9] Attrition rates reported by Finn et al. (2012).
[10] See Finn and Leibbrandt (2013) for detailed survey description.
[11] For a comprehensive overview of KIDS see May et al. (2000) or May et al. (2005).
[12] In the black sample 721 out of 1139 households in 1993 (63.7%) could be re-interviewed in 2004 (own-calculations).

KIDS may not be entirely representative for all black Africans in KwaZulu-Natal (e.g. Agüero et al. 2007).

3.2 Empirical Strategy

This section briefly describes the econometric approach to estimate income measurement error using the NIDS and KIDS panel datasets. This largely follows existing studies that have highlighted the problem of measurement error in KIDS when dealing with income estimations (Fields et al., 2003a; Woolard and Klasen, 2005). A natural starting point for the analysis is the true income Y^*_{it}, which is not observable. Instead, only self-reported income Y_{it} is available, which is potentially biased by ε_{it}. This can be expressed as

$$Y_{it} = Y^*_{it} + \varepsilon_{it} \qquad (2)$$

The measurement error is particularly problematic for determining income dynamics when it occurs in the initial year, because this can produce a spurious negative association between reported base year income and the measured income change (Fields et al. 2003a). When the true relationship between the initial income and income change is *negative,* it implies that true income might be converting towards the overall mean (Fields et al. 2003a). However, when measurement error contributes to the negative relationship it causes an overestimation of the true effect or, in other words, a downwards bias of the initial income coefficient, falsely leading to the conclusion that there is *less* persistence in the income process than there actually is (Antman and McKenzie 2007). To deal with this problem Antman and McKenzie (2007) propose using the lagged income variable $Y_{i,t-2}$ instead of the basic year income $Y_{i,t-1}$. In the absence of autocorrelation in the measurement error this approach will yield consistent estimates.[13] In the present case it means that the initial income variable ln(Income per Capita)$_{i,t-1}$ is instrumented by ln(Income per Capita)$_{i,t-2}$.[14] Therefore, the two-stage least square equation set to determine the effect of different households' characteristics on the change of income has the following form:

First Stage:

$$\text{Ln (Income per Capita)}_{i,t-1} = \alpha + \beta_1 X_{it} + \beta_2 \Psi_{it} + \beta_3 {*}\ln(\text{Income per Capita})_{i,t-2} + \varepsilon_{it} \quad (3)$$

Second Stage:

$$\Delta\text{Ln (Income per Capita)}_{i,t} = \alpha + \beta_1 X_{it} + \beta_2 \Psi_{it} + \beta_3 {*}\ln(\text{Income per Capita})_{i,t-1} + \varepsilon_{it} \quad (4)$$

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[13]Appling the Wooldridge test for serial correlation the H_0 hypothesis that the data is affected by autocorrelation is rejected.

[14] In the following, the term income refers to per capita income in real terms.

If the lagged initial income variable is a good instrument, equation (4) will give a consistent coefficient, β_3. In order for ln(Income per Capita)$_{i,t-2}$ to be a valid instrument it must be exogenous and it must be correlated with the endogenous variable ln(Income per Capita)$_{i,t-1}$, i.e.:

$Cov\ (ln(Income\ per\ Capita)_{i,t-2}, \varepsilon_{it}) = 0$ *and* $Cov\ (ln(Income\ per\ Capita)_{i,t-2}, ln(Income\ per\ Capita)_{i,t-1}) \neq 0$

The instrumental variable first stage regression shows that the instrument has a significant effect at a 1% level on initial income (as shown later in column 2 of Table 1). Second the weak identification test rejects the H_0 hypothesis that initial income is not adequately instrumented on a 1% level. Therefore, it can be assumed that ln(Income per Capita)$_{i,t-2}$ is a valid instrument under the assumption that there is no serial correlation higher than of second order. To test for the robustness of the results an asset index is used as a second instrument. The resulting IV regression has the following form:

First stage:

$$Ln\ (Income\ per\ Capita)_{i,t-1} = \alpha + \beta_1 X_{it} + \beta_2 \Psi_{it} + \beta_3 {*} ln(Asset\ index)_{i,t-1} + \varepsilon_{it} \qquad (5)$$

Second stage:

$$\Delta Ln\ (Income\ per\ Capita)_{i,t} = \alpha + \beta_1 X_{it} + \beta_2 \Psi_{it} + \beta_3 {*} ln(Income\ per\ Capita)_{i,t-1} + \varepsilon_{it} \qquad (6)$$

Finally, to test for over-identification the full set of instruments is used, including ln(Income per Capita)$_{i,t-2}$ and the asset index.

