Journal of African Economies, 2018, Vol. 27, number 1, 92–107
doi: 10.1093/jae/ejx016
Advance Access Publication Date: 12 September 2017
Article

The Recent Growth Resurgence in Africa and Poverty Reduction: The Context and Evidence

Augustin Kwasi Fosu[a,b,c,*]

[a]Institute of Statistical, Social and Economic Research (ISSER), University of Ghana, Legon, Ghana, [b]Faculty of Economic and Management Sciences, University of Pretoria, Pretoria, South Africa, and [c]Aalto University, Helsinki, Finland

*Corresponding author: Augustin Kwasi Fosu. E-mail: afosu@isser.edu.gh

†I am grateful to the JAE editor in charge of the manuscript, Doug Gollin, and an anonymous referee for helpful comments. I also thank Dede Gafa for valuable research assistance, and the African Development Bank for grant support as part of the project, 'Growth-Poverty Nexus: Overcoming Barriers to Sustainable Development.'

Abstract

While economic growth in Africa has resurged substantially since the mid-to-late 1990s, the amount of poverty reduction seems much less spectacular. Building on other studies, the paper explores the translation of the recent growth to poverty reduction using 1985–2013 PovcalNet (World Bank) data. It assesses the relative abilities of various panel-data methodologies to predict poverty changes based on income-inequality decompositions. Surprisingly, SYSGMM performs substantially worse than Fixed Effects and Random Effects. The analysis is conducted for both the $1.25 and $2.00 poverty lines, and for the 'spread' and 'depth' of poverty, as well as for the usual popular measure, the headcount ratio. Although income growth appears to be the main force behind poverty reduction in Africa, the decomposition reveals striking differences, across countries and poverty measures, with respect to the relative roles of inequality and income.

Key words: growth resurgence, income, inequality, poverty reduction, Africa

JEL classification: D31, I32, O11, O49, O55

1. Introduction

There has been increasing recognition of the importance of poverty reduction as a development objective in both the economic literature and policy community. Indeed, poverty eradication was enshrined as the Millennium Development Goal 1 (MDG1), and is currently the Sustainable Development Goal 1 (SDG1).[1]

The developing world (DW) as a whole has experienced a substantial reduction in poverty since the 1980s, at an annual average rate of about 1 percentage point (Chen and Ravallion, 2008). The progress has not been uniform across and within regions, however. While most Asian countries have exhibited tremendous poverty reduction, the progress in Africa, particularly sub-Saharan Africa (SSA), has been slow, with poverty incidence, spread and depth remaining at relatively high levels (Chen and Ravallion, 2007, 2008; Thorbecke, 2013). In order for Africa to achieve faster progress on poverty in the years ahead, therefore, national policymakers and their development partners must embark on policies that are likely to most efficiently and effectively reduce poverty. That would in turn imply the need to examine the factors that influence the continent's progress on poverty.[2]

The main objective of the present paper is to advance the understanding of the issue of income vis-a-vis inequality influencing the direction of poverty in African countries. It builds on previous studies that have shown the importance of these two factors in poverty reduction. In addition to providing the most recent up-to-date relative impacts of the changes in income and in inequality, based on the World Bank PovcalNet data, the paper employs various panel-data methodologies to assess their relative abilities to predict poverty changes based on income-inequality poverty decompositions. Judged by their relative predictive powers, it is possible to deduce the 'optimal' choice among methodologies.

The choice among the popular panel estimating methods—Random Effects (RE), Fixed Effects (FE) and Systems Generalised Methods of Moments (SYSGMM)—is often guided by the usual statistics that are meant to ensure that the estimates meet the various desirable statistical properties: unbiasedness, efficiency, absence of endogeneity and/or consistency (asymptotic). For *predictive* purposes, however, it is not entirely clear that these estimating properties would necessarily be translated into relatively accurate predictions. Using a large sample of African countries with the necessary data over time, the present approach explores the relative desirability of the various methodologies with respect to predicting in-sample changes in poverty over time, based on decompositions of poverty growth into changes in income and in inequality. Such decompositions should prove useful, as they shed light on the relative importance, at the country level, of poverty-reduction policies directed at improving income growth vis-à-vis income distribution.

Moreover, in the light of growing concerns that the headcount ratio, the usual statistic of analysis, fails to capture the level of actual poverty, the paper further provides analyses of the measures of the 'spread' and 'depth' of poverty. This additional evidence is particularly germane, given the observation that African countries' performance on poverty reduction, relative to the rest of the world, is less impressive on these measures than on the headcount (see, e.g., Chen and Ravallion, 2008).

