Binding constraints of economic growth on poverty: A dynamic panel data analysis

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1. INTRODUCTION

The relationship between economic growth and poverty has raised significant research interest in the field of development economics since early 1990. Particular interest has been in the quest to understand the best possible poverty-reducing policies. The last three decades to 2015 have been characterised by higher economic performances for most of the developing countries. Economic growth in developing countries taken together, remain robust even to the exclusion of China and India Fosu (2017). Growth has been hailed as the key condition for sustainable poverty reduction Dollar, and Kraay (2002) . This assertion has been backed by the Chinese success story in reducing poverty since early 1990, confirming that high growth rates can enhance the level of development and reduce poverty. However, consensus seems to be emerging that economic policies that target growth alone are necessary but not enough to alleviate poverty for certain countries or regions in the developing world Besley, and Cord (2007). Rising income inequality trends in some regions such as Latin America and the Caribbean, Eastern Europe and Central Asia as well as in Sub-Saharan Africa are currently being blamed for the less-than commensurate effects of growth on poverty ('World Bank report', 2005). Fosu (2015) for instance, identifies the uneven distribution of the benefit of growth in many countries of Sub-Saharan Africa region as well as other developing regions, as a major cause of the persistence in poverty despite the high annual average GDP growth rates which even surpasses the population growth rates.

Empirically, significant number of studies, including Datt, and Ravallion (1992) tried to understand the growth-poverty nexus. They have done so by, among other things, closely investigating the role played by income distribution, as an important intermediate predicting factor of the poverty effect of growth in mean income. The existing literature on the role played by the income distribution is mixed. On the one hand, some results highlight the leading role of economic growth in reducing poverty, with zero effect of income distribution. The studies conducted by Ravallion and Chen (1997), and Dollar and Kraay (2002) are the most illustrative. One of the reasons advanced for the lack of income distribution effect on poverty is that the income of the poor increases equi-proportionately as those of wealthy. Romer, M. and Gugerty (1997)and Gallup et al., (1998) also demonstrate that, on average, the incomes of poor people tend to increase in the same proportion as the income of the rich people.

On the other hand, other studies argue that income distribution is an important mediating factor in the effect of growth in mean income on poverty. Thorbecke (2013) notes that income inequality is one of the most important filters between growth and poverty. In this respect, evidence has been shown that the poverty effect of growth is high when inequality is low. For example, Fosu (2010) assesses the constraining effects of income inequality on Africa's poverty reduction efforts. Using the so-called standard growth-poverty model, he finds that the poverty effect of a change in mean income is a decreasing function of inequality. He concludes that high inequality is extremely harmful to the speed at which growth is impacting poverty. Moreover, Ravallion (2005) argued that intuitively the higher the initial level of inequality in a country, the less the poor will benefit from growth, unless the growth is accompanied by significant distribution changes to lower inequality.

Another growing conjecture, advanced by Ravallion (2012) is that the effect of income inequality and/or initial inequality on the responsiveness of poverty to changes in mean income is only a part of the story of what is now known as binding constraints of growth to poverty. He emphasises the additional and critical role that initial levels of poverty can play as a binding constraint to the poverty-reducing effects of growth. His thesis relies on the neoclassical growth-convergence theory (Solow, 1956 and Barro, 1991). According to the theory, the economy of a country that starts with low mean income may enjoy rapid income growth compared to high-income countries, with both converging to a long-run steady state mean income level. Furthermore, for lower mean income countries, poverty reduction would seem an inevitable result of economic growth. Such developments may never transpire for most of them due to their high initial level of poverty posing a drag on the pace at which growth translates into poverty reduction. Empirically, Ravallion (2012) tests this claim on a sample of 90 developing countries. He calculates an average elasticity of initial level of poverty with respect to the changes in mean income of 2 and an absolute mean income elasticity of -2.5. However, the main concern with his methodology is that it fails to include the initial inequality and the initial poverty, both interacted respectively with the changes in mean income and the changes in inequality. This omission of the interactions terms possibly introduces a significant bias in the estimate of poverty responsiveness and hence inaccurate policy prescriptions.

Inspired by Ravallion's (2012) conjecture, this work builds on the well-known growth-poverty identity model by Bourguignon (2003), to develop a new and more encompassing framework that accounts for the initial level of poverty. The development of the augmented framework closely follows the reasoning of Bond (2002). The resulting framework is a dynamic growth-poverty model that can be termed an autoregressive growth-poverty model. Using the framework, we empirically reassess the responsiveness of poverty to changes in mean income in a two-step systems GMM. The data is a panel of 112 developing countries from World Bank's spanning 1981 to 2013. It allows assess whether: (1) the initial level of poverty is indeed muffling the speed at which growth is effective in reducing poverty; (2) both initial levels of poverty and inequality are equally binding constraints to the effects of economic growth on poverty reduction and, (3) the cross-regional differences in the trends of poverty reduction can be explained by only the initial distributional effects, initial poverty effects or both.

Contrary to the identity model, in the new framework, initial poverty appears to be the only significant binding constraint of growth to poverty reduction and it plays the main role in explaining inter-regional poverty differences. We also find that the identity model overestimates the speed at which growth is alleviating poverty compared to the autoregressive model. Regional differences in income and inequality elasticities suggest that redistribution policies should be prioritised in Eastern Europe and Central Asia, Middle East and North Africa and East Asia and Pacific. However, for Sub-Saharan Africa and South Asia, growth-enhancing measures must be emphasized for sustainable poverty reduction.

2. REGIONAL DIFFERENCES IN MEAN INCOME, INEQUALITY AND POVERTY

There is a great deal of regional variations in mean income, inequality and poverty from 1981 to 2013. Table 1 provides the changes in mean income (in GDP per capita) growth, changes in inequality and poverty for Sub Saharan Africa (SSA), South Asia (SA), Middle East and North Africa (MENA), Latin America and the Caribbean (LAC), Eastern Europe and Central Asia (ECA) and East Asia and Pacific (EAP). The sample is divided into three periods, the decades of 1981 to 1990; 1991 to 2000 and 2000 to 2013. We also separately present in Figure 1, 2 and 3 each region's trend in mean income, Gini index and poverty rates for the entire time period.

Table 1. Inter-regional mean income, inequality and poverty trends differences across regions

	Mean income (GDP per capita growth)			Inequality (Gini index)			Poverty (Headcount, $1.9/day)		
Region	(1981-1990)	(1991-2000)	(2001-2013)	(1981-1990)	(1991-2000)	(2001-2013)	(1981-1990)	(1991-2000)	(2001-2013)
SSA	0.21	0.29	2.33	0.05	−0.27	−0.35	−0.09	−1.36	−2.58
SA	3.38	3.40	4.35	0.76	0.39	−0.47	−3.64	−3.64	−15.96
MENA	0.61	1.50	2.41	−0.28	−0.26	−0.28	−0.26	−1.74	−11.67
LAC	−0.36	2.02	2.31	0.05	0.30	−0.79	2.41	−2.30	−7.42
ECA	1.50	−0.08	4.91	0.65	1.39	−0.11	2.60	8.19	−14.47
EAP	2.34	2.89	3.60	0.17	0.06	−0.31	−3.29	−4.85	−12.12
All regions	0.91	1.11	3.27	0.24	0.35	−0.37	0.48	0.38	−8.97

Notes: The table displays the calculated regional average in mean income (in GDP per capita), Gini index and Headcount rate, (in percentages changes).
Source: Computed by authors using data from POVCALNET of the World Bank.

According to the results of Table 1, the developing world regions as a whole experienced considerable income growth during the sub-period 2001-2013, with a modest decline in inequality and a significant fall in poverty compared to the sub-periods 1981-1990 and 1991-2000. Region-specific trends are as follow:

a) Sub-Saharan Africa's per capita income rose by 2.33 during 2001-2013 compared to 0.21 and 0.29 in 1981-1990 and 1991-2000 respectively. The latter period corresponds with a slight fall in inequality and considerable poverty reduction of about 22.7 times more in 2001-2013 compared to its 1981-1990 levels. However, compared to other regions, SSA has the lower levels of poverty reduction.

b) South Asia (SA) registered a considerable per capita income growth during all the three periods. Though the period corresponds with a relatively mild reduction in inequality, the ensued growth translated into a significantly high reduction in poverty level. Its poverty reduction figures are the highest among all the regions. The sample does not include India. The figures rates may slow somewhat with the inclusion of India, however, the progress will still remain impressive.

c) The Middle East and North Africa (MENA) also experienced some economic growth during in the period 2001-2013. The region also registered a modest inequality reduction and a higher poverty reducing trend in the same period compared to 1981-1990 and 1991-2000.

d) Growth in the Latin America and the Caribbean (LAC) region for the period 2001-2013 has been in par with SSA, however, the because of a very high reduction in inequality, poverty fell by up to 7.42 points compared to only 2.58 in SSA with similar levels of economic growth.

e) Eastern Europe and Central Asia (ECA) experienced the highest growth relative to all the other regions in the period 2001-2013 with modest inequality reduction. The high growth has resulted in the second highest fall in poverty of 14.47 points.

f) Finally, East Asia and Pacific recorded relatively high income growth with proportionate inequality reduction during the last time interval compared to both first sub-periods. The growth brought about a significantly high and increasingly consistent poverty reduction for all the sub-periods. This trends in all the three variables for this region can be explained by the Chinese story due to influence in the region.

Overall, we can classify the regions into low growth, modest inequality reduction and low poverty reduction (SSA); Low growth, low inequality reduction but high poverty reduction (MENA); low growth, high inequality reduction and high poverty reduction (LAC); High growth, low inequality reduction but high poverty reduction (ECA); high growth, high inequality reduction and high poverty reduction (SA) and Modest growth, modest inequality reduction and high poverty reduction (EAP). With such diversity, it is necessary to robustly assess the correct poverty elasticity of the growth in an appropriate framework for regionally customized policy measures.