First stage:

$$Ln\ (Income\ per\ Capita)_{i,t-1} = \alpha + \beta_1 X_{it} + \beta_2 \Psi_{it} + \beta_3 {*} ln(Income\ per\ Capita)_{i,t-2} + \beta_4 {*} ln(Asset\ index)_{i,t-1} + \varepsilon_{it} \qquad (7)$$

This estimation strategy using the second lagged income variable $Y_{i,t-2}$ is followed for both the NIDS and the KIDS panel data, for which a third wave has recently been released. The income regressions for NIDS will have the form of (3)-(7) as well. Having a set of instruments allows testing for over-identification by calculating the Hansen J-test statistic to establish whether the instruments are uncorrelated with the disturbance process.

4. Results

This section presents the results of a dynamic model with a focus on income convergence and the direction and size of income measurement error.

4.1 Income Convergence at National Level

Table 1presents the results for the classic linear panel model and the IV approach for the period 2010-2012 in NIDS. The naïve estimation using the classic linear panel (Columns 1) with a standard set of control variables[15] results in a highly significant and negative impact of initial income of -0.548, implying a very strong convergence to the mean. When allowing for measurement error (column 3), the coefficient of initial income drops from -0.548 to -0.121, a reduction of 78%.[16] In other words, for the national panel more than three quarters of the obtained income convergence appears to be driven by measurement error.

Robustness

To test for the robustness of these results with the national panel, the results from the two instruments (i.e. Second lag income vs. Second lag of Asset index) are compared. The test does not yield significant differences (see Table 3 below), which indicates that both instruments are suitable to control for a similar level of measurement error. In addition, the panel equation is again estimated using both instruments, which further corroborates the results.[17] The coefficient on the log of initial income in this case decreases to -0.161, a reduction of 71% compared to the naïve estimator.

Overall, for both panel datasets indications for convergence to the mean are found. Income mobility appears to be substantially overestimated when measurement error is not controlled for. The magnitude of the measurement bias ranges between 71% and 78%in the national NIDS panel.

Table 1: National Income Convergence (NIDS 2010-2012)

	(1)	(2)	(3)
	OLS	IV 1st stage	IV 2nd stage
Outcome	Change in log (Income per	Ln(Income per Capita, 2010)	Change in log (Income per

[15] All control variables show the expected sign and are mostly highly significant. We find convex returns to education, which is line with the South African literature (Keswell and Poswell, 2004). Having a female household head or living in a big household seems to have a significant negative income growth effect. As expected, being employed explains a large part of who is getting ahead or falling behind. Income of black households seems to grow slower than Indian households. However, the black coefficient turns insignificant for the IV regression.

[16] All IV tests indicate that the Asset Index is an appropriate instrument. In addition an Asset Index is used. Even when all (no) household characteristics are excluded and only (no) household assets are used the coefficient for lagged income is relatively stable at the 10-20% level. This is true for KIDS as well as for NIDS.

[17] The over-identification test cannot be rejected, and other IV tests also hold, implying the validity of the instrument set.

	Capita) between 2010 and 2012		Capita) between 2010 and 2012
Ln (Income per Capita in in 2010)	-0.548***		-0.121***
	(0.021)		(0.044)
Education	-0.028***	-0.028**	-0.012
	(0.010)	(0.011)	(0.011)
Education Squared	0.006***	0.005***	0.002**
	(0.001)	(0.001)	(0.001)
Coloured	0.007	0.226***	-0.145***
	(0.065)	(0.054)	(0.056)
Indian	0.485***	0.336***	0.169*
	(0.098)	(0.087)	(0.098)
White	0.461***	0.556***	-0.007
	(0.077)	(0.073)	(0.091)
HH head employed	0.307***	0.381***	0.067
	(0.039)	(0.039)	(0.045)
Share of children in HH	-0.947***	-0.789***	-0.473***
	(0.074)	(0.078)	(0.092)
Share of adults in HH	0.112	0.122*	0.048
	(0.075)	(0.073)	(0.081)
Change number employed in HH	0.204***	-0.293***	0.361***
	(0.016)	(0.016)	(0.023)
Change in HH size	-0.073***	0.102***	-0.131***
	(0.008)	(0.008)	(0.010)
IV:Ln(Income per Capita in 2008)		0.445***	
		(0.036)	
Constant	3.338***	3.458***	0.829***
	(0.152)	(0.150)	(0.282)
Observations	5,744	5,744	5,744
R-squared	0.478	0.650	0.331
Under-identification test (Anderson canon. corr. likelihood ratio stat.)		1385.11	
Weak identification statistic (Cragg-Donald N*minEval stat.)		1566.39	

Notes. Controls not reported: age, age squared, and binary variables for rural areas, HH moved and female head. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Panel weights are used to control for the attrition bias.