Following a brief discussion of the growth-inequality-poverty literature, first, I shed light on the historical trends of poverty for Africa versus other regions of the world. This is conducted for the \$1.25 and \$2.00 per-day poverty lines and based on the three Foster–Greer–Thorbecke

1 The recently adopted SDGs may be found at: http://www.un.org/sustainabledevelopment/sustainable-development-goals/

2 For a comprehensive discussion on the recent progress on Africa's poverty see, for instance, Beegle *et al.* (2016).

(FGT) measures of poverty: poverty 'headcount', 'poverty gap' and 'squared poverty gap', which measure poverty incidence, spread and depth, respectively.[3] Second, the 'identity' model involving poverty changes as a function of changes in income and in income inequality is presented and estimated using several panel-estimation methods. Third, progress on poverty is decomposed into income and inequality changes for all the countries in the African sample. Fourth, based on the relative predictive powers of the estimating methods, the 'optimal' sets of results are selected and discussed. The final section of the paper provides a summary of the findings, with implications for policy.

2. The growth-inequality-poverty nexus

2.1 A brief review

There seems to be a general consensus that income growth is the main engine for poverty reduction globally (Deininger and Squire, 1998; Ravallion, 2001; Dollar and Kraay, 2002; Kraay, 2004). Yet, the transformation of growth to poverty reduction is nonlinear, with especially inequality playing an important intervening role. For example, Adams (2004), Bourguignon (2003), Easterly (2000), Epaulard (2003), Kalwij and Verschoor (2007) and Ravallion (1997) find that high initial inequality inhibits the effectiveness of growth in reducing poverty in global samples.

In addition, Fosu (2008, 2009, 2010a, b, c) present and estimate various nonlinear poverty functions involving the transformation of growth to poverty reduction. While Fosu (2010a) is a comparative study involving all the major global regions, the rest of these studies focus on Africa. Furthermore, Fosu (2011, 2015a) emphasise the tendency of lower initial incomes to retard the translation of income growth and changes in income distribution into poverty reduction.

Furthermore, Ravallion (2012) finds that the initial level of poverty dominates other initial conditions in determining the path of poverty, particularly by its adverse influence on growth and by limiting the rate at which growth is transformed to poverty reduction. Similarly, Thorbecke (2013) emphasises the reverse effect of poverty on growth, with further implications for poverty.

2.2 The model

Consistent with Fosu (2011, 2015a), for instance, I estimate the following 'identity' model, which is a theoretically comprehensive representation of the growth-inequality-poverty nexus.[4]

$$p = b_1 + b_2 y + b_3 y G^I + b_4 y(Z/Y) + b_5 g + b_6 g G^I + b_7 g(Z/Y) + b_8 G^I + b_9 Z/Y \quad (1)$$

where p is the growth in the poverty rate, y is income growth, g is growth in the Gini coefficient as a measure of the level of inequality, G^I is the initial Gini coefficient (expressed in

3 See Foster *et al.* (1984).

4 This 'identity' model, first derived by Bourguignon (2003), is based on an approximation to an assumed lognormal income distribution, and allows one to explain the heterogeneity of the nexus across countries and time periods. For details of the application of the Bourguignon model see, e.g., Fosu (2009, 2011) and Kalwij and Verschoor (2007); see also Epaulard (2003) for a version of this model.

natural logarithm), Z/Y is the ratio of the poverty line Z to income Y (expressed in natural logarithm), and b_j ($j = 1, 2,\ldots, 9$) are the respective coefficients to be estimated.

The sign of b_2 is anticipated to be negative, since an increase in income growth would decrease poverty growth, ceteris paribus.[5] In contrast, b_3 is expected to be positive; a higher level of initial inequality would reduce the rate at which growth acceleration is translated into poverty reduction. The sign of b_4 should also be positive, consistent with the notion, based on the lognormal income distribution, that a larger income (relative to the poverty line) would have associated with it higher income elasticity.[6]

The sign of b_5 is expected to be positive, as a worsening income distribution should increase poverty, ceteris paribus. In contrast, the sign of b_6 is likely to be negative for a diminishing poverty-increasing effect of rising inequality. The sign of b_7 would be negative as well, for in a relatively low-income economy (high Z/Y) improving income distribution (lowering g) might worsen poverty by raising the likelihood that more people would fall into poverty. Finally, b_8 and b_9 are likely to be positive: rising initial inequality or increasing poverty line relative to income should, ceteris paribus, exacerbate poverty, respectively; however, these coefficients do not affect the income or inequality elasticity of poverty.

From equation (1), the respective income and inequality elasticities are obtainable as:

$$E_y = b_2 + b_3 G^I + b_4 Z/Y \tag{2}$$

$$E_g = b_5 + b_6 G^I + b_7 Z/Y \tag{3}$$

Therefore, given the above expected signs of the regression coefficients, E_y and E_g are generally anticipated to be negative and positive, respectively, so that raising income growth should reduce the growth of poverty, while worsening inequality changes would exacerbate poverty increases. It is conceivable, though, that perverse signs of the elasticities could occur. For example, in a highly unequal (high G^I) and low-income (high Z/Y) economy, the magnitude of the combined positive-signed b_3 and b_4 could actually overwhelm the magnitude of the negative-signed b_2, thus rendering E_y positive. Similarly, in such an economy, E_g could be negative. These two elasticities are critical for determining what happens to poverty reduction over time in a given economy.