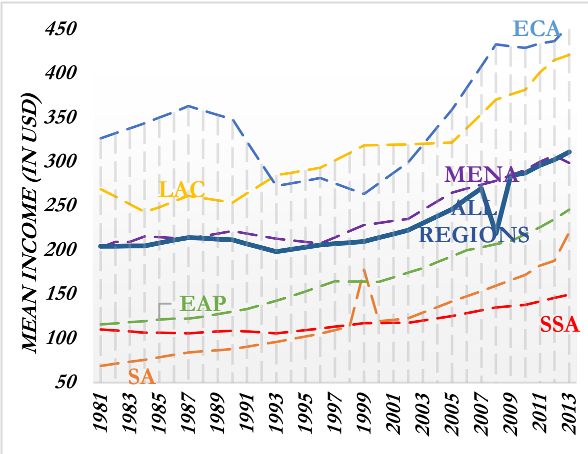

FIG.1. Regional trends in Mean income (in US Dollars)

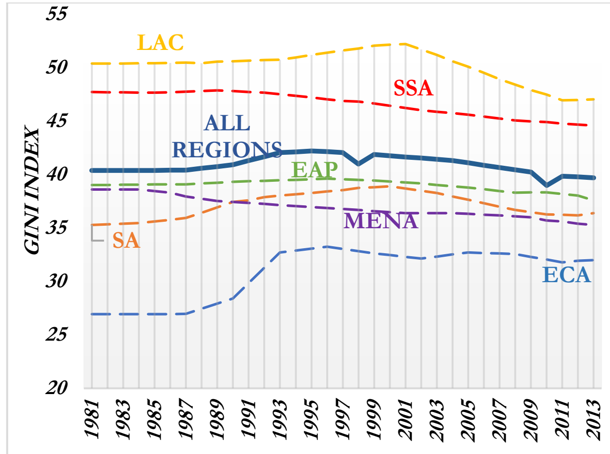

Fig.2. Regional trends in income inequality (Gini index)

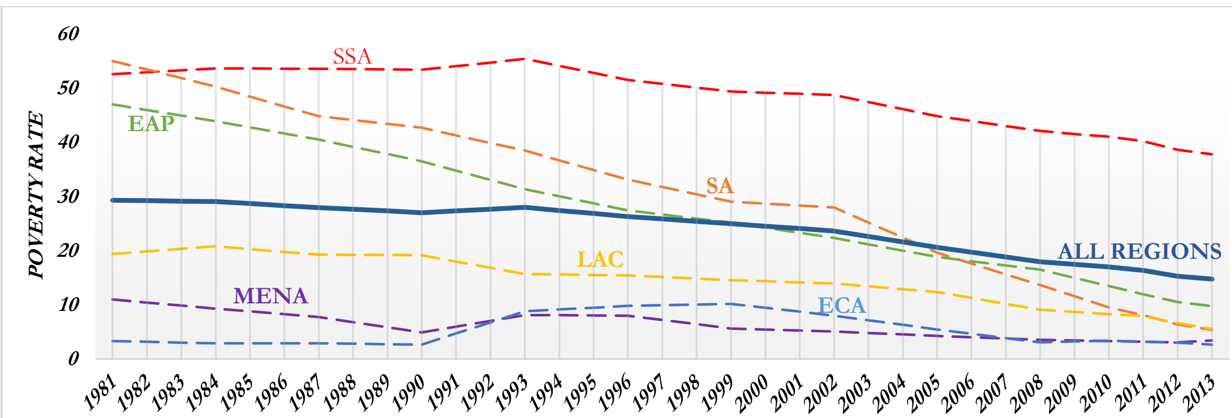

FIG.3. Regional trends in poverty rates (Headcount rates at $1.9/day). Source: Computed by authors using data from POVCALNET of the World Bank.

3. REVIEW OF THE RECENT EMPIRICAL EVIDENCE

The quest for the understanding of the growth-poverty nexus has generated considerable interest since the early 1990s. Despite the interest, the role played by income inequality and higher poverty rates in predicting the responsiveness of current poverty rates to growth in mean income are still ambiguous and controversial. Existing literature demarcates two different viewpoints that has emerged over the years. The first, exemplified by Dollar and Kraay (2002) demonstrates that growth is good for the poor. This view upholds the conclusion that inter-country or inter-regional differences in poverty reduction experiences may be largely, if not totally, attributed to differences in the change in mean income only, with little or no role for distributional changes. The Dollar and Kraay (2002) approach to the analyses of the growth-poverty nexus is based on linear models where change in poverty is subjected to changes in mean income and a host of other explanatory variables. The focus is on determining whether there is a connection between the average income and the income of the poorest quintile. Their results fail to reject the null hypothesis that changes in mean income explain almost all the changes in the incomes of the poor people. In the same vein, Ravallion and Chen (1997) tests the relationship using panel data for 67 developing countries covering the period 1981-1994 with a pooled OLS technique on the standard growth-poverty model. The findings suggest that changes in income inequality are uncorrelated with changes in poverty.

Some criticisms have been raised against the above conclusion. For instance, Ravallion (2005) suggests that the lack of distributional influence may be due to insufficient variability in inequality, and might be based on two factors. One being the limitations of data availability and the other relating to the measurement of inequality in previous literature. Using relative rather than absolute measures of inequality may yield different outcomes. This is obvious as the latter measure is more closely linked to people living under the poverty line than the former. Moreover, Ravallion (2003) sheds more light on the measurement issue of inequality as often used empirically. He shows that in developing countries, growth in mean income tends to be accompanied by consistent absolute disparities within socioeconomic groups. Arguably, absolute changes in inequality should be more efficient than relative changes in predicting poverty changes.

The second viewpoint is based on more recent studies with better data. This view supports the significant role of inequality on poverty responsiveness to growth in mean income. Key studies of this view include Ravallion and Huppi (1991), Kakwani (1993), Easterly (2000), Epaulard (2003), Bourguignon (2003), Adams, (2004), Kalwij and Kalwij and Verschoor (2007), Fosu (2010, 2015 and 2017). The methodological procedure used by most of them share common features such as the use of the interaction models that allows for the assessment of the roles of both mean income and inequality on poverty. For instance, Easterly (2000) assesses the effect of the Bretton Woods Institution's programs on poverty reduction by specifying an econometric model in which growth is interacted with inequality. He finds that the effect of the agendas is boosted by a lower level of inequality. Similarly, Bourguignon (2003) looks at the same relationship at regional level using nationally representative household surveys for 50 countries covering 1981-1998. Within the popular *growth-poverty identity model*, he applies a two-step GMM technique and finds that a higher initial level of inequality and a higher ratio poverty line over mean income (both known in the literature as distributional effect) were dampening the effect of growth on poverty. He argues that countries or regions with higher initial inequality and initial mean income closer to the poverty line experience lower responsiveness of poverty to changes in mean income.

Bourguignon's evidence has been supported first, Besley and Burgess (2003), later by Kalwij and Verschoor (2007) and more recently by Fosu (2017). Their findings show that both absolute income and inequality elasticities of poverty decrease with the initial inequality and the ratio of poverty line over mean income. They suggest that it is crucial to consider these two elements together to best understand the growth-poverty nexus.

Another relatively insignificant strand of literature consist of those who consider the role of initial poverty rates in addition to the effect of inequality. This aspect was first anticipated in Easterly (2009). With specific reference to the Sub-Saharan Africa region, he argues that for their higher poverty rates, higher and sustained growth rates are required to reach the same equivalent rate of poverty alleviation. Unfortunately, his thinking never evolved into any empirical evidence until Ravallion (2012) provided a supportive illustration. Ravallion (2012) suggests that a higher initial level of poverty might be constraining the poverty effect of growth more than other initial conditions such as the initial mean income or the initial inequality levels. He supports his claim by relying on the predictions of convergence, which when applied to poverty, concludes that poorer countries should tend to grow faster than developed countries and in the long run, such economic development will translate into significant poverty reduction. By testing the role of initial level of poverty in an interacted model, he identifies higher initial poverty rates as the main constraint to the process. His elasticity with respect to initial level of poverty is 2, whilst an absolute mean income elasticity is -2.5. However, a key gap in his methodological approach is the fact that it fails to accommodate initial inequality and the initial poverty both interacted respectively with the change in mean income and the change in inequality. These terms are very important in distinguishing the residual role of inequality once initial poverty is controlled for.

Asadullah and Savoia (2018) use a panel data of 89 developing countries and applies ordinary and iteratively reweighted least square techniques to assess whether adoption of global Millennium Development Goals (MDG) by low-income countries facilitates and explains convergence in reducing poverty. Contrary to Ravallion (2012) his finding showed that countries with higher initial poverty rates tended to experiment faster poverty reduction. He argues that the trend differences in poverty reduction across countries was explained by the State capacity or abilities to manage their territories. Once again, his methodology considers the initial mean income and initial poverty level but fails to control for initial inequality as one of the key initial conditions that may also explain inter-country diversity in reducing poverty. We argue that all these have to be controlled for in a single framework in order to identify the truly binding constraints and correctly isolate the true elasticities.

Following from what has been discussed above, this study stands halfway between the two last viewpoints and methodological approaches. Its originality resides in its capability to provide a new comprehensive methodology that is less challenging in explaining the regional trend differences in reducing poverty. This new methodology relies on the premise of the functional approximations of the identity model as developed by Bourguignon (2003).

4. METHODOLOGY AND DATA

4.1. Methodological approach

4.1.1. Model specification

The starting point in modelling the growth-poverty nexus is adopted from Bourguignon (2003). In the fundamental framework, the logarithm of poverty is a function of the logarithm of the growth in mean income taken as a proxy for economic growth and the logarithm of the Gini coefficient taken as a proxy for the income distribution. This can be formalised as follows:

$$lnp_{it} = C_t + b_1 lnminc_{it} + b_2 lnGini_{it} + \omega_i + \varepsilon_{it} \quad (1)$$

Where lnp_{it} is the logarithm of any Foster, Greer and Thorbecke (1984) family of poverty measures, C_t is the time-constant region-specific trend, $lnminc_{it}$ is the logarithm of the mean income, lnG_{it} is the logarithm of the inequality index, ω_i is the region's unobserved heterogeneous fixed effect, the b_j are parameters to be estimated and ε_{it} is the idiosyncratic error term. As written, Equation (1) is expressed in natural logarithms in order to minimise the outliers and facilitate easy interpretations to straightforward elasticities. By differentiating the (1) to eliminate the region's individual fixed effect bias and by allowing the time-constant region-specific trend, we get the following *standard growth-poverty model*:

$$\Delta lnp_{it} = C_t + b_1 \Delta lnminc_{it} + b_2 \Delta lnGini_{it} + \Delta\varepsilon_{it} \quad (2)$$

Where Δlnp is the poverty growth rate, $\Delta lnminc_{it}$ is the mean income growth rate, $\Delta lnGini_{it}$ is the inequality growth rate, the b_j are the absolute growth and inequality elasticities of poverty and $\Delta\varepsilon_{it}$ is the idiosyncratic error term. However, the impact of growth in mean income on poverty can be assessed using Equation (2) following Besley end Burgees (2003), Kalwij and Verschoor (2007) with and/or without including the income distribution component. In doing so, the estimates will only be considered as empirical poverty elasticities which are linked to the actual changes in the Lorenzo curve rather than being the true poverty elasticities. From Equation (2), the income and inequality elasticity of poverty can be determined as follows:

- Income elasticity of poverty

$$\varepsilon_{minc} = \frac{\partial \Delta lnp_{it}}{\partial \Delta lnminc_{it}} = b_1 \quad (2a)$$

- Inequality elasticity of poverty

$$\varepsilon_{gini} = \frac{\partial \Delta lnp_{it}}{\partial \Delta lngini_{it}} = b_2 \tag{2b}$$

Furthermore, most recent pieces of evidence including Fosu (2015, 2017) prefer the *growth-poverty identity model* instead of the standard growth-poverty model. The reason behind such preference is its ability to include the initial level of inequality ($Gini_{it-1}$) and the ratio poverty line over the mean income ($Z/minc_{it}$),) as the extent to which the change in mean income and the change in inequality are effective in reducing poverty. Ravallion (1997) also supports the importance of this inclusion in modelling the growth-poverty nexus. He argues that a high inequality level muffles the impact of growth on poverty. Equation (2) is extended to incorporate this consideration and also include different interaction terms involving growth and inequality respectively with the initial inequality and the ratio poverty line over the mean income. This extension gives the empirical used by Bourguignon (2003), Kalwij and Verschoor (2007) and Fosu (2015, 2017) as follows:

$$\Delta lnp_{it} = C_t + b_1 \Delta lnminc_{it} + b_2 \Delta lnminc_{it} Gini_{it-1} + b_3 \Delta lnminc_{it} \ln Z/minc_{it}) + b_4 \Delta lnGini_{it} + b_5 \Delta lnGini_{it} G_{it-1} + b_6 \Delta lnGini_{it} \ln Z/minc_{it}) + G_{it-1} + \ln Z/minc_{it} + \Delta\varepsilon_{it} \tag{3}$$