4.2 Income Convergence in KwaZulu-Natal

The analysis of the KIDS panel from the province of KwaZulu-Natal follows the above results with national data. Table 2 shows the result of the dynamic model for the period 1998-2004. Using a similar set of control variables from the KwaZulu-Natal panel, very similar results are found for the national KIDS panel.

For reference purposes, column (1) shows the classic linear panel model directly using initial log of income (in 1998) as explanatory variable for the change in log income between 1998 and 2004. Columns (2) and (3) show the first and second stage of the IV regression that allows for measurement error by instrumenting log of initial per capita income (in 1998) by the log of such income in 1993, the first wave of the data.

For the classic linear panel model the initial income variable is highly significant and has a strong negative impact on income change. The outcome of this naïve estimator implies that those with one unit higher log initial income in 1998 experience 84.8% lower log of income change. That indicates a very strong conversion to the overall mean income, but also confirms the findings of previous studies (e.g. Woolard and Klasen, 2005; Agüero et al., 2007). However, using the IV approach results in a significantly lower coefficient, which highlights the problem of measurement error and suggests that such error leads to an overestimation of mobility and convergence. Since the time interval between the waves is much shorter in the national data (only 2 years compared to 6 years in the KIDS data), such a result would imply even faster income convergence at the national level.

The bias is smaller in the KIDS data from the KwaZulu-Natal province and ranges between 33% and 44% of estimated income convergence. The preferred estimates using two instruments suggest a bias in estimated income convergence by 77% for the NIDS panel and 39% for the KIDS data.

Validity of IV Approach

Column (2) of the first stage shows that the instrument – the lag of ln(real per capita income), i.e. the 1993 rather than 1998 values, from Wave 1 of KIDS – is highly significant. Second, the Underidentification test (Anderson canon. corr. LM statistic), as well as the Cragg-Donald statistic of the weak identification test, indicate that the instrument is valid.

Table 2: Income Convergence in KwaZulu-Natal Province (KIDS 1998-2004)

	(1)	(2)	(3)
	OLS	IV 1st stage	IV 2nd stage
Outcome	Change in log (Income per Capita) between 1998 and 2004	Ln(Income per Capita, 1998)	Change in log (Income per Capita) between 1998 and 2004
Ln (Income per Capita in 1998)	-0.848***		-0.557***
	(0.037)		(0.124)
Education of household head	-0.022	0.036	-0.034
	(0.024)	(0.025)	(0.025)
Education of household head^2	0.005***	0.002	0.005***
	(0.002)	(0.002)	(0.002)
Female household head	-0.278***	-0.108	-0.228***
	(0.074)	(0.081)	(0.081)
Black	-0.438***	-0.354**	-0.272
	(0.142)	(0.142)	(0.167)
Employed	0.865***	0.183**	0.795***
	(0.084)	(0.079)	(0.093)
HH size	-0.084***	-0.019**	-0.075***
	(0.010)	(0.009)	(0.011)
IV: Ln(Income per Capita in 1993)		0.360***	
		(0.045)	
Constant	5.001***	3.440***	3.391***
	(0.398)	(0.413)	(0.800)
Observations	714	714	714
R-squared	0.540	0.428	0.491
Under-identification test (Anderson canon. corr. likelihood ratio stat.)		49.38	
Weak identification test (Cragg-Donald N*minEval stat)		63.25	

Notes. Controls not reported: age, age squared, and binary variables for rural areas and KwaZulu (former homeland. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Robustness Analysis

To strengthen the credibility of these results, several additional investigations into the effect of measurement error are pursued. First, the results are tested for robustness by introducing a different instrument, namely household wealth, which is measured by an Asset Index.[18] Using the lag of household wealth as instrument for initial income yields virtually the same result as above (see Table 6 in the Appendix). In fact, the coefficients for initial income are not significantly different between lagged income and lagged

[18] The Asset Index is constructed using Multiple Correspondence Analysis (MCA). It is more common to use a related technique, Principal Component Analysis, but it has been shown that it is more correct to use MCA where the variables are not continuous or normally distributed. The index covers a wide range, from the material the dwelling was constructed to whether a household owns certain goods, such as a video-recorder or a TV.

household wealth, as summarized in Table 3. Second, in a further analysis, income and wealth are both used as instruments for initial income (see Table 7 in the Appendix) with very similar results.[19] Overall, the conclusion emerges that income change in the KIDS data was indeed measured with measurement error between 34% and 44%.