Thus poverty would decline faster as: (1) income growth is higher, (2) the decline in inequality is larger, (3) initial inequality is smaller or (4) as income relative to the poverty line is higher. Furthermore, the income growth and inequality-lowering effects on poverty would be respectively larger as: (a) initial inequality is lower and (b) as income relative to the poverty line is higher. These last two effects, therefore, work via the income and inequality elasticities of poverty. That is, both elasticities would decrease with initial inequality but increase with income relative to the poverty line; hence, initial inequality plays only a part of this growth-to-poverty transformation process.

5 For details on the expected signs of the coefficients see, for instance, Bourguignon (2003) and Epaulard (2003). See also Duclos and Araar (2010, pp. 92–97) for further insights on poverty decomposition, and Ferreira (2010) for a discussion on the poverty dynamics related to growth and income distribution.

6 I ignore the sign and adopt the convention of referring to the income elasticity by its magnitude.

3. The data and estimation

The World Bank (2015) PovcalNet database provides the main source for the present analysis. The panel derived from this database is extremely unbalanced; the data emanate from available country surveys, which are for different years across countries and are far from regular within countries. Thus, considerable adjustments are required in order to obtain reasonably reliable regional estimates for the time series (Chen and Ravallion, 2008). The data are therefore revised by the World Bank as necessary, with implications for regional comparability over time. For example, Fosu (2015a) finds less-than-stellar performance for SSA compared with South Asia (SA) since the mid-1990s when 2014 rather than 2009 PovcalNet data are used. This revelation suggests that as the data are revised and improved, updated studies are called for.

Before proceeding with the estimation of equation (1), I first present graphically the data on the SSA region,[7] comparatively with the other global regions.[8] The comparison for the \$1.25 per day poverty line is provided for the three FGT poverty measures as Appendix Figures A1.1a, A1.1b and A1.1c, respectively, while that for the \$2.00 is shown as respective Appendix Figures A1.2a, A1.2b and A1.2c. It is apparent from these graphs that SSA performed poorly on poverty in the 1980s and early 1990s, but has since about 1993 improved on its poverty record. This result holds for all the three FGT measures. However, on a comparative basis with the DW generally, the African region does not seem to have fared as well even in the more recent period, for the gaps with particularly SA and East Asia and the Pacific have been widening, as they have with the DW as a whole. Furthermore, the SSA gap with the rest of the world is wider for the poverty gap than for the headcount ratio (poverty incidence), and for the squared poverty gap than for the poverty gap. Thus, it appears that *relative* to the other FGT measures, the headcount actually understates Africa's gap on poverty *comparatively* with the rest of the world (see Chen and Ravallion, 2008). Hence, equation (1) will be estimated for the measures of the 'spread' and 'depth' of poverty, that is, in addition to the headcount.

3.1 Estimation

Equation (1) is estimated using the World Bank PovcalNet unbalanced panel data over the 1985–2013 sample period for the poverty rates at the \$1.25 and \$2.00 per-day lines, yielding the respective sample sizes of 117 and 103–104 involving at most 41 and 39 African countries, respectively. Summary statistics for the levels of the poverty rates, income inequality (Gini coefficient) and mean income are reported for the \$1.25 and \$2.00, in the Appendix tables B1.1 and B1.2, respectively.[9] Note that the averages are non-weighted and, due to missing data, sample composition may vary over time.

7 Because the World Bank data incorporate North Africa's data into the Middle East and North Africa (MENA) group, the aggregate evidence cited here for Africa is that of SSA; hence, 'Africa' and 'SSA' are used interchangeably at present. At the country-specific level, however, both North African and SSA countries are analysed together.

8 These regional data are considered to be more accurate than aggregating the available country data into the respective regional aggregates, as various adjustments were required to render the estimates relatively representative (Chen and Ravallion, 2008).

9 We do not report the summary data for the growth rates because they would not be reliable, as the periods are not standardised across observations. That is, growth rates are over different period lengths depending on data availability, so that their averages are not statistically meaningful.

Using the above unbalanced panel data, equation (1) is estimated by applying three procedures: RE, country FE and the two-gap system generalised method of moments (SYSGMM). The results for the \$1.25 poverty line are presented in Tables 1a–1c for the headcount, poverty gap and squared poverty gap measures, respectively. Similarly for the \$2.00 poverty line, the respective results for these poverty measures are reported in Tables 2a–2c. [10]

The estimates are generally as expected. In particular, all the estimated coefficients, especially those required for estimating the income and inequality elasticities, exhibit the anticipated signs and are generally significant [see equations (2) and (3) and the accompanying exposition]. Considering, first, the results for the \$1.25 (Tables 1a–1c), all the relevant coefficients for the headcount (the first six variables) display the expected signs and are significant: income growth reduces poverty, but at a decreasing rate with inequality (measured by the Gini coefficient) and also with the poverty line relative to income. In contrast, increases in the Gini coefficient raise poverty, but at a decreasing rate with respect to the poverty line relative to income. Similar results are obtained for the poverty gap and squared poverty gap, although fewer coefficients are significant in the latter case.