From this equation (3), the growth and inequality elasticities of poverty can be computed as follows:

- Income elasticity of poverty

$$\varepsilon_{minc} = \frac{\partial \Delta lnp_{it}}{\partial \Delta lnminc_{it}} = b_1 + b_2 lngini_{it-1} + b_3 \ln Z/minc_{it}) \tag{3a}$$

- Inequality elasticity of poverty

$$\varepsilon_{gini} = \frac{\partial \Delta lnp_{it}}{\partial \Delta lngini_{it}} = b_4 + b_5 lngini_{it-1} + b_6 (\ln Z/minc_{it}) \tag{3b}$$

However, these elasticities in Equations (3a) and (3b) appear to be incomplete since the *growth-poverty identity model* does not account for an important stylised fact which is the initial level of poverty. Ravallion (2012) accounts for this in a *growth-poverty convergence model* and finds that a higher initial level of poverty is extremely harmful to the speed at which growth in mean income reduces poverty. The idea of including the initial level of poverty in the growth-poverty modelling inspires us to develop a new growth-poverty model in which the actual poverty change is subject to its earlier shocks. We refer to this as an *autoregressive growth-poverty model*. The fundamentals of the new framework follows Bond (2002) and Bourguignon (2003) by adding an autoregressive poverty shock term v_{it} to Equation (1) as follows:

$$lnp_{it} = c_t + \beta_1 lnminc_{it} + \beta_2 lnGini_{it} + (\alpha_i + v_{it} + e_{it}) \tag{4}$$

Where α_i is the region unobserved heterogeneous fixed effect, v_{it} is an AR (1) process and can be expressed as follows:

$$v_{it} = \theta v_{i,t-1} + m_{it} \tag{5}$$

With $\theta < 1$ and e_{it}, m_{it} ~ *MA (0),* e_{it} being serial uncorrelated (measurement) errors.

Three main reasons support the subjection of the actual changes in poverty to its earlier shocks: (1) the factors that underlie the changes in mean income and the changes in income distribution are from the economic and political structural transformation policies. These factors, by their very nature, produce results in the long-run rather than short run, "ceteris paribus". This makes it possible to predict the likelihood of someone who is poor at time *t* to still be poor at time *t+1* when there are no changes in both mean income and inequality; (2) According to Ravallion (2012), the prior wealth status affects the current work productivity. He advances this idea relying on what has been demonstrated in Dasgupta and Ray (1987) model that individuals are more productive only when their previous nutritional consumptions have been maximised. In other words, poor people tends to be less productive due to their nutritional consumption gap. This argument is extended to what Cunha and Heckman (2007) supports by showing that a country in which a greater share of its population grew up in poverty will observe a continuous negative effect on the aggregate production and therefore actual poverty will tend to be sustained by its previous level; (3) The poverty trap model predicts a lower saving-investment level for an individual with a lower life expectancy (most of whom are poor). The model shows that poor people have higher impatience for consumption preference. This situation often leads to higher initial poverty rate and thus lower productivity which in fact will sustain future poverty. As such, Equation (1) can be transformed into a dynamic panel equation by substituting (5) into (4) yielding the following:

$$lnp_{it}= c_t + \beta_1 lnminc_{it} + \beta_2 lnGini_{it} + \alpha_i + (\theta v_{i,t-1} + m_{it_{it}} + \quad e_{it}) \tag{6}$$

Knowing that the initial level of poverty is a linear function of the initial level of the mean income and the initial level of income distribution, Equation (4) may be transformed by lagging both sides as follows:

$$lnp_{it-1}= c_t + \beta_1 lnminc_{it-1} + \beta_2 lnGini_{it-1} + \alpha_i + (v_{it-1}+e_{it-1}) \tag{7}$$

With $v_{it-1} = lnp_{it-1}$ - c_{t-1} - $\beta_1 lnminc_{it-1}$ - $\beta_2 lnGini_{it-1}$ - α_i+e_{it-1}.

By substituting the v_{it-1} equation into Eq. (6), we get:

$lnp_{it}= c_t+\beta_1 lnminc_{it}+\beta_2 lnGini_{it}+ \alpha_i+ [\theta(lnp_{it-1} - c_{t-1} - \beta_1 lnminc_{it-1} - \beta_2 lnGini_{it-1} - \alpha_i + e_{it-1} + m_{it}+e_{it})$ and can be rearranged otherwise as follow:

$$lnp_{it} = c_t + \pi_1 lnminc_{it}+ \pi_2 lnGini_{it}+ \pi_3 lnp_{it-1}+ \pi_4 lnminc_{it-1}+ \pi_5 lnGini_{it-1} + (\alpha_i + w_{it}) \tag{8}$$

With $w_{it}= m_{it}+ \quad e_{it}$ (9)

The error term (v_{it} + e_{it}) in Equation (4) is serially correlated at all lags while the error term w_{it} in Equation (8) is serially uncorrelated provided there are no measurement errors in the explanatory variables [w_{it}=e_{it} with (m_{it}) = 0]. Observing Equation (8), the similarity with the so-called *standard growth-poverty model* in Equation (1) is clearly apparent. The only difference is the autoregressive poverty shock term (lnp_{it-1}). Besides, each of the independent variables, Equation (8) have a dynamic common factor representation. Consequently, Equation (8) can be estimated through fixed or random effect techniques, when the emphasis is on capturing the region-specific fixed effect. In doing so, the π_j estimated parameters may be biased due to the region fixed effect (α_i) which is assumed correlated with: (a) the idiosyncratic error term (w_{it}) and (b) the vector of the predetermined regressors such as (lnp_{it-1}), (see Bond 2002). To bypass these drawbacks, Equation (8) needs to be differentiated in order to remove the individual region fixed effect bias, thus, it translates into the following:

$$\Delta lnp_{it}=c_t+\pi_1\Delta lnminc_{it}+\pi_2\Delta lnGini_{it}+\pi_3\Delta lnp_{it-1}+\pi_4\Delta lnminc_{it-1}+\pi_5\Delta lnGini_{it-1}+\Delta w_{it} \tag{10}$$

Where, Δlnp_{it-1} is the change in the initial level of poverty, $\Delta lnminc_{it-1}$ and $\Delta lnGini_{it-1}$ represent respectively the change in the initial level of mean income and the change in initial level of inequality and the idiosyncratic error term $\Delta w_{it}= \rho(m_{it-1}$-$m_{it-2})$ + (e_{it-1}-e_{it-2}).

We then extend Equation (10) to the distribution effects and the initial level of poverty, respectively interacted with the change in mean income ($\Delta lnminc_{it}$) and the change in inequality ($\Delta lnGini_{it}$), which provides the following output:

$$\Delta lnp_{it}=c_t+\pi_1\Delta lnminc_{it} +\pi_2 lnGini_{it-1}\Delta lnminc_{it} +\pi_3\ln(Z/minc_{it})\,\Delta lnminc_{it} +\pi_4\Delta lnp_{it-1}\Delta lnminc_{it} + \pi_5\Delta lnminc_{it-1}+\pi_6\Delta lnGini_{it} + \pi_7\Delta lnGini_{it-1}+\pi_8\Delta lnp_{it-1}\Delta lnGini_{it} + \pi_9 lnGini_{it-1}\Delta lnGini_{it}+ \pi_{10}\ln(Z/minc_{it})\,\Delta lnGini_{it} +\pi_{11} lnGini_{it-1} +\pi_{12}\ln(Z/minc_{it})+\Delta w_{it} \tag{11}$$

Equation (11) interacts the changes in the initial level of poverty respectively with changes in the mean income and the changes in inequality, which is not needed at this stage of the analysis, therefore, we slightly amend it by substituting the initial level of poverty instead of the changes in initial level of poverty without modifying the core of Equation (11) and this gives the following final equation:

$$\Delta lnp_{it}=c_t+\pi_1\Delta lnminc_{it}+\pi_2 lnGini_{it-1}\Delta lnminc_{it}+\pi_3\ln(Z/minc_{it})\,\Delta lnminc_{it}+\pi_4 lnp_{it-1}\Delta lnminc_{it}+\pi_5\Delta lnminc_{it-1}+\pi_6\Delta lnGini_{it}+\pi_7\Delta lnGini_{it-1}+\pi_8 lnp_{it-1}\Delta lnGini_{it}+\pi_9 lnGini_{it-1}\Delta lnGini_{it}+\pi_{10}\ln(Z/minc_{it})\,\Delta lnGini_{it}+\pi_{11}lnGini_{it-1}+\pi_{12}\ln(Z/minc_{it})+\Delta w_{it} \tag{12}$$

Fosu (2017) described a very comprehensive way to the expected signs for each of the $\pi_j$except those linked to the initial level of poverty. As an increase in mean income should dull poverty, the sign of π_1 is expected to be negative. π_2 and π_4 are expected to be positive, for both higher level of initial inequality and initial poverty, the growth effect of poverty reduction should be less austere. The sign of π_3 should be positive as well, based on the lognormal income distribution hypothesis that suggests that a larger income which is considerably distant from the poverty line would be associated with higher mean income elasticity. In addition, the sign of π_6 is expected to be positive, for a rising inequality, one should expect a poverty increasing trend, ceteris paribus. In contrast toπ_6, $\pi_9$is likely to be negative, given the diminishing poverty-increasing effect of rising inequality. The sign of $\pi_{10}$is also expected to be negative, as in a relatively poor country with low mean income (higher $\ln Z/minc_{it}$), improving the share of wealth (lowering$lngini_{it}$) might worsen poverty by increasing the probability of a large number of people falling under the poverty line. Finally, π_{11} and π_{12} are likely to be positive: rising initial income inequality or an increase in the poverty line relative to the mean income should aggravate poverty. In order to determine the income and the inequality elasticities of poverty, Equation (12) is derived (at a poverty line of USD $1.9/day) with respect to change in mean income and change in inequality as follows:

- Income elasticity of poverty

$$\varepsilon_{minc}=\frac{\partial\Delta lnp_{it}}{\partial\Delta lnminc_{it}}=\pi_1+\pi_2 lnGini_{it-1}+\pi_3\ln(Z/minc_{it-1})+\pi_4 lnp_{it-1} \tag{12a}$$

- Inequality elasticity of poverty

$$\varepsilon_{gini}=\frac{\partial\Delta lnp_{it}}{\partial\Delta lnGini_{it}}=\pi_6+\pi_9 lnGini_{it-1}+\pi_{10}\ln(Z/minc_{it-1})+\pi_8 lnp_{it-1} \tag{12b}$$

The income and the inequality elasticities of poverty in (12a and 12b) are quite different with those in equations (3a and 3b) due to the additional term (lnp_{it-1}) which interfere into the derivative process. This innovation makes our procedure to deviate and differentiate to those derived within the identity model. After equation (12a) and (12b) being computed for each of the six regions of the world, the changes in poverty are disaggregated into income growth and inequality growth overtime, following closely Fosu (2017), by applying the following formula:

$$\Delta lnp_{it}=\Delta lnminc_{it}\,\varepsilon_{minc}+\Delta lnGini_{it}\,\varepsilon_{gini} \tag{13}$$