Table 3: Effect of measurement error on initial income

KIDS	Lagged Income	IV: Second lag Income	IV: Lag Asset Index	IV: Set (combining the two instruments
Coefficient	-0.848*** (0.037)	-0.557*** (0.124)	-0.476*** (0.124)	-0.521*** (0.097)
Drop in %		34%	44%	39%

NIDS	Lagged Income	IV: Second lag Income	IV: Lag Asset Index	IV: Set (combining the two instruments
Coefficient	-0.548*** (0.021)	-0.121*** (0.044)	-0.161*** (0.069)	-0.128*** (0.043)
Drop in %		78%	71%	77%

Notes: Standard error in brackets

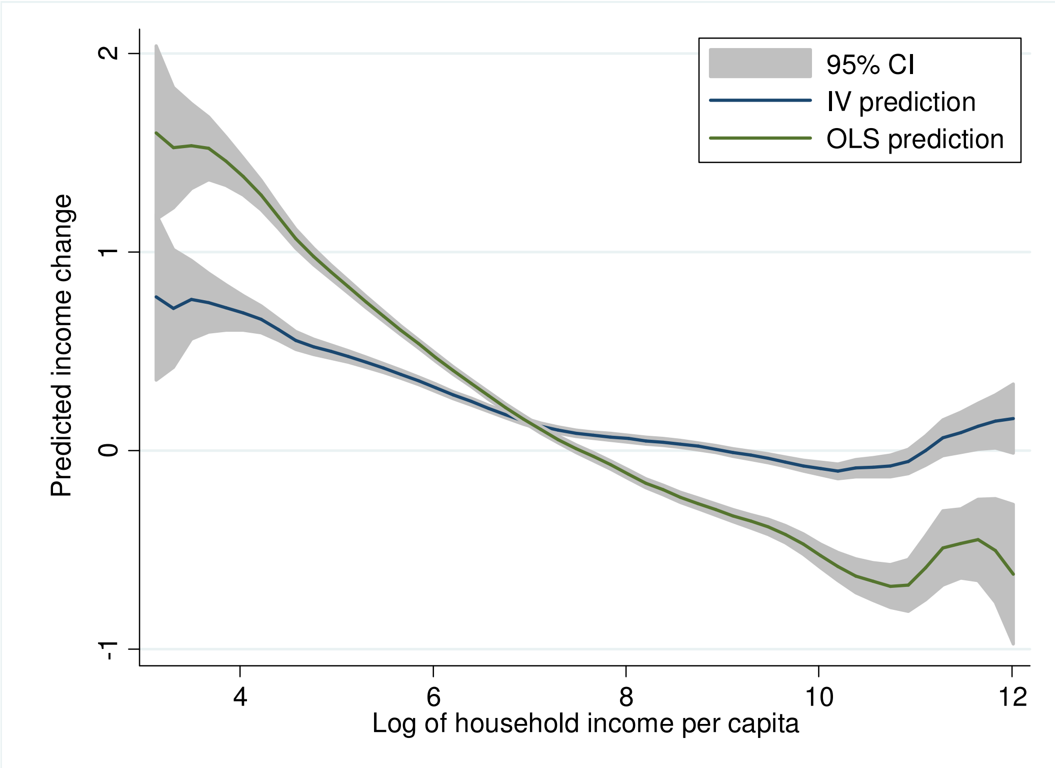
4.3 Measurement Error and Income mobility

In the previous section the IV regression analysis has shown that the degree of mobility was significantly overestimated. In this section income and poverty transition estimates are presented.

Figure1 shows the change of log per capita income by income level for the NIDS data for the naive OLS estimates and the IV results. As expected, most of the measurement error is due to bias in the tails. In terms of magnitude, the bias which is measured by the difference between the OLS and IV estimates is nearly twice as large among the poorest decile when compared to the bias arising for the highest decile. This suggests that income mobility at the poorest end has indeed been much lower than more naive estimators would suggest (Fields et al., 2003a; Woolard and Klasen, 2005). Survey tools need to be especially sensitive to correct measurement among the tails of the distribution.