The results for the \$2.00 are qualitatively similar to those of the \$1.25 (Tables 2a–2c); however, the estimated coefficients enjoy much less precision as compared with those of the \$1.25. In particular, most of the coefficients are insignificant in the headcount equations (Table 2a). Nonetheless, the SYSGMM estimated coefficients exhibit much better precision than the FE and RE for the \$2.00 results.

Customarily, the SYSGMM results would be technically superior to those of the other two methods, since this procedure can potentially control for possible endogeneity of the regressors, provided the over-identifying restrictions are satisfied. Indeed, in nearly all cases,[11] the Sargan and Hansen tests indicate that the null hypotheses of 'absence of endogeneity' cannot be rejected. Hence, one would ordinarily select and report the GMM results.

However, an important objective of the present paper is to decompose poverty reduction into contributions by income and inequality. Hence, the predictive powers of the various methods are at stake. In this regard, equations (2) and (3) are employed to estimate the income and inequality elasticities, E_y and E_g, the results are reported in Appendix tables B2.1a, B2.1b and B2.1c for the headcount, poverty gap and squared poverty gaps, respectively, in the case of the \$1.25, and in respective Appendix tables B2.2a, B2.2b and B2.2c for the \$2.00. As these results show, the income elasticity is generally negative, while the inequality elasticity tends to be positive. There are several notes, however. First, in the case of the \$1.25, the SYSGMM estimates produce a lot more unanticipated signs for the elasticities, as compared with FE and RE. While positive and negative signs of E_y and E_g, respectively, are theoretically feasible [see equations (2) and (3)], they should be rare empirically. Hence, the relatively large number of atypical signs for especially E_g among the SYSGMM estimates potentially portends relatively poor predictive power for this estimating procedure.

Second, the E_g estimates (in magnitude) appear correspondingly higher than those of E_y generally, consistent with earlier findings for SSA as a whole (see Fosu, 2009). These results suggest that poverty reduction would be more sensitive to changes in inequality than to income growth. Third, this inequality-elasticity advantage appears even larger for the higher orders of

10 Note that all the level variables used in the estimation are expressed in (natural) logarithm, while the growth variables are the logarithmic changes.

11 The only potential exception appears to be the Sargan test in Table 2a where the P value is 0.08.

Table 1a: Regression Results (Unbalanced Panel), African Countries, 1985–2013 (Dependent Variable: Headcount Ratio ($1.25))

Variables	(1)	(2)	(3)
	FE	RE	Two-Step System GMM
dlog Y_{it}	−10.16**	−10.75***	−38.18***
	(−2.60)	(−3.56)	(−4.98)
dlog $Y_{it} \times \log G_{it-1}$	2.43**	2.50***	9.467***
	(2.41)	(3.19)	(4.71)
dlog $Y_{it} \times \log (Z/Y_{it-1})$	0.99***	0.93***	0.997***
	(4.54)	(5.86)	(5.26)
dlog G_{it}	14.30**	11.46**	36.51***
	(2.01)	(2.07)	(2.67)
dlog $G_{it} \times \log G_{it-1}$	−3.78**	−3.04**	−9.802***
	(−2.03)	(−2.09)	(−2.71)
dlog $G_{it} \times \log (Z/Y_{it-1})$	−4.77***	−4.39***	−6.921***
	(−8.64)	(−9.93)	(−6.66)
log G_{it-1}	0.06	−0.01	−0.0858*
	(0.47)	(−0.16)	(−1.76)
log (Z/Y_{it-1})	−0.15**	−0.02	−0.0256
	(−2.61)	(−1.27)	(−1.56)
Constant	−0.31	0.03	0.325*
	(−0.61)	(0.15)	(1.80)
Observations	117	117	117
Number of Countries	40	40	40
R-sq within	0.63	0.6	
R-sq between	0.09	0.62	
R-sq overall	0.36	0.61	
Hausman [P]	14.98 [0.06]	14.98 [0.06]	
Sargan [P]			4.409 [0.818]
Hansen [P]			3.363 [0.910]

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Notes: The dependent variable, dlogP_{it}, is the log-difference of the poverty measure; heteroscedastic robust *t*-statistics in parentheses. 'Hausman' is the specification test with *P* value in brackets. Under GMM: All regressors involving dlogY_{it} are considered endogenous and are instrumented; estimation employs the 2-step SYSGMM; instruments: sub-regional dummy variables, logY_{it-1} and log G_{it-1} interacted with regional dummy variables, dlogPOP$_{it}$, log$Y_{it-1} \times \log G_{it-1}$, log $Y_{it-1} \times \log(Z/Y_{it-1})$ and log $G_{it-1} \times \log G_{it-1}$. 'Sargan' and 'Hansen' statistics test for over-identification of instruments (*P*-values in brackets). *P, Y, G, Z*, and POP are poverty rate, income, the Gini coefficient, poverty line and population, respectively.

the FGT measures, suggesting that the spread and severity of poverty are relatively more sensitive to changes in inequality than the headcount is. Fourth, both the income and inequality elasticity estimates for the higher FGT measures seem correspondingly higher generally than those of the lower orders, suggesting that the spread and severity of poverty would be more responsive than the headcount to growth and income distribution-improving policy measures. These results are important, for they suggest that the responsiveness of the poverty rate measured by the headcount, as in the case of MDG1 for instance, would constitute a relative lower bound and should thus suffice for assessing the spread and severity of poverty as well.