4.1.2. *The algebra of the income and inequality elasticities of poverty*

Under this section, the theoretical conceptualisation of the derivative process of the income and inequality elasticities of poverty is developed based on the well-known lognormal income distribution assumption. This builds on what Bourguignon's (2003) formulates. He shows that a poor individual is any one whose income *(Y)* at a time *t* is below a certain threshold *Z* (*Z* being the poverty line). This assumption is equal to the probability of that individual income *Y* to be lower than the income threshold *Z* required for him to stop being poor. This can be artimetically expressed as follows:

$$P_t=\text{prob}\ (Y_t<\text{Z})\equiv\text{function(Z)} \tag{14}$$

the function (Z) expresses the distribution of the individual incomes. Assuming a lognormal distribution to Equation (14), which in fact is a probability distribution with a log-normally distributed income, where for instance log(Z) is observed only for positive values of Z. therefore, the poverty incidence measure can be determined for each individual to which income is observed in the limit of a logarithmic chi-square distribution[1] (starting from 0 to < *Z)* and this can be formalised as follows:

$$P_t = \Phi(\frac{\ln((Z/minc_t)}{\sigma_t} + 0.5\sigma_t) + 2\Phi(\frac{\sigma_t}{\sqrt{2}}) - 1 \tag{15}$$

With Φ (.) denoting the cumulative distribution density function, σ_t as an average deviation of each individual income to the mean population income (standard deviation). The first component of the equation (15) is representing the pure mean income growth effect on poverty and the second is representing the inequality growth effect on poverty. The relative change in poverty over time caused by the mean income growth and any change in the share of the population income can be disaggregated otherwise between income growth and inequality growth as follows:

$$\frac{\boldsymbol{dP_t}}{\boldsymbol{d_t}} = \varepsilon^p_{minc} \frac{dminc_t}{d_t} \frac{P_t}{minc_t} + \varepsilon^p_{Gini} \frac{dGini_t}{d_t} \frac{P_t}{Gini_t} + \mu_t, \tag{16}$$

With ε^p_{minc} as the income elasticity of poverty, ε^p_{Gini} as the inequality elasticity of poverty and μ_t as an error term capturing the residual coming from the first order approximation condition. This disaggregation is what support the decomposition presented in equation (13).

We now consider the distribution effect into the relation described in (16), with the aim to understand how the mean income growth is affected by the initial inequality. As poverty is set up in equation (15), it can be observed that it is subject to the ratio poverty line over mean income$(Z/minc_{it})$ and the standard deviation of the logarithm mean income (σ_t). Since the income elasticity is expected to be negative, this may lead to a strict conclusion that decreasing in the ratio poverty line over mean income and in the standard deviation of the logarithm of mean income will impact negatively on poverty (Epaular, 2003 and Kalwij and Verschoor, 2007). Moreover, a region's economy with a higher initial poverty ratio will tend to register lower poverty impact of growth. These two assumptions lead to rewriting the income elasticity of poverty in the following way:

$$\varepsilon^p_{minc} = \frac{dp_t}{dminc_t}\frac{minc_t}{p_t} \equiv -\frac{1}{\sigma_t}\frac{\phi_t(\frac{ln\left(\frac{Z}{minc_{it}}\right)}{\sigma_t}+(0.5)\sigma_t)}{\Phi_t(\frac{ln\left(\frac{Z}{minc_{it}}\right)}{\sigma_t}+(0.5)\sigma_t)} + \frac{1}{1-p_{it-1}} \leq 0, \tag{17}$$

With the ratio 1/ (1- p_{it-1}) representing the direct effect of poverty[2]on growth as well as for inequality in Equation (18). It shows that, at a high initial poverty incidence ratio (p_{it-1}), the impact of growth and on poverty dampens considerably with the direct poverty effect. In addition, the impact of the initial inequality as illustrated in Eq. (18) is a pure positive linear function of the standard deviation of the population mean income (σ_t)**,** unless in some isolated cases (especially for low average income countries) it can be negative. Once again, the impact of income inequality on poverty will decrease with a higher ratio poverty line over mean income and with a higher initial poverty incidence ratio. Formalising this yields the following expression:

$$\varepsilon^p_{Gini} = \frac{dp_t}{d\sigma_t}\frac{\sigma_t}{p_t} \equiv \frac{\phi_t(\frac{ln\left(\frac{Z}{minc_{it}}\right)}{\sigma_t}+(0.5)\sigma_t)}{\Phi_t(\frac{ln\left(\frac{Z}{minc_{it}}\right)}{\sigma_t}+(0.5)\sigma_t)} \left(\frac{-ln(Z/minc_{it})}{\sigma_t} + (0.5)\sigma_t\right) - \frac{1}{1-p_{it-1}} \geq 0. \tag{18}$$

4.2. Estimation techniques

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[1] The lognormal assumption underlined here is linked to the assumption made on the idiosyncratic error term w_{it} in equation (4) to be serially uncorrelated given the fact that measurement errors in the selected sample are minimized since poverty incidence index is computed only for observed income or consumption values.

[2] The following direct poverty effect is developed and added to the framework developed by Bourguignon (2003), Kalwij and Verschoor (2007). Ravallion (2012) developed a similar direct effect of poverty (1- p_{it-1}) when he derived the decomposition of the poverty convergence elasticity.

Several empirical studies including Fosu (2017) estimate the growth-poverty model using the panel fixed and random effect techniques. The aim of using such techniques is to effectively control for the unobserved heterogeneous country or region fixed effects. One of the main problems with the use of the fixed or random techniques is that estimates are likely to be downward biased. Such bias arises if the country/region-specific effect is time-invariant and correlated with the error term or if the error term is correlated with at least one of the predetermined regressors, allowing for time-invariant variables to play a role as explanatory variables (Bond 2002). Kalwij and Verschoor (2007) clearly advance three main reasons that show how the error term of the growth-poverty equation (Equation 12 of this study) should obviously be correlated with at least one of the predictors: (a) the first reason is that of measurement errors of income explained by the fact that income and poverty indicators rely on the same survey data whereby growth is sometimes measured as expenditure or sometimes measured as income. As such, not accounting for this may lead to bias.[3](b) The characteristics of the heterogeneous fixed effects that impact income growth may also impact the changes in poverty, and hence, not accounting for this, may lead to standard omitted variables bias, and finally, (c) the problem of overstating poverty and understating income may subject the final outcome to bias. Deaton (2005) illustrates this by arguing that in most of the survey, the participation rates among rich people tend to be lower compared to the participation rate of poor people. Consequently, not correcting for this may also raise the consistency problem of the estimated parameters. In addition to these three reasons, the fixed and random effect estimation techniques do not control for a possible case of bias that arises from a possible case of endogeneity between variables under observation.

Another group of researchers prefer the two or three stages least square techniques in estimating the single growth-poverty equation. Most of them opt for the Three-stage least square (3SLS) over the Two-stage least square (2SLS) due to its relevance in yielding efficiency in a small sample and especially when the cross-sectional dimension of the data is not large enough. This includes the work of Theil (1971) and Besley (1988). These econometric techniques have been proven empirically efficient compared to the pooled ordinary least square on the differentiated dynamic model. The pooled OLS generally yield upward biased estimates while the fixed and random effect techniques yield downward biased estimates.[4] The efficiency of the 2SLS or 3SLS resides also in their abilities to control for bias caused by the double causality between growth and poverty on one side and between growth and inequality on the other hand, using instrumental variables (see Thorbecke 2013). Applying the two or the three stages least square estimators on Equation (12), which is an equation of the type suggested by Anderson and Hsiao (1981), will not yield efficiency compared to the generalised method of moment (GMM). This is especially the case, particularly where the time period of the data under observation is more than three ($T>3$). This is justified by the fact that when the time period is largely superior to three, more instruments become available for the differentiated equation. (Arrelano, and Bond (1991) suggested for the efficiency issue, the GMM in instead of the Anderson-Hsiao estimators.

For the above-mentioned reasons, the two-step system GMM estimators are employed and takes into considerations endogeneity issues as explained. Blundell et al., (2000) justified the choice of such estimators compared to the difference GMM estimator on such a model. They argued that the two-step system GMM allow systematically the use of the lagged levels values of the endogenous variables dated at *time t-2* and earlier lags as instruments for the equation in first difference and the lagged first

[3] 65% of usable observation cases are measured in term of expenditures and 35% of cases in income. For more details, refer to Povcalnet data set.

[4] The debate on the biasness of the fixed and the random effect techniques is well illustrated herein the methodological approach developed, see equation (8) above.

difference values dated at time *t-1* only as instruments for the equation in level. As previously suggested by Ravallion (2001) and later by Kalwij and Verschoor (2007) to instrument for endogeneity issues, the logarithm of the mean income in its first lagged values ($lnmininc_{t-1}$), the growth of GDP per capita income taken in logarithmic values ($D.lnGDP_{pc_{it}}$) are also used. In contrast to Kalwij and Verschoor (2007), and Fosu (2015 and 2017) on the use of the population growth rate as an additional instrument[5], we preferred instead the globalisation index from the economic cycle research institute (overall KOF globalisation index)[6] based on the new trade theories that support the link between growth, inequality and poverty (see Dorn and Schinke, 2018 and Thorbecke, 2013). We also use several interaction terms between GDP per capita, Globalisation index, the initial mean income and the initial inequality with the regional dummy variables as supplementary instruments. In including these extra-instruments, the aim is to avoid measurement errors arising when data on per capita income are collected. However, one of the key assumptions that need to be underlined for the used instruments to be valid is that the instruments must be orthogonal to the idiosyncratic error term (w_{it}). The robust Hansen *J-statistic* test for over-identification is presented to illustrate the validity of the incorporated group of instruments in the first stage regressions, the F-test statistics is conducted to assess regional differences in the power of the change in mean income to reduce poverty and the Arrellano and Bond (1991) test for serial correlation and heteroscedastic errors is also reported as an additional test for the goodness of the fit.

4.3. Data and variables description

The data for most of the variables in Equation (12) are from Povcalnet dataset.[7]This dataset was most recently revised by the World Bank by adjusting the figures to 2011 purchasing power parity. It deals specifically with issues related to economic growth, income inequality and poverty and contains data running from 1981 to 2013. The data are designed at the regional or country-level based on nationally representative household surveys. Most of the surveys were conducted by national government statistical organisations. The survey covered eight indicators, five of which are related to our variables of interest in this study[8]: the three FGT poverty indicators (poverty incidence, depth and severity) expressed in percentage are given for each region or/and for each country and are collected at an international poverty line of \$1.9 per person per day, although percentages can change according to a relatively defined poverty line.

For pragmatic reasons, we preferred to refer to the headcount index rather than the depth and the severity index. The mean income or mean consumption used as a proxy to economic growth is defined to conform to how the survey was conducted, either in consumption or income aggregates. The Gini index used as a proxy for income distribution is calculated from the same underlying welfare indicators as the FGT measures. Some specific issues relating to the data are worth mentioning: (1) starting from 1981 to 2008, the data are presented in three-yearly periodicity for each region or country. Between 2008 and 2010, the periodicity is two-yearly and from 2010 to 2013, the observations are yearly. This situation is due to the uneven country or regional coverage of the dataset whereby for instance 23 countries from different regions have only one coverage survey, and this makes it difficult to have suitable and reliable time series data for these particular countries. (2) At the \$1.90 international

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[5] KOF is an acronym for the German word "Konjunkturforschungsstelle" meaning: Economic cycle research institute. The choice of the use of the overall KOF globalization index instead of the population growth rate as suggested by Kalwij and Verschoor (2007) and Fosu (2015) reside in its relevant link with growth, inequality and poverty.