[19] Having two instruments allows testing for over-identification of the IV set. The Hansen J statistic is 0.271 and the Chi-sq(1) P-value equals 0.6024. The statistic is far from the rejection of its null, implying that the over-identification restrictions are valid and the set of instruments is appropriate.

Figure 1: Income change by income level in 2010, NIDS



Notes. The OLS prediction is the steeper curve.

Transition by Quintile

To further quantify the degree of measurement error by income level a transition table can be useful, which shows mean changes between quintiles. Table 4 presents the transition of households with and without measurement error. It uses the predicted income changes to show by how much income mobility in South African panel data is overestimated due to measurement error.[20] As one can see, there seem to be much less movement in and out of poverty when using the predicted income changes. Instead of 43.95% there are now only 31.98% of households which move out of poverty and only 7.06% instead of 17.69% move below the poverty line of R636per capita income.

[20] We estimate 2012 per capita income by adding the predicted income change to 2010 per capita income levels.

Table 4: Transition matrix with and without measurement error, NIDS

Measured values			
		Household was poor in 2012	
		NO	YES
Household was poor in 2010	NO	2563 (82.31%)	511 (17.69%)
	YES	1156 (43.95%)	1474 (56.05%)
Predicted values (for 2012)			
		Household was poor in 2012	
		NO	YES
Household was poor in 2010	NO	2894 (92.94%)	220 (7.06%)
	YES	841 (31.98%)	1789 (68.02%)

Note: A household is defined poor when it has below R636 per capita income in 2012 prices.

Income convergence for different groups

Given the vast differences in income sources and the average consumption basket between urban and rural households, and other socio-demographic predictors, such as race, it is worth analyzing income convergence in terms of location and race, as the degree of measurement error can differ along these dimensions. For example, given the lower income at baseline, measured convergence may be larger within the black population than among the white population. If so, the coefficient for initial income would be larger such that $ß_{black} > ß_{white}$. To test this hypothesis, the results of the classic linear panel and IV regressions are presented for sub-groups by race and by location (urban vs. rural) in Table 5, for both the provincial and national data.

As expected, there seems to be higher convergence using the naïve estimate in the black and coloured sample (evident in the increase of the initial income coefficient). In addition, convergence seems to be higher in rural areas as well as measurement error. However, since the number of household observations decreases quite drastically when one only looks at specific sub-groups, the results lose some of their comparability.

Table 5: Measurement Error by Race and Location, NIDS and KIDS

NIDS	Full sample	Black/ Coloured	White/ Indian	Urban	Rural
Lagged Income (OLS)	-0.548***	-0.558***	-0.509	-0.526***	-0.611***
IV set	-0.128***	-0.162***	-0.227***	-0.178***	-0.138***
Change of OLS results when using IV in %	76.7%	71.7%	55.2%	74.2%	77.4%
Observation	5744	5534	264	2969	2829
KIDS	**Full sample**	**Black**	**Indian**	**Urban**	**Rural**
Lagged Income (OLS)	-0.848***	-0.855***	-0.775***	-0.824***	-0.863***
IV set	-0.515***	-0.577***	-0.157	-0.557***	-0.509***
Change of OLS results when using IV in %	39.3%	32.5%	79.7%	32.4%	41.0%
Observation	714	609	105	252	462

*** p<0.01, ** p<0.05, * p<0.1

5. Concluding Remarks

An unbiased measurement of household income and expenditures is central to income mobility analysis. This paper is concerned with the effect of measurement error when estimating income dynamics in South Africa. Using the recently published nationally representative income panel dataset (NIDS) and an additional provincial income panel (KIDS), this paper tests for the existence of measurement bias. By employing an instrumental variables approach using two different instruments it is possible to control for the effect of measurement error and to quantify its likely impacts on estimates of income convergence.

The results suggest that self-reported income in the survey data suffers from mean-reverting measurement bias, leading to a substantial overestimation of income convergence in both panel datasets. The preferred estimates suggest that previously estimated income dynamics have been overestimated by approximately 77% for the national panel and by 39% for the provincial panel. It also underscores the importance of having well designed survey instruments to mitigate the risk of measurement error during data collection. Future research is required to address differences in questionnaire design and further analyze the behavioral aspects of misreporting household income.