Table 1b: Regression Results (Unbalanced Panel), African Countries, 1985–2013 (Dependent Variable: Poverty Gap ($1.25))

Variables	(1)	(2)	(3)
	FE	RE	Two-Step System GMM
dlog Y_{it}	−18.70*	−18.77**	−79.90**
	(−1.80)	(−2.45)	(−2.40)
dlog $Y_{it} \times \log G_{it-1}$	4.56*	4.43**	20.00**
	(1.71)	(2.23)	(2.33)
dlog $Y_{it} \times \log(Z/Y_{it-1})$	1.40**	1.24***	1.372**
	(2.39)	(3.09)	(2.17)
dlog G_{it}	44.99**	37.32***	83.34**
	(2.33)	(2.63)	(2.23)
dlog $G_{it} \times \log G_{it-1}$	−11.86**	−9.85***	−22.15**
	(−2.35)	(−2.64)	(−2.23)
dlog $G_{it} \times \log(Z/Y_{it-1})$	−10.38***	−9.42***	−11.98***
	(−7.04)	(−8.43)	(−3.16)
log G_{it-1}	0.09	−0.08	−0.343**
	(0.23)	(−0.70)	(−2.30)
$\log(Z/Y_{it-1})$	−0.32**	−0.06*	−0.0805*
	(−2.11)	(−1.70)	(−1.70)
Constant	−0.48	0.30	1.299**
	(−0.34)	(0.68)	(2.39)
Observations	117	117	117
Number of Countries	41	41	41
R-sq within	0.58	0.55	
R-sq between	0.05	0.39	
R-sq overall	0.35	0.53	
Hausman [*P*]	11.77 [0.16]	11.77 [0.16]	
Sargan [*P*]			4.916 [0.766]
Hansen [*P*]			3.855 [0.870]

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: See notes for Table 1a.

The results for the $2.00 are similar (see Appendix tables B2.2a–B2.2c), except that the frequencies of unanticipated signs of E_y and E_g are much lower compared to those of the $1.25, foreboding higher respective predictive powers for the $2.00 compared to the $1.25. Indeed, all the E_y estimates for the $2.00, including those of the SYSGMM, now signify the correct (negative) sign. These results are a bit puzzling, though, given the observation above that the estimated coefficients in the regressions seemed more precise for the $1.25 than for the $2.00. Apparently, the higher precision of the regression estimates does not necessarily translate into a greater likelihood of obtaining theoretically anticipated signs for the derived elasticities.

3.2 Decomposition of poverty changes

Following Fosu (2011, 2015a), the E_y and E_g estimates are now employed to decompose p as:

$$p = yE_y + gE_g + r \tag{4}$$

Table 1c: Regression Results (Unbalanced Panel), African Countries, 1985–2013 (Dependent Variable: Squared Poverty Gap ($1.25))

Variables	FE	RE	Two-Step System GMM
dlog Y_{it}	−26.90	−26.45**	−120.8**
	(−1.51)	(−2.03)	(−2.07)
dlog $Y_{it} \times \log G_{it-1}$	6.64	6.30*	30.35**
	(1.45)	(1.86)	(2.02)
dlog $Y_{it} \times \log(Z/Y_{it-1})$	1.79*	1.54**	1.692
	(1.79)	(2.26)	(1.45)
dlog G_{it}	80.25**	66.32***	137.3**
	(2.43)	(2.75)	(2.15)
dlog $G_{it} \times \log G_{it-1}$	−21.20**	−17.56***	−36.52**
	(−2.45)	(−2.77)	(−2.15)
dlog $G_{it} \times \log(Z/Y_{it-1})$	−16.67***	−15.12***	−18.75***
	(−6.60)	(−7.95)	(−2.75)
log G_{it-1}	0.14	−0.17	−0.592**
	(0.21)	(−0.83)	(−2.10)
$\log(Z/Y_{it-1})$	−0.52*	−0.11*	−0.149*
	(−1.96)	(−1.82)	(−1.72)
Constant	−0.75	0.61	2.237**
	(−0.31)	(0.80)	(2.17)
Observations	117	117	117
Number of Countries	41	41	41
R-sq within	0.56	0.54	
R-sq between	0.04	0.24	
R-sq overall	0.36	0.51	
Hausman [*P*]	10.89 [0.21]	10.89 [0.21]	
Sargan [*P*]			5.236 [0.732]
Hansen [*P*]			3.886 [0.867]

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: See notes for Table 1a.

where p, y and g are growth rates of poverty, income and inequality (the Gini coefficient), respectively; E_y and E_g are the respective income and inequality elasticities with respect to poverty[12] and r is the residual term.[13] The objective then is to choose an estimating procedure among the ones presented here that minimises r. Two selection criteria are employed: the root mean squared (RMSE) and mean absolute error (MAE). The results are presented in Tables 3a and 3b for the $1.25 and $2.00, respectively.