[6] The Overall KOF globalisation index were collected from: datalib.edina.ac.uk/catalogue/kof

[7] The Povcalnet data set is the most revisited (2009a, 2009b) World Bank data dealing specifically with growth, inequality and poverty issues. The data are reachable through the following link:
http//iresearch.worldbank.org/PovcalNet/PovDuplicateWB.aspx

[8] The three indicators linked to this study are: the headcount ratio, the mean income and the Gini index.

poverty line, 25 countries within the *higher income countries/regions* have very low poverty rate. Among these countries, Spain for example has the highest poverty rate (1.27%) in 1981 and Italy (1.45%) in 2013. As such, this picture cannot support any relevant idea of assessing the poverty effect of growth. For this reason, we exclude these 25 higher income countries from the sample.

The final sample is made of 112 countries from six regions of the world. Except Fosu (2017) which used 123 countries, our sample is similar to, but larger than those of Besley and Burgess (2003) with 78 countries, Bourguignon (2003) with 50 countries, Kalwij and Verschoor (2007) with 58 countries. The improvements in sample size is due to better coverage by the national governments such that majority of the countries have more usable and reliable survey-based data. The criteria defined for a country to be part of the sample is that of having at least two periods of survey coverage.[9]This criteria was maintained for the simple reason of having such a possibility of construction a spell. We also discarded 26 countries in which the first survey is conducted in 2009 or after in order to avoid misleading results due to the short span to 2013. Between the 26 countries, 12 countries belong to Sub-Saharan Africa region, 5 countries in East Asia and Pacific, 3 countries in Latin America and the Caribbean, 2 countries in South Asia and 4 countries in the Middle East and North Africa.

We end up with 571 usable observations for the 112 countries in which 49 countries have more than 4 years per country of usable observations and longer, 18 countries have 3 years per country of usable observations and 45 countries have 2 years per country of usable observations. Most of the estimations are based on annualised variations rather than pooling together variations with the different gap in the length of years. This is also for the simple reason of avoiding and minimising bias that should result from missing data in the selected sample. The annualised data are obtained by linear interpolation technique following Noor et al., (2014) except for the instrumental variables. This technique has been applied in similar studies, including Besley and Burgess (2003), Kalwij and Verschoor (2007) and has been proven better in providing reliable data for such kind of analysis compared to the mean imputation techniques used by Fosu (2017). The values Interpolated are systematically computed by STATA 14 for each variable with missing data.

5. EMPIRICAL RESULTS

This section presents the empirical results from the estimation of models (2) with and without inequality and the estimation of models (3) and (12). Table A (in the appendix) reports the summary statistics for the annualised data of mean income, Gini index and poverty headcount rate by regions.[10] There is a great deal of cross-regional variations in the means of the variables which our models also seek to explain.

5.1. Empirical results and discussion

The results of columns (I), (II) and (III) in table 2 correspond to the specification of model (2) while that of column (IV) relates to model (3). The column (I) contain the result of the point estimate of poverty response to the changes in mean income equal to −2.40 (corrected standard error 0.18) at \$1.90/day. This estimate corresponds to what Ravallion and Chen 1997 called as an "empirical elasticity" linked to the actual changes in the Lorenzo curve rather than being the true income elasticity of poverty. This value is very closed to the −2.32 (standard error 0.50) obtained by Kalwij and Verschoor (2007), using a sample size of 58 developing countries at \$2/day poverty line. It is a double

[9] The data used for China and Indonesia are averaged from the urban and the rural data.

[10] The world average poverty rate is found to be low (24%) during the 1981-2013 period. This is due to the fact that our sample excluded India for the lack of reliable data of income inequality according to what we defined as criteria for a country to be selected in the sample.

of the value of -1.25 (standard error -3.60) obtained by Fosu (2017) for a sample of 123 developing countries at a poverty line of \$2.5/day. The model parameters appear to deal well with the endogeneity in the mean income-inequality-poverty nexus according to the results of the Wald $\chi^2_{0.05}$test (test statistics=178.62) of the excludable instruments and the consistency in the choice of instruments as suggested by Bond et al. (1995). In addition, the reported goodness of fit is the Arellano and Bond (1991) statistics. It also provides a specification test on whether there is a presence of autocorrelation in the series and the results indicate that series are correlated only at the second order ($\rho_2 =$ -0.73). Similar conclusion on the autocorrelation in the series are made for the rest of the estimates in all columns of Table 2. Although the results pass the model specification test, i.e. the Hansen *J*-statistic is statistically significant, making them consistent, there is need for caution in the interpretation, since the distributional effect is not considered.

The results of column (II) replicates the estimates of Besley and Burgess (2003) which was first adopted by both Kalwij and Verschoor (2007) and Fosu (2017). This allows us to interact the changes in mean income with each region's dummy. The importance of such procedure resides in its ability to determine regional differences through the *Wald*$\chi^2_{0.05}$or *Fisher* statistics from the joint significance test of the regions estimated parametters. The results of the joint significance test confirm a strong evidence of regional differences in poverty-response to changes in mean income, since the null hypothesis of equal mean income elasticity is rejected (the$\chi^2_{0.05}$ statistics=124.27 or the *F-test* statistics=24.85). The results also indicate that the Middle East and North Africa (-4.12) is the region with the highest income elasticity of poverty. For the same region, Kalwij and Verschoor (2007) reports an elasticity of (-8.16) for the \$2/day (the highest elasticity of poverty in their sample). Fosu (2017) finds a value of -1.48 for the \$2.5/day (not the highest in his sample). These differences can be explained by two factors. One is the difference in the number of countries included in each region. The other is the difference in the poverty line used in the studies.

The column (III) of Table 2 presents the estimates in which the distribution of income (Gini) is considered. This estimation corresponds to the full specification of model (2). We just reiterated the estimates of column (II) by including the changes in income inequality. In doing so, we wanted to recalculate the estimates more accurately to generate truer values of the income elasticity of poverty (ε^p_{minc}). The estimated parameter of the change in income distribution is found equal to 3.55 (corrected standard error 0.65). We also found that the inclusion of the change in inequality does not result in the change in the magnitude rank of the regional income elasticity of poverty as they are presented in column (II), except for the rank of South Asia compared to that of East Asia and Pacific region. This exceptional and slight change in magnitudes rank for both regions is justified by their similar proportions changes in both mean income and Gini index during the three sub-period as presented in table 1.

The results of column (IV) relate to the version of the identity model (3) and answers the question of whether the regional differences are still significant once we control for the extent to which the change in mean income is effective in predicting the change in poverty as developed in section 4.1.2. The estimated results through the joint significance *F*-test confirmed once again regional differences in the income elasticity of poverty since the null hypothesis of equal income elasticity is rejected (the statistic of *F-test*=358.55). In accord with what is developed in section 4.1.2, we notice that both poverty elasticities must be computed using the fundamentals of the model (3)

Table 2. Estimated income and inequality elasticity of poverty: effect of the initial level of income inequality

Dependent Variable: Δlnp_{it}(Poverty incidence) at \$1.90 per day/per person				
Independent Variables	Estimated parameters (S.E)		Estimated parameters (S.E)	
Variables and Equations	(I)	(II)	(III)	(IV)
$\Delta lnminc_{it}$	-2.40 (0.18)***			
$\Delta lnminc_{it} \times lngini_{it-1}$				0.13 (0.06)***
$\Delta lnminc_{it} \times \ln(Z/minc_{it-1})$				0.26 (0.03)***
$\Delta lngini_{it}$			3.56 (0.66)***	12.77 (0.43)***
$\Delta lngini_{it} \times lngini_{it-1}$				-3.11 (0.11)***
$\Delta lngini_{it} \times \ln(Z/minc_{it-1})$				-1.26 (0.06)***
$lngini_{it-1}$				0.01 (0.00)***
$\ln(Z/minc_{it-1})$				0.03 (0.00)***
$\Delta lnminc_{it} \times$ Specific regional dummy				
Regions				
• Sub-Saharan Africa		-1.15 (0.17)***	-0.92 (0.21)***	-0.61 (0.25)***
• South Asia		-2.11 (0.26)***	-3.24 (0.32)***	-2.31 (0.23)***
• Middle East & North Africa		-4.12 (0.36)***	-3.96 (0.39)***	-2.81 (0.22)***
• Latin America & Caribbean		-1.95 (0.21)***	-1.96 (0.21)***	-0.98 (0.25)***
• Eastern Europe & Central Asia		-2.60 (0.31)***	-2.54 (0.29)***	-1.51 (0.23)***
• East Asia & Pacific		-2.08 (0.26)***	-2.25 (0.23)***	-1.50 (0.22)***
N. obs	2204	2252	2252	2204
Wald $\chi^2_{0.05}(6)$ *Statistics*	*178.62*	258654.71	472.00	985
Hansen *J-stat.*	97.38[a]	105.94[b]	105.79[c]	93.72[d]
ρ_1	-2.34	-2.33	-2.35	-2.2
ρ_2	-0.73[e]	-1.01[f]	-1.33[g]	-1.20[h]
Equal income Elasticity Across regions *(F-test)* [i,j,k]		124.27	61.57	1792.76

Notes: All the 3 equations relates to model (2) and the estimates are obtained by the two step-system GMM with corrected standard errors given in parentheses. The dependent variable is the poverty incidence growth (headcount rate) at a poverty line of \$1.90 a day per person. Equation (2) includes regional dummy variables for capturing the poverty impacts of growth across regions and equation (3) includes the income distribution component. The initial levels of all variables correspond to their respective lag 1 values at the beginning of the spell (in 1981). Endogeneity issue between $\Delta lnminc_{it}$ and Δlnp_{it} are controlled through several instruments. Each independent variable interacted with $\Delta lnminc_{it}$ and $\Delta lngini_{it}$ is considered endogenous and is instrumented.
[a]Critical value is $\chi^2_{0.05}$=90. Included instruments: $lnglob, \Delta lngdp_{pc_{it}}, lnminc_{t-1}$ *and* $lnminc_{t-2}$.
[b]Critical value is $\chi^2_{0.05}$=535. Included instruments: regional dummy variables,$\Delta lngdp_{pc_{it}}$, $lnminc_{t-1}$ both interacted with regional dummy variables and $lnminc_{t-1}$ *and* $lnminc_{t-2}$. [c]Critical value is$\chi^2_{0.05}$=629.Included instruments: regional dummy variables, $lnminc_{t-1}$ *and* $lngini_{t-1}$ interacted with regional dummy and $\Delta lngdp_{pc_{it}}$ interacted with regional dummy variables, $lnminc_{t-1}$ and $lnminc_{t-2}$. [d]Critical value is $\chi^2_{0.05}$=972. Included instruments: regional dummy variables,$\Delta lngdp_{pc_{it}}$,$lnminc_{t-1}$,$lngini_{t-1}$, $lnglob_{it}$ all interacted with regional dummy variables and $lnminc_{t-1}$ *and* $lnminc_{t-2}$.
[e,f,j,h]Arellano-Bond Z-statistics for AR(1) and AR(2) in first differences. [i]*F*-test statistics, reported critical value is F(5, 2246) = 24.85, [j]*F*-test statistics, reported critical value is [j]*F*(7, 2245)=12.31 and [k]*F*-test statistics, reported critical value is *F*(5, 2192) = 358.55. ***denotes variable significant at 1% level of significance.