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Appendix

Table 6: Income Convergence in KwaZulu-Natal Province (KIDS 1998-2004)

VARIABLES	(1) OLS Income change	(2) IV 1st stage Ln(Income per Capita, 1998)	(3) IV 2nd stage Income change	(4) IV 1st stage Ln(Income per Capita, 1998)	(5) IV 2nd stage Income change
Ln (Income per Capita in 1998)	-0.848***		-0.476***		-0.521***
	(0.037)		(0.124)		(0.097)
Education of household head	-0.022	0.019	-0.037	0.021	-0.035
	(0.024)	(0.027)	(0.027)	(0.025)	(0.026)
Education of household head^2	0.005***	0.002	0.005***	0.001	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female household head	-0.278***	-0.103	-0.214***	-0.069	-0.221***
	(0.074)	(0.080)	(0.081)	(0.078)	(0.080)
Black	-0.438***	-0.339**	-0.226	-0.228	-0.252
	(0.142)	(0.145)	(0.166)	(0.139)	(0.161)
Employed	0.865***	0.190**	0.775***	0.156**	0.786***
	(0.084)	(0.080)	(0.094)	(0.077)	(0.092)
HH size	-0.084***	-0.031***	-0.072***	-0.021**	-0.074***
	(0.010)	(0.009)	(0.011)	(0.009)	(0.011)
Instrument: Household Wealth in 1998		0.535***		0.398***	
		(0.065)		(0.067)	
Instrument: Ln (Income per capita in 1993)				0.285***	
				(0.047)	
Constant	5.001***	5.635***	2.941***	3.956***	3.190***
	(0.398)	(0.364)	(0.776)	(0.420)	(0.664)
Observations	714	714	714	714	714
R-squared	0.540	0.418	0.460	0.459	0.478
F statistics for identifying instruments		59.37		64.56	
Under-identification test (Anderson canon. corr. likelihood ratio stat.)		48.13		72.26	
Weak identification statistic (Cragg-Donald N*minEval stat.)		68.69		113.01	
Hansen J statistic (overidentification test of all instruments):				0.271	
Chi-sq(1) P-val =				0.6024	

Not listed: Age& Age2 and dummies for Rural & KwaZulu
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: National Income Convergence (NIDS 2010-2012)

VARIABLES	(1) OLS Income change	(2) IV 1st stage Ln(Income per Capita, 2010)	(3) IV 2nd stage Income change	(4) IV 1st stage Ln(Income per Capita, 2010)	(5 IV 2nd stage Income change
Ln (Income per Capita in 2008)	-0.548***		-0.161**		-0.128***
	(0.021)		(0.069)		(0.043)
Education	-0.028***	-0.043***	-0.013	-0.031***	-0.012
	(0.010)	(0.013)	(0.011)	(0.011)	(0.011)
Education^2	0.006***	0.007***	0.002**	0.005***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Coloured	0.007	0.131**	-0.130**	0.135**	-0.142**
	(0.065)	(0.063)	(0.058)	(0.055)	(0.055)
Indian	0.485***	0.357***	0.198*	0.197**	0.172*
	(0.098)	(0.124)	(0.105)	(0.092)	(0.098)
White	0.461***	0.721***	0.037	0.434***	0.002
	(0.077)	(0.089)	(0.105)	(0.075)	(0.089)
Employed	0.307***	0.543***	0.090*	0.390***	0.071
	(0.039)	(0.040)	(0.053)	(0.038)	(0.044)
Number of children in HH	-0.947***	-1.158***	-0.517***	-0.842***	-0.482***
	(0.074)	(0.084)	(0.106)	(0.077)	(0.091)
Number of adults in HH	0.112	0.253***	0.054	0.172**	0.049
	(0.075)	(0.084)	(0.080)	(0.072)	(0.080)
Change in number employed in HH	0.204***	-0.355***	0.347***	-0.294***	0.359***
	(0.016)	(0.018)	(0.029)	(0.016)	(0.022)
Change in HH size	-0.073***	0.134***	-0.125***	0.105***	-0.130***
Instrument: Ln(Income per Capita in 2008)				0.158*** (0.024)	
Instrument: Household Wealth in 2008		0.343*** (0.024)		0.403*** (0.021)	
Constant	3.338***	6.516***	1.065**	3.983***	0.868***
	(0.152)	(0.116)	(0.420)	(0.169)	(0.273)
Observations	5,744	5,744	5,744	5,744	5,744
R-squared	0.478	0.588	0.357	0.656	0.336
Under identification test (Anderson canon. stat)		40.728		115.124	
Weak identification test (Cragg-Donald)		226.707		394.287	
Hansen J statistic (over identification test of all instruments):				0.364	
Chi-sq(1) P-val =				0.5460	

Not listed: Age& Age2, the number of elders in HH and a dummy for Rural
Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1