These results show, first, that the predictive powers for the $2.00 are correspondingly higher than those for the $1.25, as earlier anticipated based on the frequency of the

12 The elasticity estimates are reported as Appendix tables A2.1a, A2.1b, and A2.1c for the headcount, poverty gap and squared poverty gap, respectively, in the case of the $1.25. Appendix tables A2.2a, A2.2b and A2.2c report the respective rates for the $2.00.

13 All variables are computed between two years starting from the mid-late 1990s to the present, to correspond to the more recent period of African growth resurgence and to the availability of survey data for a given country.

Table 2a: Regression Results (Unbalanced Panel), African Countries, 1985–2013 (Dependent Variable: Headcount Ratio ($2.00))

Variables	(1)	(2)	(3)
	FE	RE	Two-Step System GMM
dlog Y_{it}	−3.12	−4.93	−9.79***
	(−0.75)	(−1.46)	(−4.17)
dlog $Y_{it} \times$ log G_{it-1}	0.52	1.03	2.28***
	(0.49)	(1.18)	(3.85)
dlog $Y_{it} \times \log(Z/Y_{it-1})$	0.51**	0.57***	0.63***
	(2.28)	(3.50)	(7.16)
dlog G_{it}	−6.77	−0.38	3.61
	(−0.84)	(−0.06)	(1.07)
dlog $G_{it} \times$ log G_{it-1}	2.01	0.23	−0.76
	(0.96)	(0.14)	(−0.89)
dlog $G_{it} \times \log(Z/Y_{it-1})$	−0.85	−1.10**	−1.13***
	(−1.42)	(−2.27)	(−5.09)
log G_{it-1}	0.19	−0.02	0.05*
	(1.23)	(−0.32)	(1.78)
$\log(Z/Y_{it-1})$	0.02	−0.00	−0.00
	(0.34)	(−0.28)	(−0.62)
Constant	−0.69	0.06	−0.18*
	(−1.23)	(0.30)	(−1.88)
Observations	104	104	104
Number of Countries	39	39	39
R-sq. within	0.32	0.29	
R-sq. between	0.03	0.34	
R-sq. overall	0.21	0.31	
Hausman [*P*]	7.90 [0.44]	7.90 [0.44]	
Sargan [*P*]			9.99 [0.08]
Hansen [*P*]			2.70 [0.75]

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: See notes for Table 1a.

theoretically anticipated signs of the income and inequality elasticities. Second, for both poverty lines, the SYSGMM is a much poorer predictor generally than the FE and RE,[14] which are both indeed quite close in predictive ability. For the $1.25, FE and RE may be judged to be the better predictors for the headcount and poverty gap, respectively, according to both RMSE and MAE. In the case of the squared poverty gap, however, there are conflicting signals from these two criteria, with RMSE selecting RE while MAE selects FE. Hence, whether FE or RE is chosen depends on the relative weights placed on extreme values of the error term, with RE preferred if extreme-value errors are weighted relatively more. In the present case, RE is selected in order to account for the extreme errors.

14 The only exception is the case of the $2.00 where SYSGMM displays lower RMSE and MAE values than FE for the headcount.

Table 2b: Regression Results (Unbalanced Panel), African Countries, 1985–2013 (Dependent Variable: Poverty Gap ($2.00))

Variables	(1)	(2)	(3)
	FE	RE	Two-Step System GMM
dlog Y_{it}	−9.38***	−9.89***	−28.41***
	(−4.29)	(−5.83)	(−3.12)
dlog $Y_{it} \times \log G_{it-1}$	2.13***	2.23***	6.95***
	(3.79)	(5.07)	(2.97)
dlog $Y_{it} \times \log(Z/Y_{it-1})$	0.67***	0.63***	0.73***
	(5.70)	(7.68)	(5.30)
dlog G_{it}	2.33	3.42	19.75**
	(0.53)	(1.07)	(2.03)
dlog $G_{it} \times \log G_{it-1}$	−0.26	−0.55	−4.85*
	(−0.23)	(−0.66)	(−1.92)
dlog $G_{it} \times \log(Z/Y_{it-1})$	−2.32***	−2.15***	−3.44***
	(−7.36)	(−8.75)	(−4.77)
log G_{it-1}	−0.01	−0.01	−0.08**
	(−0.17)	(−0.30)	(−1.98)
$\log(Z/Y_{it-1})$	−0.05	−0.00	−0.00
	(−1.62)	(−0.27)	(−0.18)
Constant	0.05	0.03	0.31**
	(0.16)	(0.33)	(2.06)
Observations	103	103	103
Number of Country	39	39	39
R-sq. within	0.75	0.74	
R-sq. between	0.52	0.76	
R-sq. overall	0.65	0.77	
Hausman [*P*]	9.19 [0.33]	9.19 [0.33]	
Sargan [*P*]			4.90 [0.67]
Hansen [*P*]			5.80 [0.56]

t-Statistics in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: See the notes for Table 1a.