Table 3 contain the estimates of the identity model as specified in Equation (3) and the autoregressive model as specified in Equation (12). Columns (V) and (VI) of the Table 3 corresponds respectively to the identity model and autoregressive. The identity model indicates an absolute income elasticity of poverty of -5.48 (corrected standard errors 2.60) and an absolute inequality elasticity of poverty is 17.70 (corrected standard errors 5.82). We find that both poverty elasticities decrease with both initial levels of income inequality and the ratio poverty line over mean income, underscoring the harmful effects of a higher inequality index and a higher ratio poverty line over mean income. Moreover, the higher magnitude of the absolute inequality elasticity of poverty compared to that of the absolute income illustrates how the change in poverty is more sensitive to inequality than to mean income. Our identity model estimates are similar to what Kalwij and Verschoor (2007) and Fosu (2017) find. Finally, column (VI) presents the autoregressive model which augments the identity model with the inclusion of the initial levels of poverty. The result indicates a large decrease in both absolute poverty elasticities, from -5.48 to -2.21 for the absolute income elasticity of poverty and from 12.17

to 2.69 for the absolute inequality elasticity of poverty. Controling for initial levels of poverty also makes the initial inequality and the ratio of poverty line over mean income to increase the magnitude of both absolute poverty elasticities. The initial level of poverty interacted with the changes in mean income and the changes in inequality is found to be negatively related to both absolute poverty elasticities.[11] As such, this is considered as an evidence to: (1) the harmful effect of a higher initial level of poverty in predicting the speed at which growth reduces poverty, (2) the dominant role that initial levels of poverty plays in constraining the effect of growth on poverty compared to other initial conditions as presented by Ravallion (2012).

However, as shown previously, Ravallion (2012) reported an estimate of the initial poverty interacted with the change in mean income equal to 2 while it is found here equal to 0.47. we notice that the Ravallion's estimate is upward biased due to the fact that it is calculated on a methodological basis that control only for the initial poverty in interaction with the changes in mean income but not the initial inequality, all involved in a unique specified framework. In other word his estimate suffer for omitted variables bias as shown in the introduction.

The comparison between both identity and autoregressive findings indicates that assessing the growth-poverty nexus through the identity model is overestimating the poverty effect of the change in mean income compared to the estimates of the autoregressive model.

Table 3. Estimated income and inequality elasticity of poverty: effect of both initial level of income inequality and initial level of poverty

Dependent Variable: Δlnp_{it}(Poverty incidence) at $1.90 per day/per person		
Independent Variables	Estimated parameters (S.E),	Estimated parameters (S.E)
Variables and Equations	(V)	(VI)
$\Delta lnminc_{it}$	−5.48 (0.16)***	−2.21 (0.20)***
$\Delta lnminc_{it} \times lngini_{it-1}$	0.97 (0.04)***	−0.43 (0.07)***
$\Delta lnminc_{it} \times \ln(Z/minc_{it-1})$	0.21 (0.02)***	−0.67 (0.04)***
$\Delta lnminc_{it} \times lnp_{it-1}$	___	0.47(0.02)***
$\Delta lngini_{it}$	12.17(0.34)***	2.69 (0.96)***
$\Delta lngini_{it} \times lngini_{it-1}$	−2.84 (0.09)***	0.76(0.30)***
$\Delta lngini_{it} \times \ln(Z/minc_{it-1})$	−1.10 (0.04)***	0.90 (0.14)***
$\Delta lngini_{it} \times lnp_{it-1}$	___	−0.97(0.04)***
$lngini_{it-1}$	0.04 (0.00)***	0.01(0.00)***
$\ln(Z/minc_{it-1})$	0.01 (0.00)***	0.03(0.00)***
$\Delta lnminc_{it-1}$		−0.24(0.01)***
$\Delta lngini_{it-1}$		0.52(0.03)***
N. obs	2202	2146
Wald $\chi^2_{0.05}(6)$ *Statistics*	496.56	2.06
Hansen *J-stat.*	103.09[a]	104.70[b]
ρ_1	−2.23	−2.34
ρ_2	−1.19[c]	−0.87[d]

***Notes*:** The estimates for the last two columns are also obtained through two-step system GMM with corrected standard errors in parentheses. The dependent variable and the daily poverty line is the same as in the previous four models. Column (5) is the "identity" model and Column (6) is the "Autoregressive" model and both models do not include regional dummy variables. Each independent variable interacted with $\Delta lnminc_{it}$ and $\Delta lngini_{it}$ is considered endogenous and is instrumented.

[a] Critical value is $\chi^2_{0.05}$=554. Included instruments: regional dummy variables,$\Delta lngdp_{pc_{it}}$,$lnminc_{t-1}$,$lngini_{t-1}$, $\Delta lnglob_{it}$ all interacted with regional dummy variables and $lnminc_{t-1}$ *and* $lnminc_{t-2}$.. [b]Critical value is $\chi^2_{0.05}$=104.00.Included instruments: regional dummy variables,$\Delta lngdp_{pc_{it}}$,$lnminc_{t-1}$,$lngini_{t-1}$,$lngini_{t-2}$, $lngini_{t-3}$,$\Delta lnglob_{it}$ all interacted with regional dummy variables and $lnminc_{t-1}$ *and* $lnminc_{t-2}$..

[c, d] Arellano-Bond Z-statistics for AR(1) and AR(2) in first differences.

[11] Our final specified model (12) was also estimated through fixed and pooled OLS for robustness purpose of our autoregressive growth-poverty estimates. We looked specifically on the estimates of the initial poverty interacted with change in mean income and change in inequality and we found that it magnitude was reducing both poverty elasticities for both fixed and pooled OLS techniques. The results for the fixed and polled OLS techniques can be provided once asked.

5.2. Predicted income and inequality elasticities of poverty

The estimated results of the" identity model" and those of the "autoregressive model" represented respectively by both columns (V) and (VI) of the table 3 refers respectively to the specified model (3) and (12). These make it possible to determine the differences in poverty elasticities across regions by deriving the results of both equations with respect to the change in mean income and the change in income distribution. Through the estimates of the model (3), we observed that the cross-regional differences depend on the differences in initial levels of income inequality and the ratio poverty line over mean income. However, for the autoregressive model, in addition to both initial inequality and the ratio poverty line relative to mean income, the initial level of poverty further explains the regional disparities in the poverty effect of growth in mean income. The income and the inequality elasticities of poverty presented in Tables 4 and 5 below are directly computed using the estimated parameters of columns (V) and (VI). Table 4 presents regional elasticities for both income and inequality within the identity model as follows:

$$\varepsilon^{p}_{minc} = \hat{\pi}_1 + \hat{\pi}_2 lngini_{it-1} + \hat{\pi}_3 \ln(Z/minc_{it-1}) \tag{19}$$

$$\varepsilon^{p}_{minc} = (-5.48) + 0.97^{*}\ lngini_{it-1} + 0.21^{*}\ln(Z/minc_{it-1})$$

$$\varepsilon^{p}_{gini} = \hat{\pi}_6 + \hat{\pi}_9 lngini_{it-1} + \hat{\pi}_{10} \ln(Z/minc_{it-1}) \tag{20}$$

$$\varepsilon^{p}_{gini} = 12.17 + (-2.84)^{*}\ lngini_{it-1} + (-1.10)^{*}\ \ln(Z/minc_{it-1})$$

Table 4. Computed income and elasticities of poverty across regions from 1981 to 2013

	Time period: 1981 to 2013	
	Income elasticity	Inequality elasticity
• Sub-Saharan Africa	−1.87	1.84
• South Asia	−2.11	2.60
• Middle East & North Africa	−2.27	3.42
• Latin America & Caribbean	−2.01	2.78
• Eastern Europe & Central Asia	−2.51	4.26
• East Asia & Pacific	−2.11	2.70
• All regions	−2.14	2.93

Source: own computation using the estimates of column (V) of table 3.

These results indicate a substantial regional diversity in poverty elasticities. The magnitudes of the inequality elasticities are higher than the income elasticities for all regions except for Sub-Saharan Africa. In general, this translates to how increases in inequality will consistently dampen the effect of growth on poverty. When looking at the region-specific cases, the results indicate for instance that Eastern Europe and Central Asia register the highest predicted income elasticity (-2.51) compared to the rest of the regions. This confirms the significant role of economic performance in these regions as illustrated in Table 1. Their higher income elasticities are mainly due to higher mean income level as well as lower Gini index compared to other regions (see Table A). These findings are consistent with those presented by Kalwij and Verschoor (2007), in which the same regions registered the highest predicted income elasticity of -3.47 in early 1980 and -3.01 in early 1990. Moreover, these results are in the same vein with those of the most recent evidence by Fosu (2017) where the highest predicted growth elasticity -3.68 for the regions. As such, these regions appear to be those in which growth had the most significant impact in reducing poverty. Conversely, the region shows a rising inequality trend (see Table 1) as evinced by an inequality elasticity of poverty of 4.26. The main policy implication that can be derived from this region's findings is that a relatively modest growth should induce relatively large poverty reduction while rising inequality will exacerbate poverty equally significantly. Sub-Saharan Africa is the region with the lowest values of both poverty elasticities. Contrary to Eastern Europe and Central Asia, Its outcomes implies that a higher and a sustained growth is required if poverty reduction efforts are to be effective. Aggressive inequality-reducing should be pursued. Figure 1 below presents the cross-regional plots of the income and inequality elasticity against the initial Gini coefficients. Regions with higher rates of initial Gini and a higher ratio of poverty line over mean income are expected to register a higher income elasticity. Conversely, regions with higher income inequality and lower ratio of mean income relative to the poverty line are expected to register lower inequality elasticity of poverty. This situation is due to one of the features of the identity model as demonstrated above. Figure 4 below presents the cross-regional plots of the income and inequality elasticities against the initial inequality index.

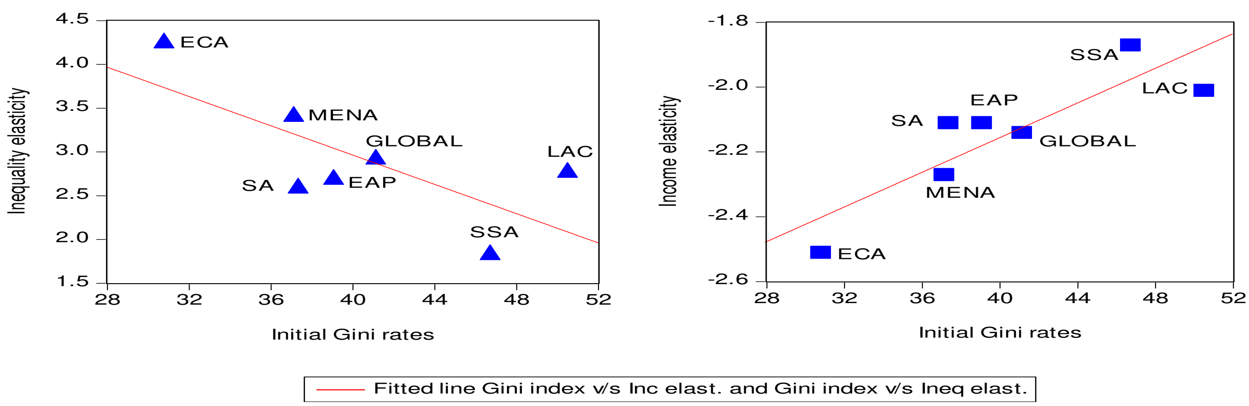

Fig.4. Income elasticity v/s initial Gini rates. **Notes:** The triangle dots represent each region inequality elasticity value while the square points represent each region income elasticity value in reference to the global line which represent the regions average income and inequality elasticity value. The ECA and MENA are the only regions with inequality elasticity values above the global inequality elasticity value. The lowest income elasticity value is with SSA region while the highest is found with ECA region.