It should be emphasised, though, that the results are very much qualitatively similar between these two estimating methods.

For the $2.00 (Table 2.2), however, there is no conflict between the two criteria; RE is selected for the headcount while FE for both the gap and squared poverty gap; SYSGMM remains quite inferior in its predictive ability, particularly for the $1.25. Although the relative predictive power of the SYSGMM improves considerably for the case of the $2.00 over the $1.25, as to be expected given the above finding of more precise coefficient estimates of the SYSGMM than the FE and RE for this poverty line, the predictive power of the SYSGMM remains inferior.[15]

15 Although the RMSE and MAE of SYSGMM are respectively lower than those of the FE and RE, in the case of the headcount for the $2.00, the SYSGMM still underperforms in either case relative to the remaining estimating method.

Table 2c: Regression Results (Unbalanced Panel), African Countries, 1985–2013 (Dependent Variable: Squared Poverty Gap ($2.00))

Variables	(1)	(2)	(3)
	FE	RE	Two-Step System GMM
dlog Y_{it}	−14.37***	−14.43***	−43.40***
	(−3.35)	(−4.56)	(−3.41)
dlog $Y_{it} \times \log G_{it-1}$	3.35***	3.33***	10.68***
	(3.03)	(4.05)	(3.29)
dlog $Y_{it} \times \log(Z/Y_{it-1})$	0.82***	0.74***	0.91***
	(3.57)	(4.82)	(4.44)
dlog G_{it}	10.12	10.17*	36.92**
	(1.17)	(1.71)	(2.40)
dlog $G_{it} \times \log G_{it-1}$	−2.10	−2.12	−9.17**
	(−0.92)	(−1.37)	(−2.28)
dlog $G_{it} \times \log(Z/Y_{it-1})$	−3.92***	−3.58***	−5.81***
	(−6.34)	(−7.82)	(−4.11)
log G_{it-1}	−0.05	−0.04	−0.12**
	(−0.33)	(−0.77)	(−2.10)
$\log(Z/Y_{it-1})$	−0.09	−0.01	−0.01
	(−1.36)	(−0.78)	(−0.38)
Constant	0.19	0.14	0.47**
	(0.32)	(0.79)	(2.20)
Observations	103	103	103
Number of countries	39	39	39
R-sq. within	0.66	0.65	
R-sq. between	0.48	0.70	
R-sq. overall	0.57	0.67	
Hausman [*P*]	6.70 [0.57]	6.70 [0.57]	
Sargan [*P*]			4.84 [0.68]
Hansen [*P*]			5.67 [0.58]

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: See notes for Table 1a.

Given the above 'optimal' selection, the decomposition results are presented in the Appendix tables B3.1a, B3.1b, and B3.1c for the headcount, poverty gap and squared poverty gap, respectively, in the case of the $1.25. Appendix tables B3.2a, B3.2b and B3.2c report the respective results for the $2.00. These results are shown, respectively, for both poverty-decreasing and poverty-increasing country groups.

To begin with, the results show that over 70% of the roughly 39 African countries in the sample have reduced their poverty levels since about the late 1990s. Generally, this proportion is larger for the headcount than for the other FGT poverty measures and for the $2.00 relative to the $1.25. In addition, the decomposition results reveal that for both the $1.25 and $2.00 and all the FGT poverty measures, on average the major contribution to poverty reduction is income growth, rather than inequality changes. However, the importance of inequality for countries' ability to reduce poverty tends to increase with the order of the measure, that is, higher for the poverty gap than for the headcount ratio, and for the

Table 3a: RMSE and MAE ($1.25)

	Headcount Ratio		Poverty Gap		Squared Poverty Gap	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
FEs	3.43	2.36	7.81	5.47	13.55	4.26
REs	3.50	2.37	7.29	5.20	12.39	8.55
Two-Step System GMM	7.81	5.51	16.17	11.46	25.55	18.34

Notes: RMSE and MAE were calculated, respectively, based on observed and predicted values of the poverty growth rate for all sample countries, with the latter based on equation (4) of text.

Table 3b: RMSE and MAE ($2.00)

Model	Headcount Ratio		Poverty Gap		Squared Poverty Gap	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
FEs	2.66	1.97	2.09	1.23	3.01	1.82
REs	1.81	1.30	2.20	1.37	3.03	1.89
Two-Step System GMM	2.16	1.57	4.17	2.89	6.78	4.71

Notes: See notes for Table 3a.

squared poverty gap relative to the poverty gap. These outcomes are to be expected, as the higher-order FGT measures accord greater importance to the deviation of incomes of the poor from the poverty line. Nonetheless, on average, growth still generally plays the major part in the case of rising poverty even for these higher-order poverty measures. These results provide support for previous findings based on the headcount (Fosu, 2015a).

There are considerable differences across countries, however. Consider the $1.25 case first. In countries such as Angola, Botswana, Cape Verde, Guinea-Bissau, Namibia, Niger, Sierra Leone and Tunisia, changes in inequality contribute considerably more to the observed poverty reductions than income growth does. This result holds for all the three FGT measures. And, in more than one-half of the countries experiencing increases in poverty (6 of 10), inequality changes generally contribute more to the worsening poverty than negative income growth does, even though the mean contribution by income is higher than that of inequality.

The results for the $2.00 are similar to those for the $1.25, though the exceptions are fewer and may not necessarily involve the same countries. However, Angola, Cape Verde and Guinea-Bissau continue to consistently show the exceptional case where decreasing inequality contributes more to poverty reduction than income growth does. Expectedly, these are countries that have succeeded in substantially reducing their initial levels of inequality, with all the three countries ranking in the top quintile in the African sample, while their income growth has been rather sub-par (Fosu, 2015b).

4. Summary of findings and implication for policy

The present paper finds that Africa as a whole has made considerable progress on poverty since the mid-1990s, about the same time that the region's (per capita GDP) growth has resurged. This performance is a reversal of the record for the previous decade-and-half when growth was quite anaemic in the region and poverty rose considerably. Correspondingly, the growth resurgence has, in general, been translated into appreciable poverty reduction. The data also reveal, however, that other regions of the world have performed even better during the same period, thus exposing an increasing Africa's progress-on-poverty gap with the rest of the DW. Furthermore, this Africa-DW gap is larger for the poverty spread and for the poverty depth measures than for poverty incidence, suggesting that Africa must perform even better on these measures if it is to catch up with the rest of the world.

Applying the FE, RE and SYSGMM regression methods to unbalanced 1985–2013 panel data, the paper estimates country-specific income and inequality elasticities. These elasticities vary substantially among countries. The estimates also differ across estimating methods, with the greatest divergence from the other two exhibited by the SYSGMM. Furthermore, the SYSGMM estimates display the largest number of theoretically unexpected signs, with wider and more frequent divergences occurring as the order of the FGT measure increases. Such 'perverse' results also seem much more severe for the $1.25 than for the $2.00 standard, however, suggesting that the predictive powers of the models would improve with the higher poverty standard.

Employing the elasticity estimates to predict country-level poverty changes since the mid-to-late 1990s, the FE and RE provide generally similar predictive abilities, which are both generally superior to that of the SYSGMM. The relative poor performance of the SYSGMM was much more pronounced for the $1.25 than for the $2.00. Indeed, in no case was the SYSGMM prediction found to display the minimum predictive error among the three estimating procedures. Such a finding is methodologically important, as it suggests that controlling for endogeneity with SYSGMM does not necessarily translate into superior predictive ability, and that the FE and RE methods are preferable for prediction purposes.

The results show that the vast majority of the nearly 40 sample African countries have reduced their poverty levels since about the late 1990s. This outcome holds for all the FGT measures and for both poverty lines. Furthermore, income growth has been the main driver of this progress on poverty. Yet, there are considerable disparities across African countries, with certain countries, albeit a relatively small number, relying primarily on improving income distribution for poverty reduction. Among the majority of countries experiencing poverty exacerbation, furthermore, worsening income distribution was generally a major culprit. Such disparities suggest that country-specific analyses would be required in order to tease out the idiosyncratic characteristics of each country that might give rise to the optimal mix of growth-enhancing versus inequality-reducing policies.

Nonetheless, the result that growth has by far been the main factor behind the recent progress on poverty in African countries generally suggests that growth-enhancing factors be accorded major importance. In this regard, recent findings from a comprehensive growth project (Ndulu *et al.*, 2008a, 2008b)—'Explaining African Economic Growth' (the Growth Project)—must be accorded significant attention. A major result of that study is that a 'syndrome-free' (SF) regime—a state of political stability with reasonable market-friendly policies - is critical for sustaining growth in Africa. An SF regime is not only a necessary condition for attaining sustained growth, but also a near-sufficient condition for avoiding growth collapse (Fosu and O'Connell, 2006). Furthermore, the historically poor performance of African economies could be traced to the excessive power of the executive branch of government that tended to spawn growth-inhibiting 'policy syndromes' (ibid.). Hence, attenuating such power of the executive would appear to be an appropriate growth-enhancing policy. Indeed, strengthening the constraint on the executive in Africa may increase the prevalence of SF regimes, independently or by limiting the potentially pernicious effect of ethnicity, and thus improve growth (Fosu, 2013), and in turn reduce poverty.

Better yet might be policies that enhance both income growth and income distribution. Such policies, including those that improve the complementarity between physical and human capital and insure against downside risks of economic undertakings, could produce a virtuous circle between economic growth and poverty.

Supplementary material

Supplementary material (appendix tables and figures) is available at *Journal of African Economies* online.

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