In the autoregressive model, both poverty elasticities are increasing with the distributional effects and decreasing only with the initial poverty (pure poverty effect). Contrary to the identity model, the effect of growth and inequality on poverty is bigger with higher initial inequality index, higher ratio of poverty line over mean income and lower with initial poverty rate. Figures 6 and 7 (in the appendix) demonstrate this in cross-country plots of both poverty elasticities against the logarithm of initial headcount poverty rates, with -4 as the lowest initial poverty rate and 5 as the highest. From these cross-country plots, the results indicates lower magnitudes for both poverty elasticities with higher initial poverty rate. The following are the computations of both poverty elasticities within the autoregressive model:

$$\varepsilon^{p}_{minc} = \hat{\pi}_1 + \hat{\pi}_2 lngini_{it-1} + \hat{\pi}_3 \ln(Z/minc_{it-1}) + \hat{\pi}_4 lnp_{it-1} \tag{21}$$

$$\varepsilon^{p}_{minc} = -2.21 + (-0.43)^{*}\, lngini_{it-1} + (-0.67)^{*} \ln(Z/minc_{it-1}) + 0.47^{*} lnp_{it-1}$$

$$\boldsymbol{\varepsilon^{p}_{gini}} = \hat{\pi}_6 + \hat{\pi}_9 lngini_{it-1} + \hat{\pi}_{10} \ln(Z/minc_{it-1}) \ \ \hat{\pi}_8 lnp_{it-1} \tag{22}$$

$$\boldsymbol{\varepsilon^{p}_{gini}} = 2.69 + 0.76^{*}\, lngini_{it-1} + 0.90^{*} \ln(Z/minc_{it-1}) + (-0.97)^{*}\, lnp_{it-1}$$

Table 5. Computed income and elasticities of poverty across regions from 1981 to 2013

	Time period: 1981 to 2013	
	Income elasticity	Inequality elasticity
• Sub- Saharan Africa	−1.82	1.63
• South Asia	−1.87	1.83
• Middle East & North Africa	−2.28	3.03
• Latin America & Caribbean	−1.78	2.08
• Eastern Europe & Central Asia	−2.61	3.84
• East Asia & Pacific	−1.97	2.12
• All regions	−2.07	2.45

Source: These values are computed using the estimates of column (VI) of table 3.

Relative to the results of the identity model presented in Table 4, the results of Table 5 indicate the lowest income elasticity is within the LAC region while the lowest inequality elasticity is still within the SSA region. From these results, we deduce that regions with higher initial poverty rate and lower mean income register less poverty responsiveness to growth. This is the case with Sub-Saharan Africa, South Asia as well as East Asia and Pacific regions. Furthermore, regions with a lower ratio of poverty line over mean income (such as Latin America and Caribbean) and regions with lower income inequality but higher initial poverty rate both tend to experience lower poverty responsiveness to growth. Another key observation is on Eastern Europe and Central Asia, despite the region's increasing inequality trend as well as its lower ratio of poverty line over mean income, it still registers the highest poverty effect of growth compared to the rest of the region. This is due to its low level of initial poverty (see Figure 3). These features are only brought to light by the autoregressive growth-poverty model.

Figure 5 below presents the cross-regional plots of the income and inequality elasticities against the initial headcount rates and Table B (in the appendix) presents the cross-country income and inequality elasticities within the autoregressive framework.

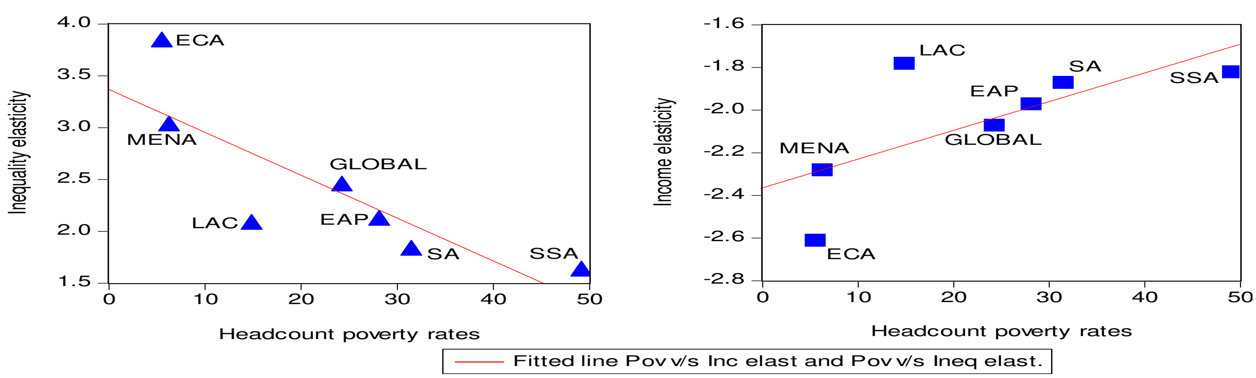

Fig.5. Income and inequality elasticity v/s initial poverty rates. **Notes: T**he triangle dots represent each region income elasticity value in reference to the global line representing the regions average income elasticity value. The ECA and MENA are the only regions with income elasticity values above the global income elasticity value. The lowest income elasticity value is with LAC region while the highest remain with ECA region.

5.3. Explaining the trends in poverty changes by Region since 1981 to 2013

We now use Equation (13) to explain the inter-regional diversity in the change of poverty from 1981 to 2013. This process seeks to achieve two things. First is to identify the major sources of the changes in poverty and second is the formulation of actual policy measures to take the most advantage of the projected future economic upturn in the developing world in order to maximise poverty reduction and human welfare. For these purposes, we use the computed poverty elasticities of Table 6 within the autoregressive framework at $1.90/day in order to see how the changes in mean income and changes in inequality predict changes in poverty. Table 6 below present the results of the change in poverty against the predicted change in poverty:

Table 6. Poverty Growth against Predicted Poverty Growth by region at $1.90/day (in %) from 1981-2013

	pov_g^a	(1). Income effect $(\varepsilon_{minc}^{p} * \Delta lnminc_{it})^b$	(2). Inequality effect $(\varepsilon_{gini}^{p} * \Delta lngini_{it})^c$	[(1)+(2)] $predict.pov_g^d$
• Sub-Saharan Africa	−1.50	−1.71	−0.35	−2.06
• South Asia	−8.78	−6.59	0.27	−6.32
• Mid East and North Africa.	−5.44	−2.98	−0.82	−3.80
• Latin America and Caribbean.	−3.10	−2.95	−0.44	−3.39
• East Europe and Central Asia.	−2.19	−2.68	2.20	−0.48
• East Asian and Pacific.	−7.36	−5.95	−0.13	−6.08
• All Regions.	−3.37	−3.12	0.07	−3.05

Notes: The income and the inequality elasticity of poverty used for specific-region are from equation (6) and are well reported in table 6. The predicted total effect on poverty induced by the income effect and inequality effect is given by the addition of column (1) and (2).[a]*povg* is the annualised mean poverty growth by region, [b]*The income effect*= changes in annualised mean income times the income elasticity of poverty, [c]*the inequality effect*= changes in annualised inequality times inequality elasticity of poverty and [d]*predict.povg*=income effect sum inequality effect.

As shown previously, the income elasticity of poverty is expected to be negative whereas the inequality elasticity of poverty is expected to be positive. Consequently, an increase in mean income and a decrease in inequality should obviously convert to substantial poverty alleviation. From the above results of Table 6, we notice in general that the income effect dominates that of inequality in the total change in poverty for most of the regions, although the impact of inequality is no longer negligible. Region-by-region cases indicate that South Asia has the highest poverty-reducing effect (-6.59) where the mean income growth induces a large reduction in poverty. This however, is accompanied by a weak (0.27) inequality. Comparing South Asia's predicted poverty reduction rates with that of Sub-Saharan Africa, once again the main policy implication is that a modest economic growth is more likely to produce large poverty reduction in South Asia whilst higher and sustained growth rate are required for Sub-Saharan Africa if poverty reduction has to be realized significantly. The case of Eastern Europe and Central Asia requires particular attention since its growth effect on the change in poverty is largely offset by its increasing inequality trend, subjecting the region to lower predicted change in poverty. This regions situation is in line with what we illustrated above, that a region which exhibits a higher magnitude of income elasticity of poverty, generally tends to also register a higher magnitude of inequality elasticity of poverty. This is due to the fact that the region with a higher mean income compared to the poverty line tends to have higher magnitudes of both poverty elasticities

6. CONCLUSION AND POLICY IMPLICATION

This study has revisited the roles of both initial inequality and poverty in determining the speed at which growth in mean income impacts on poverty. The growth-poverty identity framework developed by Bourguignon (2003) and later by Kalwij and Verschoor (2007), is combined with the methodology of Bond (2002) as the basis for a new approach, termed as the autoregressive growth-poverty model. The new framework subjects current poverty changes to its earlier shocks. The new framework is estimated with a panel data of 112 developing countries, constructed mainly from World Bank's Povcalnet dataset in a two-step GMM estimator.

From the identity model estimates, we reached the same conclusion of Bourguignon (2003), Besley and Burgees (2003), Kalwij and Verschoor (2007) and Fosu (2017) that the absolute poverty elasticities were decreasing with both initial levels of income inequality and the initial density of mean income near the poverty line for all the regions.

The autoregressive model, which emphasises the role of initial levels of poverty in predicting the poverty responsiveness of growth in mean income, shows that the parameters for both poverty elasticity were less in magnitude compared to those of the identity model. Thus, the identity model overestimates both poverty elasticities compared to the autoregressive model. In addition to this surprising drop in the magnitude of both poverty elasticities, the distributional effects are increasing the magnitude of both absolute poverty elasticities. These discrepancies were considered as an evidence of what Ravallion (2012) stressed on as the dominant role played by a higher initial poverty over other initial conditions in predicting the poverty effect of growth in mean income. The conclusion of the identity model emphasises the negative effect of the initial inequality and the poverty line relative to mean income. However, the autoregressive framework shows that not only is the initial poverty the only binding constraint, controlling for it makes the other initial condition work in favour of both income and inequality elasticities of poverty.

Our results suggest that generally, countries with higher initial levels of poverty tend to have less poverty responsiveness to changes in mean income. At the regional level, the case of Sub-Saharan Africa (-1.82) and South Asia (-1.87) income elasticities compared to other regions were the most demonstrative. We also showed that in Latin America and the Caribbean (-1.78) the lower income elasticity was due to it lower ratio poverty line over mean income. Moreover, regional comparisons highlight for instance that a modest economic growth is more likely to produce large poverty reduction in South Asia whilst higher and sustained growth rate are required for Sub-Saharan Africa if poverty reduction has to be achieved significantly.

Overall, the autoregressive framework suggest that poverty reduction policies should discriminated according to region-specificities. Growth versus inequality policies as measures of improving poverty reduction efforts cannot be a one-size-fits-all approach. The cross regional variations in income and inequality elasticity suggest that redistribution policies will yields more fruits in poverty reduction in Eastern Europe and Central Asia, Middle East and North Africa. However, for regions like Sub-Saharan Africa and South Asia, growth-boosting measures must triumph for sustainable poverty reduction. For further research, we suggest that attention should be on complementary country-specific studies.

Appendix

Table A. Summary statistics

For the world as a whole				
	Mean	Standard Dev.	Minimum	Maximum
Mean income (in USD)	230.02	169.60	5.99	1054.52
Gini (in %)	41.08	10.24	16.63	62.78
Poverty headcount (in %)	24.24	25.81	0.00	99.98
For each region of the world				
Variable: ***Mean income (in USD)***				
Sub-Saharan Africa	118.02	97.19	21.17	699.05
South Asia	117.47	52.84	44.12	382.31
Meddle East &North Africa	237.17	90.84	95.80	579.42
Latin America &Caribbean	307.86	135.60	70.03	805.12
Eastern Europe &Central Asia	342.21	197.18	47.49	1054.52
East Asia and Pacific	167.41	124.60	5.99	772.62
Variable: ***Gini (in %)***				
Sub-Saharan Africa	46.65	8.93	27.13	65.76
South Asia	37.30	5.77	25.88	46.78
Meddle East &North Africa	37.06	4.90	27.62	47.42
Latin America &Caribbean	50.38	5.79	33.91	60.49
Eastern Europe &Central Asia	30.81	6.09	16.64	53.70
East Asia and Pacific	39.02	6.28	21.60	55.43
Variable: ***Poverty Headcount (in %)***				
Sub-Saharan Africa	49.17	24.02	0.00	95.06
South Asia	31.46	22.23	0.30	81.00
Meddle East &North Africa	6.24	6.56	0.00	34.83
Latin America &Caribbean	14.83	13.93	0.00	68.62
Eastern Europe &Central Asia	5.50	11.40	0.00	75.70
East Asia and Pacific	28.11	24.76	0.04	99.98

Source: Own computation using annualised Povcalnet data set from 1981-2013.

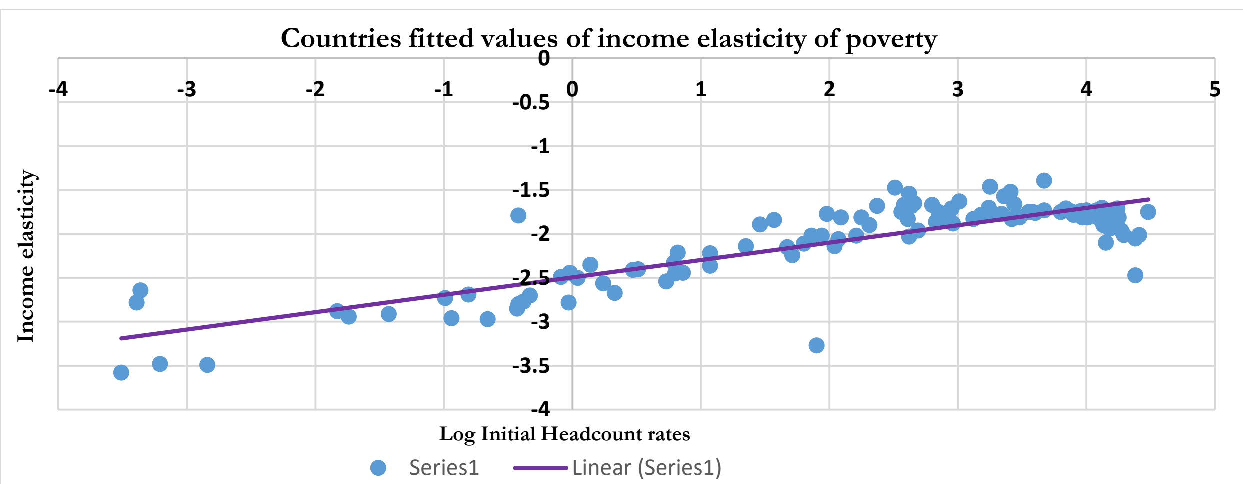

Fig.6. Plot of income elasticity of poverty values (in the horizontal axis) against the logarithm values of the initial headcount rates (in the vertical axis) for the entire sample comprising 112 Counties. The couple (-4 5) for the headcount rate indicates the lowest and highest initial poverty rate and the couple (0 -4) for the income elasticity indicates respectively the country's lowest and the highest income elasticity of poverty.

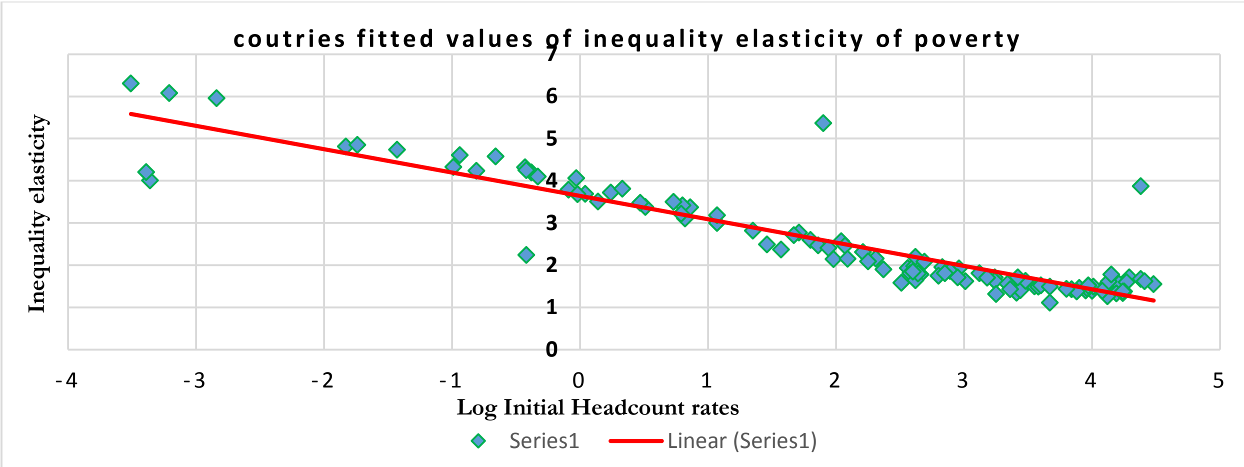

Fig.7. Plot of inequality elasticity of poverty values (in the horizontal axis) against the logarithm values of the initial headcount rates (in the vertical axis) for the entire sample comprising 112 Counties. The couple (-4 5) for the headcount rate indicates the lowest and highest initial poverty rate and the couple (0 6) for the inequality elasticity indicates respectively the country's lowest and the highest inequality elasticity of poverty.

Table B. Income and Inequality elasticity of poverty by countries (within the Autoregressive model)

Country	Income elasticity	Inequality elasticity	Country	Income elasticity	Inequality elasticity
Region: SSA			**Region: ECA**		
Botswana	-1.52	1.35	Albania	-2.67	3.81
Cabo-Verde	-1.76	1.71	Armenia	-2.06	2.46
Central African Republic	-2.01	1.71	Azerbaijan	-2.50	3.69
Chad	-1.82	1.46	Belarus	-2.96	4.61
Comoros	-1.75	1.93	Bosnia And Herzegovina	-2.77	4.20
Congo, Democratic Republic of	-2.05	1.67	Bulgaria	-2.73	4.33
Congo, Republic of	-1.71	1.43	Croatia	-2.88	4.81
Cote d'Ivoire	-1.86	1.95	Czech Republic	-3.48	6.08
Ethiopia	-1.78	1.46	Estonia	-2.69	4.24
Gambia	-1.81	1.47	Georgia	-1.90	2.16
Ghana	-1.75	1.55	Hungary	-3.49	5.96
Guinea	-1.94	1.60	Kazakhstan	-2.85	4.32
Guinea-Bissau	-1.73	1.39	Kosovo	-2.54	3.50
Kenya	-1.70	1.63	Kyrgyz Republic	-1.96	2.08
Lesotho	-1.87	1.56	Latvia	-2.91	4.74
Madagascar	-1.76	1.33	Lithuania	-2.64	4.04
Malawi	-1.71	1.34	Macedonia	-2.33	3.22
Mali	-1.96	1.60	Moldova	-2.02	2.41
Mauritania	-1.83	1.81	Montenegro	-2.78	4.21
Mauritius	-2.44	3.37	Poland	-3.27	5.37
Mozambique	-2.01	1.62	Romania	-2.40	3.38
Namibia	-1.39	1.11	Russia	-2.70	4.10
Niger	-1.81	1.38	Serbia	-2.80	4.25
Nigeria	-1.81	1.49	Slovak Republic	-2.94	4.85
Sao Tome and Principe	-1.75	1.50	Slovenia	-3.58	6.31
Senegal	-1.81	1.52	Tajikistan	-2.02	2.31
Seychelles	-2.35	3.51	Turkey	-2.41	3.48
Sierra Leone	-1.70	1.26	Turkmenistan	-1.78	1.70
South Africa	-1.46	1.32	Ukraine	-2.78	4.06
Swaziland	-1.90	1.61	Uzbekistan	-1.75	1.44
Tanzania	-1.82	1.38	**Region: LAC**		
Togo	-1.74	1.40	Belize	-1.65	1.78
Zambia	-1.74	1.45	Bolivia	-1.67	1.81
Region: EAP			Brazil	-1.54	1.64
China	-1.66	1.41	Chile	-1.89	2.49
Fiji	-2.11	2.60	Colombia	-1.68	1.90
Indonesia	-1.75	1.49	Costa Rica	-1.77	2.14
Lao People's DR	-1.76	1.52	Dominican Rep.	-1.81	2.09
Malaysia	-2.49	3.79	Ecuador	-1.67	1.75
Micronesia, FS	-1.83	1.98	El Salvador	-1.68	1.80
Mongolia	-2.03	2.20	Guatemala	-1.63	1.62
Papua new Guinea	-1.80	1.51	Guyana	-1.71	1.71
Philippines	-1.80	1.83	Haiti	-1.73	1.39
Solomon Islands	-1.73	1.49	Honduras	-1.57	1.43
Thailand	-2.45	3.42	Jamaica	-2.14	2.82
Timor-Leste	-2.10	1.78	Mexico	-1.81	2.15
Tonga	-2.22	3.00	Nicaragua	-1.75	1.81
Vietnam	-1.81	1.63	Panama	-1.47	1.58
Region: SA			Paraguay	-1.84	2.37
Bangladesh	-1.77	1.56	Peru	-1.71	1.85
Bhutan	-1.83	1.71	Trinidad and Tobago	-2.44	3.68
Maldives	-1.88	1.92	Uruguay	-2.47	3.87
Nepal	-1.74	1.38	Venezuela	-1.79	2.24
Sri-Lanka	-2.14	2.57			
Region: MENA					
Algeria	-2.36	3.18			
Djibouti	-1.82	1.86			
Iran	-2.21	3.11			
Iraq	-2.24	2.77			
Jordan	-2.97	4.58			
Morocco	-2.15	2.71			
Tunisia	-2.02	2.47			
West Bank and Gaza	-2.56	3.72			

Notes: This table displays the cross-country income and inequality elasticity of poverty calculated from the estimates of equation (12) as setting in the test.